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Mixed-Integer Programming with Enterprise Risk Analysis for Vehicle Electrification at Maritime Container Ports

Robert M. Baker, M.IEEE
Dept. of Systems and Information Engineering
University of Virginia
United States Coast Guard
Charlottesville, VA, USA
ugf4qj@virginia.edu

Megan C. Marcellin, M.IEEE
Dept. of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
mcm5ft@virginia.edu

Robert J. Riggs
Dept. of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
rr3bd@virginia.edu

Daniel C. Hendrickson
Vice President, Asset Management & Special Projects
Port of Virginia
Norfolk, VA, USA
dhendrickson@vit.org

Thomas L. Polmateer
University of Virginia
Charlottesville, VA, USA
tp3qh@virginia.edu

T. Donna Chen
Dept. of Civil and Environmental Engineering
University of Virginia
Charlottesville, VA, USA
tdchen@virginia.edu

Tariq Iqbal, M.IEEE
Dept. of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
tiqbal@virginia.edu

David L. Slutzky
Fermata LLC and University of Virginia
david@fermataenergy.com

James H. Lambert, F.IEEE, P.E.
Dept. of Systems and Information Engineering
University of Virginia
Charlottesville, VA, USA
lambert@virginia.edu

***Abstract*—There is urgency for electrifying fleet vehicles as a means to reach net-zero emissions and promote sustainability, including at maritime container ports. Ports are exploring the incorporation of electric terminal tractors and supporting infrastructure in an effort to minimize the environmental effects of their operations while simultaneously improving service performance. The challenges include planning of investments in infrastructure that will meet charging requirements of these terminal tractors while maintaining operational efficiencies. This paper develops an optimization and associated risk register for strategic capacity expansion of electric vehicle fleets at maritime container ports. The approach includes multi-criteria decision analysis (MCDA) and a characterization of enterprise risk as a disruption of system order. A demonstration of schedule optimization uses linear programming models for thirty-two combinations of plug-in, wireless, and wireless dynamic charging infrastructure configurations to determine optimal charger locations. In a robust ensemble model, the optimization accompanies a comprehensive risk analysis that disrupts importance orders across seven scenarios: (1) Environmental Change, (2) Policy Revision, (3) Technology Innovation, (4) Cyber Attack, (5) Market Shift, (6) Electrical Grid Stress, and (7) Workforce Interruption. The results support the decisions and enterprise risk management for a $1.5 billion strategic plan for port infrastructure. The plan involves selecting charging station locations, determining charging schedules, and selecting charger models while considering multiple performance criteria such as safety, operational efficiency, cost-effectiveness, and reliability. The approach is generally applicable for a variety of complex systems to mitigate schedule and cost risks while improving sustainability. The audience of the paper includes owners and operators of transportation and energy infrastructures, asset managers, logistics service providers, and others.**

***Index Terms*—multi-criteria analysis, linear programming, systems analysis, scheduling, electric vehicles, order disruption, scenario-based preferences**

I. Introduction

Maritime ports are essential to global trade and transportation, with terminal tractors serving as critical equipment for cargo handling and logistics operations. These tractors are designed to travel short distances and deliver shipping containers to ship-to-shore gantry cranes, rubber-tired gantry cranes, and container handlers located at rail yards and container stacks within maritime ports. Thus, these vehicles are great candidates for electrification due to their highly predictable, fixed route operations. The electrification of terminal tractors presents a promising avenue to achieving sustainable goals such as reducing emissions, improving air quality, and minimizing the environmental impact of port operations.

Electrification presents port authorities with economic opportunities such as earning government subsidies and tax credits, decreasing fuel and maintenance expenses, and even earning revenue by selling power back to electrical utility companies [1]. However, the success of electric terminal tractors integration is dependent on efficient charging infrastructure design, optimal scheduling strategies, and reliable power distribution from the electrical grid [2]. This paper aims to address the unique challenges of electrifying maritime port charging infrastructure using a combination of optimization and risk analysis.

II. Methods - Systems Analysis

A. Problem Formulation

A maritime port has a large menu to choose from when it comes to investing in electric terminal tractors, chargers, and charging locations. In this case, potential charging locations, charging technologies and models, and terminal tractor models were sourced from market research and stakeholder perspectives. The network diagrams in Fig. 1 depict four charging system investment options along a realistic terminal tractor route for a port moving more than three million containers per year. Each node within the network diagram represents a potential charging location where a plug-in, wireless, or dynamic wireless charging system could be installed. The charger types considered in this report are defined in the following manner [3]:

- *Wired:* plug-in style charger with CCS2 cable connection.
- *Wireless*: inductive charging occurring on a pad while a terminal tractor is stationary.
- *Dynamic Wireless:* inductive charging occurring beneath a roadway while a terminal tractor is transiting.

Given the differences in charging outputs and vehicle battery capacities available on the market, multiple options of charger manufacturers and battery capacities were considered. Thirty-two combinations of candidate infrastructure investments were modeled in this demonstration.

B. Linear Optimization Model

This section presents the charging infrastructure optimization model, which is largely adapted from Wang et. al.'s [6] optimization of electric fleet vehicles in urban networks. To transition the model to this application, the movement of terminal tractors is initially observed, which serves as the basis for creating the transportation network illustrated in Fig. 1.

Each model varies in terms of investment strategy, terminal tractor model, and charger models. In each instance, a terminal tractor makes four hundred moves in the following sequence: it starts at the service center (v_2) and takes North Bulkhead St. (v_3) to the North Rail Yard (v_4) where it picks up a

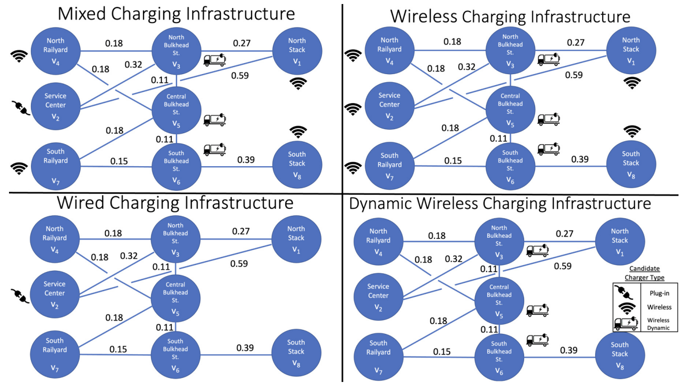

Fig. 1. Alternative investments in charging infrastructure at a maritime container port. The energy required (E), in terms of kWh, to traverse each arc is labeled in black near each arc.

container. The tractor then delivers that container to the South Stack (v_8) via Central and South Bulkhead St (v_5) (v_6). Once the container is dropped off at the South Stack, the tractor backtracks up South Bulkhead St. to the South Rail Yard (v_7) to retrieve another container. It takes that container and delivers it to the North Stack (v_1) via Central and North Bulkhead St. The tractor then bypasses the service center and returns to the North Rail Yard for another container and the pattern repeats for a total of four hundred moves. The number of moves was thoughtfully determined by considering the battery life of a MAFI T-230e terminal tractor and estimating the anticipated number of moves it could perform before needing a recharge. This analysis was carried out in strict accordance with the route structure.

In the "mixed charging infrastructure" models, the service center is bypassed after the first iteration because it is more operationally efficient for drivers to charge at wireless or dynamic wireless chargers whenever available. At plug-in charging locations, additional labor is required to charge the terminal tractors, either by the truck driver or a port employee who needs to connect the charger to the vehicle. On the other hand, in the "wireless" models, the service center is included in each iteration as a candidate charging location, as there is no additional labor required to charge the tractors there. Similarly, in the "wired" models, the service center is also included in each iteration since it's the only feasible location to install a wired charger in those models.

With the route structure sufficiently captured, the variables and parameters are then defined in Table I and II. Then, the models' objective and constraints can be written into algebraic form for optimization.

1) Objective Function: Ports have a keen interest in minimizing both the installation costs of terminal tractor charging infrastructure and the recharging expenses incurred during operations [7]. So, the model's objective is expressed as follows [6]:

$$\min Z = \sum_{q \in Q} \sum_{k=1}^{n_q} C_{g(q,k)} y_{q,k} + \sum_{i \in N} S_i v_i \tag{1}$$

TABLE I

VARIABLE ASSIGNMENTS AND DESCRIPTIONS FOR CHARGING INFRASTRUCTURE OPTIMIZATION MODELS

Model Component	Variable	Units	Description
Set	I	$\{1, 2, 3, \ldots, n_i\}$	Nodes within a network
Set	Q	$\{1, 2, 3, \ldots, n_q\}$	Routes within a network
Set	K	$\{1, 2, 3, \ldots, n_k\}$	Stops at each node within a route
Parameter	E	kWh	Energy required to transit from stop k to stop k+1 within route q.
Parameter	R	kWh	Charging upper bound at route q, stop k
Parameter	C	\$	Unit cost of charging at route q, stop k
Parameter	U	kWh	Terminal tractor battery capacity
Parameter	l	$\in \{0 \ldots 1\}$	Minimum battery percentage during operations
Decision Variable	v	$\in \{0, 1\}$	Decision to install a charger at node i
Decision Variable	y	kWh	Decision of how much energy to charge at route q, stop k
Extraneous Variable	x_a	kWh	Terminal tractor charge level upon arrival at route q, stop k
Extraneous Variable	x_d	kWh	Terminal tractor charge level upon departing route q, stop k

TABLE II

SAMPLE OF PARAMETERS OF CHARGING INFRASTRUCTURE FOR ELECTRIC VEHICLES AT MARITIME CONTAINER PORTS

Index	Initiative	Terminal Tractor	U	Plug-In Charger	R_plugin	S_plugin	Wireless Charger	R_wireless	S_Wireless	Dynamic Wireless Charger	R_dynamic	S_Dynamic
x.01	Mixed Charging	MAFI T-230e 150kWh	150	Heliox Flex 180 kW	150	$6,192.33	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.02	Wireless Charging	MAFI T-230e 150kWh	150	-	-	-	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.03	Wired Charging	MAFI T-230e 150kWh	150	Heliox Flex 180 kW	15	$6,192.33	-	-	-	-	-	-
x.04	Dynamic Charging	MAFI T-230e 150kWh	150	-	-	-	-	-	-	ENRX 180 kW charger	1.44	$94,927.00
x.05	Mixed Charging	Capacity 260 kWh	260	Heliox Flex 180 kW	180	$6,192.33	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.06	Wireless Charging	Capacity 260 kWh	260	-	-	-	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.07	Wired Charging	Capacity 260 kWh	260	Heliox Flex 180 kW	15	$6,192.33	-	-	-	-	-	-
x.08	Dynamic Charging	MAFI T-230e 150kWh	150	-	-	-	-	-	-	Electreon 70 kW charger	0.56	$94,927.00
x.09	Dynamic Charging	Capacity 260 kWh	260	-	-	-	-	-	-	ENRX 180 kW charger	1.44	$94,927.00
x.10	Dynamic Charging	Capacity 260 kWh	260	-	-	-	-	-	-	Electreon 70 kW charger	0.56	$94,927.00
x.11	Mixed Charging	MAFI T-230e 150kWh	150	Heliox Flex 180 kW	150	$6,192.33	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.12	Wireless Charging	Capacity 260 kWh	260	-	-	-	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.13	Mixed Charging	Capacity 260 kWh	260	Heliox Flex 180 kW	180	$6,192.33	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.14	Wireless Charging	MAFI T-230e 150kWh	150	-	-	-	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.15	Wired Charging	MAFI T-230e 150kWh	150	Heliox 360 kW	30	$8,551.33	-	-	-	-	-	-
x.16	Wired Charging	Capacity 260 kWh	260	Heliox 360 kW	30	$8,551.33	-	-	-	-	-	-
x.17	Wireless Charging	Capacity 260 kWh	260	-	-	-	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.18	Wireless Charging	Capacity 260 kWh	260	-	-	-	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00
x.19	Wireless Charging	MAFI T-230e 150kWh	150	-	-	-	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.20	Wireless Charging	MAFI T-230e 150kWh	150	-	-	-	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00
x.21	Mixed Charging	MAFI T-230e 150kWh	150	Heliox Flex 180 kW	150	$6,192.33	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.22	Mixed Charging	Capacity 260 kWh	260	Heliox Flex 180 kW	180	$6,192.33	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.23	Mixed Charging	MAFI T-230e 150kWh	150	Heliox Flex 180 kW	150	$6,192.33	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00
x.24	Mixed Charging	Capacity 260 kWh	260	Heliox Flex 180 kW	180	$6,192.33	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00
x.25	Mixed Charging	MAFI T-230e 150kWh	150	Heliox 360 kW	150	$8,551.33	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.26	Mixed Charging	Capacity 260 kWh	260	Heliox 360 kW	260	$8,551.33	Wave 250 kW	21	$12,384.67	ENRX 180 kW charger	1.44	$94,927.00
x.27	Mixed Charging	MAFI T-230e 150kWh	150	Heliox 360 kW	150	$8,551.33	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.28	Mixed Charging	Capacity 260 kWh	260	Heliox 360 kW	260	$8,551.33	InductEV 450kW	37.5	$18,577.00	ENRX 180 kW charger	1.44	$94,927.00
x.29	Mixed Charging	MAFI T-230e 150kWh	150	Heliox 360 kW	150	$8,551.33	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.30	Mixed Charging	Capacity 260 kWh	260	Heliox 360 kW	260	$8,551.33	Wave 250 kW	21	$12,384.67	Electreon 70 kW charger	0.56	$94,927.00
x.31	Mixed Charging	MAFI T-230e 150kWh	150	Heliox 360 kW	150	$8,551.33	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00
x.32	Mixed Charging	Capacity 260 kWh	260	Heliox 360 kW	260	$8,551.33	InductEV 450kW	37.5	$18,577.00	Electreon 70 kW charger	0.56	$94,927.00

[1] "R" for each charger was determined by incorporating five-minute duration constraint at each node with its charger's power output.

[2] "S" for each charger was derived from [4] and [5].

Equation (1) minimizes the overall cost of charging terminal tractors by considering the unit cost of charging at each charging station as well as each station's installation cost. To scale for the number of terminal tractors that each charging station can support, the S parameter in (1) is in terms of installation cost per supported tractor. Each model renders a decision (yes or no), v_i to install a charger at given node in the network and how much energy, $y_{q,k}$ to charge at each node.

2) Constraints: This section describes the nine constraints that are featured in each of the thirty-two models. Equations (2), (3), (4), (7), (9), and (10) are adapted from [6]. Equations (5), (6), and (8) were created as a part of this study to reflect the operational requirements of the Port of Virginia.

$$x_{d,q,k} - x_{d,q,k} - y_{q,k} = 0 \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{2}$$

$$x_{d,q,k} - x_{a,q,k+1} \geq E_{q,k} \quad \forall q \in Q, k = 1, 2, 3, ..., n_q - 1 \tag{3}$$

$$l \cdot U \leq x_{d,q,k} \leq U \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{4}$$

$$x_{d,q,n_q} \geq 0.95U \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{5}$$

$$x_{d,q,1} = U \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{6}$$

$$y_{q,k} \leq R_{q,k} v_g(q,k) \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{7}$$

$$y_{q,k,i} \geq R \quad \forall q \in Q, k = 1, 2, 3, ..., n_q, i = 3, 5, 6 \tag{8}$$

$$x_{d,q,k}, x_{a,q,k}, y_{q,k} \in R^{+} \quad \forall q \in Q, k = 1, 2, 3, ..., n_q \tag{9}$$

$$v_i \in \{0, 1\} \quad \forall i \in N \tag{10}$$

Equation (2) expresses the law of the conservation of energy as applicable to an electric terminal tractor network. The battery level upon departure at a node $x_{d,q,k}$, minus the battery level upon arrival at the same node $x_{a,q,k}$, minus the amount of charge gained at the node $y_{q,k}$ is equal to zero.

Equation (3) ensures that a terminal tractor will have a sufficient level of charge to reach the next node along the route. It does this by specifying that the battery level upon departing one node, minus the battery level upon arrival at the next node, must be greater than or equal to the amount of energy required to transit between the two nodes $E_{q,k}$.

Equation (4) ensures that the terminal tractor maintains a charge level above a specified threshold l and is not charged beyond the battery's capacity U. Equation (5) is a policy based constraint that forces the terminal tractors to finish the shift with greater than a 95% charge so that it is ready for the next shift. Equation (6) ensures that the terminal tractor starts each route with 100% charge.

Equation (7) constrains the decision of how much energy to charge at each node $y_{q,k}$ by mandating that $y_{q,k}$ is less than or equal to the amount of charge available at a given node $R_{q,k}$, multiplied by the decision to install a charger at that node v_i. This constraint collaterally ensures that terminal tractors can only charge at a location where a charger is installed. This constraint is effectively a duration constraint since $R_{q,k}$ is largely based on the port's operational requirements. In other words, terminal tractors are constrained to charging for a maximum amount of time at each stop so they can continue moving containers throughout the port and allow opportunities for other tractors to charge.

Equation (8) further confines that charging decision $y_{q,k}$ at nodes 3, 5, and 6 to ensure they do not receive less charge than available. This constraint is necessary since nodes 3, 5, and 6 are candidates for dynamic wireless charging. If the terminal tractors were free to accept less charge at nodes 3, 5, and 6 in an effort to minimize the objective function, this would mean that they would be traveling over the port's posted speed limit of twenty miles per hour, violating established policy.

Equations (9) and (10) are variable restrictions. The battery level upon departure and arrival from a node and the amount of charge acquired at any node must be a positive number. The decision to install a charger at a node within the network is a binary variable.

C. Optimization Model Results

The thirty-two models in Table II were solved in A Mathematical Programming Language (AMPL) Independent Development Environment (IDE) version 3.6.10 [9]. Within AMPL, the Gurobi 10.0.1 solver was used to find the optimal charging station locations and charging schedules. Fig. 2 describes the optimal solution per model and represents the cost to install charging infrastructure per supported vehicle and operational costs for four hundred terminal tractor moves. The results indicate that in general, the cost-optimized order of infrastructure investment strategies is as follows:

1) Wired Charging Infrastructure
2) Mixed Charging Infrastructure
3) Wireless Charging Infrastructure
4) Dynamic Wireless Charging Infrastructure

As depicted in Fig. 2, the optimization program is biased towards minimizing the infrastructure installation cost. This preference stems from the fact that the scale of this parameter significantly outweighs the cost of charging in the models. Looking through the lens of optimization, the preferred investment strategy is a charging infrastructure design consisting only of a plug-in charger at the service center ($x.03$). Table III shows the charging schedule for this model.

TABLE III
LINEAR OPTIMIZATION PREFERRED MODEL AND CHARGING STATION LOCATIONS: MODEL ($x.03$) - WIRED

Node	v	sum y (kWh)	Charging Cost	Utilization
1 - North Stack	0	0	$-	0.00%
2 - Service Center	1	104.11	$12.49	100.00%
3 - North Bulkhead St.	0	0	$-	0.00%
4 - North Railyard	0	0	$-	0.00%
5 - Central Bulkhead St.	0	0	$-	0.00%
6 - South Bulkhead St.	0	0	$-	0.00%
7 - South Railyard	0	0	$-	0.00%
8 - South Stack	0	0	$-	0.00%
	Total:	104.11	$12.49	

III. Methods - Risk Analysis

Following the optimization, a risk analysis is conducted to account for uncertainties and potential risks associated with each charging infrastructure configuration. While cost considerations are a significant factor in electric charging infrastructure investment for ports, other criteria and potential risks must be considered to make a holistic decision. Factors include, but are not limited to: safety, operational disruption cost from installation, charger interoperability, maintenance costs, charger footprint, and time savings. By considering supplementary criteria in the optimization model, through a risk analysis, the relative rankings of infrastructure models are significantly altered. This augmentation enriches the decision-making process by creating more pronounced disparities in the ranks of each candidate infrastructure plan. The introduction of these supplementary criteria empowers decision-makers to gain deeper insights and make more informed choices in selecting the most suitable infrastructure plan for the given context.

A. Risk Analysis Methodology

This study uses the risk register approach presented by Hassler et. al [10] and adapts it to the criteria and emergent conditions pertaining to container ports. Fig 3 displays the overall process of assembling the risk register.

A set of initiatives $X = \{x_i, ..., x_k\}$ have previously been defined in this paper and are listed in Table II. Each initiative is evaluated on a set of performance criteria $C = \{c_1, ..., c_k\}$ developed by port leadership, academic consultants, and subject matter experts. This criteria is noted in Table IV.

After establishing performance criteria, each initiative is assessed by the degree of which the initiative satisfies the performance criteria. Appraising each initiative with performance criteria allows for baseline a system ranking to be generated. In this study, a baseline system ranking is the order of preference for investing in a candidate terminal tractor charging infrastructure plan. The fundamental idea behind the risk register methodology is to develop emergent conditions $E = \{e_1, ..., e_i\}$, which form disruptive scenarios $S = \{s_1, ..., s_k\}$, and challenge the resilience of the system components. In this application, emergent conditions such

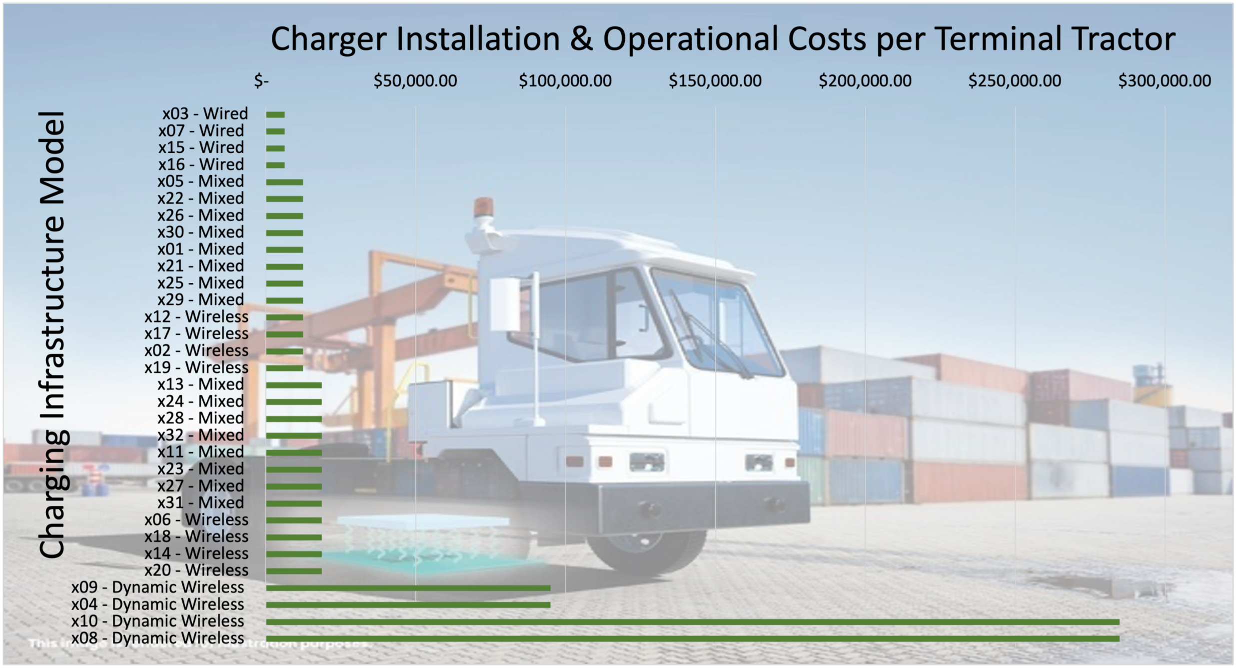

Fig. 2. Cost of charging infrastructure installation and operational cost per supported terminal tractor. The background image depicts a terminal tractor being charged on a wireless charging pad. Image Source: [8]

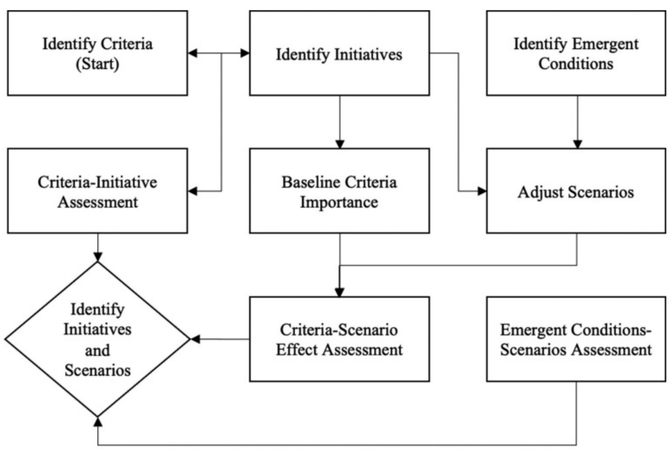

Fig. 3. Conceptual diagram of enterprise risk assessment methodology for electric terminal tractor charging infrastructure investment [11]

as energy price fluctuations, electrical grid stability, battery degradation, and ransomware attacks are of particular interest. Tables V and VI show the emergent conditions and disruptive scenarios for this case study.

Imposing disruptive scenarios onto the system order changes the weight of each performance criteria from one scenario to the next [12]. As an example, when introducing a cyber attack ($s.04$) to the baseline system, vehicle systems safety ($c.09$) becomes increasingly more relevant as the vehicles, their on-board control systems, and associated charging infrastructure are at imminent risk [13]. On the contrary, a terminal tractor's battery capacity ($c.12$) becomes less relevant during a cyber

TABLE IV
PERFORMANCE CRITERIA FOR TERMINAL TRACTOR CHARGING INFRASTRUCTURE

Index	Criteria
c.01	Charging Speed (kW)
c.02	Charging Efficiency
c.03	Time Savings
c.04	Charger Installation Costs
c.05	Maintenance Costs
c.06	Footprint
c.07	Interoperability
c.08	Human Safety
c.09	Vehicle Systems Safety
c.10	Operational Costs
c.11	Installation Disruption Cost
c.12	Battery Capacity (kWh)

TABLE V
EMERGENT CONDITIONS FOR CHARGING INFRASTRUCTURE INVESTMENT

Index	Emergent Condition
e.01	Increased Energy Cost
e.02	Decreased Energy Cost
e.03	Inclement Weather
e.04	Reduced speed limit
e.05	Autonomous Terminal Tractors
e.06	Increased Battery Capacity
e.07	Battery Degradation
e.08	Decreased Trade
e.09	Workforce Strike
e.10	Ransomware Attack
e.11	Brownout
e.12	Foreign Object Damage
e.13	Human Damage
e.14	Increased trade
e.15	Wear and Tear
e.16	Denial of Service Attack
e.17	Increased Speed Limit

TABLE VI
DISRUPTIVE SCENARIOS FOR CHARGING INFRASTRUCTURE INVESTMENT

Index	Scenario
s.01	Environmental Change
s.02	Policy Revision
s.03	Technology Innovation
s.04	Cyber Attack
s.05	Market Shift
s.06	Electrical Grid Stress
s.07	Workforce Interruption

attack ($s.04$) since it is unaffected in this scenario. The risk register employs this ideology to compute a disruption score for each scenario, using the linear additive value function in (11). In this function, W represents a vector of scenario impact scores.

$$V(x_i)_k = W_k X_i \tag{11}$$

By utilizing a matrix of impact scores for each initiative and scenario, we can rank the initiatives based on the logic in (12):

$$\text{IF } V(x_i)_k > V(x_j)_k \text{ THEN } x_i \succ X_j \tag{12}$$

The scores for each initiative $X = \{x_i, ..., x_k\}$ under all scenarios $S = \{s_1, ..., s_k\}$, are then stored in variable $R(x_i)_k$. Then, a disruptiveness score $D(S_k)$ can be can be calculated for each scenario using the sum of square ranking in (13).

$$D(s_k) = \sum_{i=1}^{n} (R(x_i)_b - R(x_i)_k)^2 \tag{13}$$

As emphasized by Donnan et al. [14], the disruptiveness scores offer invaluable insights to stakeholders, enabling them to pinpoint the scenarios with the most significant impact on their operations. Consequently, this invaluable information enhances strategic planning and empowers effective risk mitigation efforts.

B. Risk Assessment Results

Using the methodology described in Section III-A, the results in Fig. 4 and Fig. 5 were obtained. In Fig 4, the baseline ranking for each charging infrastructure plan is represented by black lines. These lines indicate the relative positions of the initiatives under normal circumstances. The blue lines depict the promotion potential of each initiative during disruptive scenarios, signifying how their rankings may improve. On the other hand, the red lines illustrate the demotion potential, indicating how the rankings might be negatively impacted in such scenarios.

In this case study, initiative ($x.06$) is the preferred charging infrastructure plan when considering stakeholder criteria and model performance through disruptive scenarios. Table VIII displays the optimized charger investment strategy for initiative ($x.06$) which is determined by the methods described in Section II. In this model, the optimization solution is to invest in a terminal tractor with a 260 kWh battery and install a 450 kW wireless charger. It is evident that this initiative is strongly favored, as it fulfills a substantial portion of the port's criteria. The high-range terminal tractor battery, combined with the wireless charger's exceptional power transfer rating, leads to significant time savings. Additionally, the chargers' small footprints and low maintenance costs in this model further contribute to its attractiveness. This initiative is ranked first in the baseline rankings and is the most robust initiative (with the exception of the lowest ranked initiative, ($x.21$) as it can only demote by four rankings throughout all considered disruptive scenarios). The difference between an initiative's promotion and demotion potentials is interpreted as the initiative's robustness through disruptive scenarios [12].

An important feature to observe from the disrupted rankings are the volatilities of the initiatives. In contrast to robust initiatives, volatile initiatives have both high promotion and demotion potential, indicated by a wide range along the x-axis of Fig. 4. In this case study, initiative ($x.09$) represents a dynamic wireless charging infrastructure configuration and is initially ranked 9th in the baseline evaluation. Under emergent conditions, this initiative's rank fluctuates, reaching the top-ranked priority or falling to the 30th position depending on the scenario. The volatility observed in initiatives like ($x.09$) serves as a crucial warning to stakeholders, prompting them to thoroughly investigate the underlying causes of this fluctuation and take necessary countermeasures to address any potential risks. For a comprehensive understanding of scenario disruptiveness and initiative robustness, refer to Table VII.

Fig. 5 provides a graphical representation of the normalized disruption caused by each scenario. Among these scenarios, ($s.06$) - *Electrical Grid Stress* stands out as the most disruptive one. Given the common concerns about electrical grid instability, especially for major electricity consumers like container ports [15] [16], this result leads to valuable insights. Realizing the severity of grid stress through this analysis, the port can then take proactive measures to address grid instability. For instance, the port may consider investing in emerging Vehicle to Grid (V2G) technologies, such as bi-directional chargers [17]. These technologies enable electric vehicles (EVs) to act as supplementary power sources for the grid, enhancing its resilience during critical periods of stress. As an additional countermeasure to address electrical grid stress, ports can make investments in optimized energy storage systems. These energy storage systems could then bolster the resilience of the port's microgrid. By incorporating such optimized energy storage solutions, ports can better manage fluctuations in electricity supply, ensuring continuous and reliable power availability even when the external grid faces challenges [18]. By leveraging the described methodology, ports can effectively devise tailored countermeasures to tackle disruptive scenarios beyond the ones named in this research. By implementing these measures, ports can notably reduce their risk exposure and optimize performance.

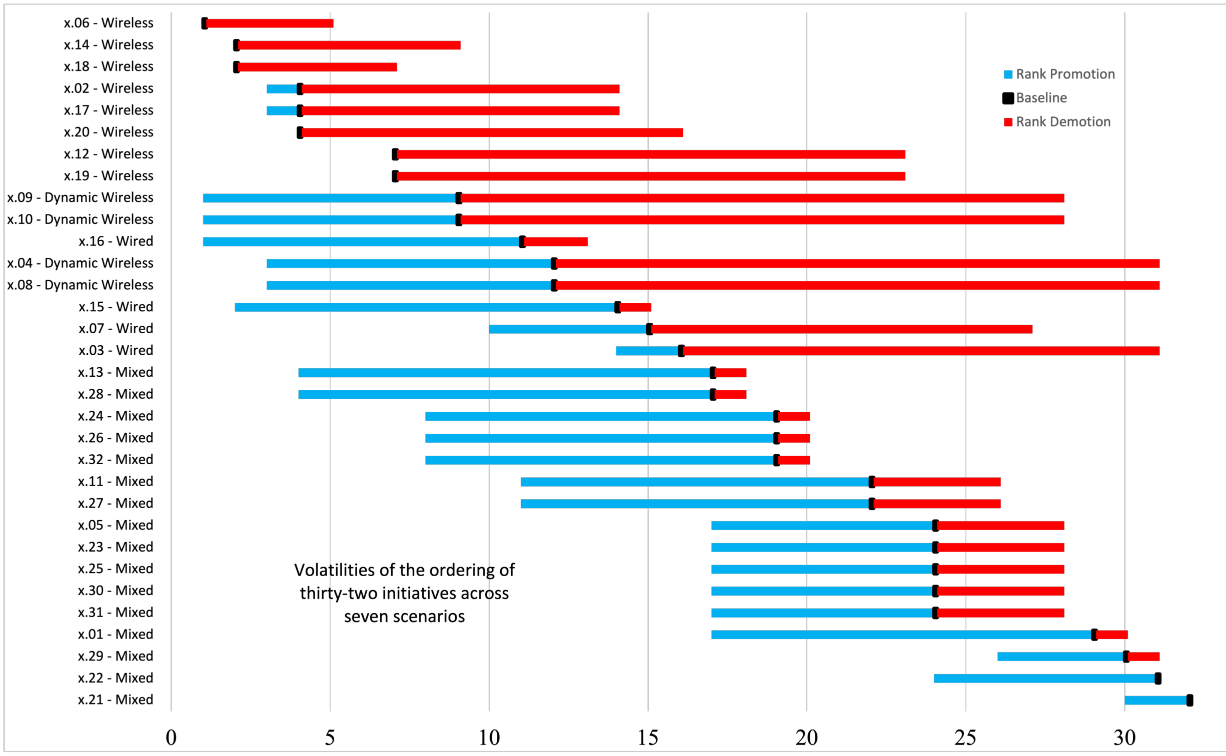

Fig. 4. Results of risk assessment of selected terminal tractor charging infrastructure initiatives. The black line is the baseline ranking of each initiative according to stakeholder criteria. The blue and red lines are the promotions and demotions in ranking, respectively, of each initiative throughout disruptive scenarios.

TABLE VII
SUMMARY OF RESULTS FOR RISK ANALYSIS OF TERMINAL TRACTOR CHARGING INFRASTRUCTURE

Result Type	**Description**
Most-disruptive scenarios	Electrical Grid Stress ($s.06$) and Technology Innovation ($s.03$) are the most-disruptive scenarios.
Least-disruptive scenarios	Environmental Change ($s.01$) is the least-disruptive scenario with Market Shift ($s.05$) as a close second.
Most-robust initiatives	Mixed Charging Model ($x.21$) is the most-robust initiative, however, it is ranked low throughout all scenarios. Mixed Charging Infrastructure Model ($x.06$) is the dominating initiative. It has a baseline rank of priority #1 and falls no further than the #5 ranked initiative through all scenarios. All other initiatives have the potential to shift more than 4 places in the rankings.
Other robust initiatives	Wireless Charging Model ($x.18$) and Mixed Charging Model ($x.29$) are considered robust initiatives. Both initiatives only shift by a magnitude of 5 rankings throughout the sample of disruptive scenarios. ($x.18$) can be ranked as high as #2 and as low as #7 while ($x.29$) can be ranked as high as #26 and as low as #31.

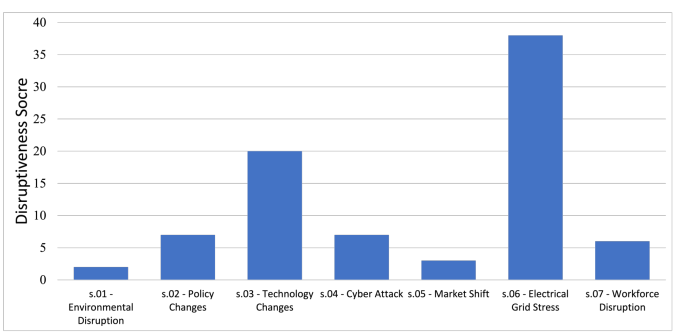

Fig. 5. Disruptiveness scores for each scenario. Each score is normalized on a scale of 0-100 with 0 being the least disruptive and 100 being the most disruptive.

IV. CONCLUSIONS

An innovation of this paper is to combine traditional optimization techniques with enterprise risk analysis to demonstrate the dynamic reordering of investment candidates during disruptive scenarios in industrial electrification applications. This valuable approach empowers port authorities and fleet managers to use the findings as a solid foundation for making informed and confident decisions concerning fleet vehicle electrification.

Future work includes scaling the optimization and risk models to consider smart charging strategies, which incorporate V2G technology, peak shaving, and additional battery parameters into charging schedules [19]. Additional models

TABLE VIII
CHARGING STATION LOCATIONS IN THE RISK ANALYSIS PREFERRED MODEL - $(x.06)$ - WIRELESS

Node	v	sum y (kWh	Charging Cost	Utilization
1 - North Stack	0	0	$-	0.00%
2 - Service Center	0	0	$-	0.00%
3 - North Bulkhead St.	0	0	$-	0.00%
4 - North Railyard	1	91	$10.92	100.00%
5 - Central Bulkhead St.	0	0	$-	0.00%
6 - South Bulkhead St.	0	0	$-	0.00%
7 - South Railyard	0	0	$-	0.00%
8 - South Stack	0	0	$-	0.00%
	Total:	91	$10.92	

could be constructed to include collaboration between humans and robots [20] [21]. These robots are engineered with the capability of anticipating human behaviors like interpreting hand signals. Such interpretation skills, combined with adequate dexterity, would make for an effective robot teammate to assist humans with plug-in charging operations.

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