NORTHWESTERN UNIVERSITY
TRANSPORTATION CENTER

Argonne NATIONAL LABORATORY

LOwering CO2: Models to Optimize Train Infrastructure, Vehicles, and Energy Storage (LOCOMOTIVES)

Summary of Expansions and Updates to the Northwestern University Freight Rail Infrastructure & Energy Network Decarbonization (NUFRIEND) Framework

Final Technical Report

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Final Technical Report

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Section A - Executive Summary

The project aimed to develop a comprehensive modeling and optimization framework to facilitate the decarbonization of freight rail transportation in the United States, focusing on the temporal deployment of alternative technologies. Progress across four quarters is highlighted, encompassing various milestones and key activities.

The project initiated with the establishment of a management plan, team assignments, and continued stakeholder engagement through our Industry Advisory Board (IAB). Data consolidation efforts were conducted, informing the suite of operational parameters for the selected technology portfolios. A research framework was established, with an emphasis on establishing the interface between rollout scenarios, optimization models, and evaluation tools. In the second quarter, specific rollout scenarios were refined with enhanced granularity and matched to their respective performance metrics, leading to the completion of the alpha optimization framework. Techno-economic analyses were initiated on battery-electric locomotives and applied to other technologies thereafter. In the third quarter, the defined rollout scenarios were extended to 2050 and were integrated into a beta optimization framework. The framework's capabilities were broadened to include hybrid locomotive deployment simulations, expanding its applicable suite of energy technologies. Continued stakeholder engagement and refinement of the technology-to-market plan underscored the project's practical relevance. The project culminated with the completion and testing of the full rollout optimization framework, including hybrid locomotive simulations. The project's deliverables, including the NUFRIEND Framework and open-source code and user guide documenting its functionalities and updates, were finalized for public access.

Throughout the project, technology-to-market initiatives remained pivotal, ensuring alignment with industry needs. With the development of the NUFRIEND Rollout Optimization Framework and updates to the existing NUFRIEND Dashboard, continual stakeholder engagement and feedback from industry and government stakeholders allowed for the refinement of a fully functioning simulation framework. Meetings with the Industry Advisory Board (IAB) and specific railroad companies facilitated crucial feedback and guidance. Notable advancements, including dashboard updates for improved user interaction and functionality, were initiated based on feedback from stakeholders and industry experts following presentations such as those made at the ARPA-E Energy Innovation Summit and the NUTC Business Advisory Council Meeting.

The project has achieved significant milestones in its endeavor to facilitate the decarbonization of freight rail transportation in the United States. Through the development of the NUFRIEND Optimization Framework alongside the integration of hybrid diesel-battery locomotive configurations (and updates made to prior work), the project has provided a robust and flexible simulation platform for evaluating alternative energy technologies. Stakeholder engagement has been paramount throughout the project, with invaluable feedback from industry leaders and government officials shaping the refinement of tools and frameworks. The technology-to-market initiatives have garnered widespread interest and enthusiasm, positioning the NUFRIEND Dashboard as a valuable decision-making tool for industry stakeholders. As the project nears its conclusion, the team remains committed to disseminating findings, engaging stakeholders, and ensuring the continued impact and relevance of the NUFRIEND Framework in the ongoing efforts to mitigate emissions and enhance sustainability in freight rail operations.

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Section B - Accomplishments and Objectives

The actual performance against the stated milestones is summarized below:

Table 1 - Key milestones and deliverables compared against the actual performance

WBS	Milestone Title	Summary
M0.1	Management plan delivered	**Milestone:** The team provides the management plan that will include team leaders for specific tasks, and teams meeting frequency, etc. **Actual Performance:** Management plan submitted with team leaders identified and team meeting system established.
M0.2	Signed IP agreements	**Milestone:** IP agreement(s) is signed with priority concept team(s). **Actual Performance:** IP agreements signed.
M5.1	Data consolidation	**Milestone:** Data are consolidated from the previous project, including freight demand, rail GIS, railroad operating, energy source LCA and TEA data, and locomotive performance data. **Actual Performance:** All data from previous phase have been consolidated and reviewed for gaps/missing components that would be necessary for evaluation and optimization of time-dependent infrastructure and technology rollouts.
M5.2	Data collection	**Milestone:** Necessary data are acquired and analyzed with spatio-temporal dimensions including train operating data for different energy sources from testing and/or microsimulations, raw data for LCA and TEA estimates over different time horizons and across different geographies for all energy technologies. Focus is laid on the capability of locomotives with hybrid consists. Opportunities are identified for more granular data sharing from Class I railroad engagement. **Actual Performance:** Additional data needs are being met by combining flow forecasts from FAF5 to project CCWS data, projecting emissions and energy technology cost data over time, and producing locomotive powertrain simulations for hybrid locomotive operations.

WBS	Milestone Title	Summary
M5.3	Rollout scenarios defined	**Milestone:** Scenarios of rollout plans are defined to analyze across time horizons (e.g., 5, 10, …, 50 years, etc.), objectives (e.g., cost vs. emissions reduction), constraints (e.g., cost/emissions targets, budgets, rail restrictions, etc.), energy technology combinations, and railroads. Determine key parameters for the cost, environmental, and operational analyses. Plan validation methods for scenario results. **Actual Performance:** Rollout scenarios for testing outlined, focusing on a time horizon through 2050, and including hybrid locomotives as a new potential energy technology, in addition to those considered in the first project phase. Freight rail demand forecasts for high and low demand growth conducted through 2050 for use in scenario specification, including commodity- and market-specific growth forecasts. Collection of energy technology, cost, and emissions parameters completed.
M5.4	Performance metrics	**Milestone:** Performance metrics of interest are identified within the categories of cost, emissions, and operational impacts. The Full roll-out model (FRM) is expected to include many time-dependent parameters, including but not limited to projected ES performance and cost, freight rail fleet turnover, ES manufacturing scale/capacity, infrastructure buildout, diesel, and other fuel costs, operational performance metrics, etc. These may include computational performance (i.e., solution time and solution quality). Document is submitted for PD approval. **Actual Performance:** Performance metrics to measure environmental impacts, in terms of greenhouse gas emissions reductions (in ton CO_2), economic impacts, in terms of levelized cost of operations (in \$/ton-mile, \$/kWh, or \$/kgH_2), and operational impacts, in terms of additional delay or resulting rerouting, are outlined.
M6.1	Full rollout Optimization Framework Defined	**Milestone:** An expanded optimization framework template for the software modules is defined. This includes platform workflow, user input and output interactions, and data flow. This should detail how the optimization module interacts and passes information with the LCA and TEA simulation modules as well as the spatio-temporal characteristics of the problem. Provide details of new optimization approach and modifications relative to existing simulation framework and additional data requirements and flows. Provide mathematical formulation(s) for new approach. Document is submitted for PD approval.

WBS	Milestone Title	Summary
		Actual Performance: Structure of the Full Rollout Optimization Framework is described and visualized in a framework flowchart (see Figure 2). Module interactions and user inputs are outlined.
M7.1	Go/No-Go Alpha Optimization Framework	**Milestone:** The initial implementation of the optimization framework that connects Alpha module placeholders is completed, including the extension to hybrid consists. Data structures and flows through the model are established and incremental code testing methods are developed. The I/O table is documented. The performance metrics defined in M1.4 are validated through test scenarios defined in M1.3 for the implemented Alpha Framework to inform next steps. **Actual Performance:** Alpha Optimization Framework and components for time-dependent technology rollout optimization completed. Framework tested on currently available data and scenarios outlined in M5.3 and evaluated on metrics outlined in M5.4.
M7.2	Techno-economic analysis	**Milestone:** Techno-economic analysis is expanded based on existing frameworks to evaluate the levelized cost of hydrogen for fuel cell locomotives (in $/kg_H2) and electricity for fast charging of battery electric locomotives (in $/kWhe) at different points of time, region, and scale of deployment. **Actual Performance:** The time-dependent parameters relevant to battery-electric and hydrogen locomotives are evaluated. This includes the energy storage cost, battery density, emissions related electricity generation, electricity prices, and hydrogen prices from 2023-2050.
M7.3	Beta Optimization Framework	**Milestone:** Beta level submodules are created for each component and integrated into the framework. This includes models for LCA, TEA, and optimization models for the rail network, infrastructure, train operations, ES technologies and locomotive powertrains (including hybrid consists). This terminates with an optimal rollout strategy and a metric evaluation module, which outputs target levels of GHG, LCOTKM, and operational measures. Life cycle analysis (LCA) of various fuels/powertrain technologies - based on GREET model, is expanded in the tool for calculating the carbon reduction potential (in gCO2e/MJ and gCO2e/Mt-km)) for each energy and locomotive technology pathway, time horizon, and across regions (relative to conventional diesel locomotives) for freight rail applications on various duty cycles. Optimal rollout strategy results are documented, as well as I/O tables and user interface per FOA request. The performance metrics defined in M1.4 are validated through test scenarios defined in M1.3 for the implemented Alpha Framework for further refinement.

WBS	Milestone Title	Summary
		Actual Performance: Beta Optimization Framework and components for time-dependent technology rollout optimization integrated. Framework tested on currently available data and scenarios outlined in M5.3 and evaluated on performance metrics outlined in M5.4. Platform/display tool under development to showcase the results of the framework and scenario runs.
M7.4	Full Rollout Optimization Model	**Milestone:** Full roll-out model validation. Data collected are used to conduct validation of optimization model estimates over a varying set of conditions (e.g., energy sources, hybrid consists, time horizons, railroads, parameter confidence intervals, etc.) and characterize the model accuracy. Illustrative examples of full roll-out model scenarios are documented. Using the inputs from previous tasks, such as the adoption rates of transitional technologies, refueling cost, etc., we further analyze the best locations and build-out roadmaps for deploying the refueling infrastructure such as charging stations, battery storage, hydrogen refueling to support the roll-out of new ES technology adoption spatially and temporally for different decarbonization scenarios. The results are evaluated based on the fleet-wide aggregated energy consumption, GHG emissions, and costs of selected or all possible ES systems and fuel pathways to identify the decarbonization options with rail freight. Document is submitted for PD approval. **Actual Performance:** Validation of framework developed in M7.3 completed, using the scenarios defined in M5.3 on metrics laid out in M5.4. We compare/interpret these results with those used in first project phase for static deployment. Display tool developed development to showcase the results of the framework and scenario runs. To be released with open-source code and final report.
M8.1	Initial technology to market plan submitted to ARPA-E	**Milestone:** Initial T2M plan includes the continued engagement of Class I railroads with the existing dashboard tool to begin collaboration and data partnerships. Assess value of technology based on market impact to determine appropriateness of further work. Document is submitted for PD approval. **Actual Performance:** Initial T2M plan features the continuation of engagement with the project's Industry Advisory Board, featuring members of the US Class I railroads. Emphasis is placed on gaining information and valuable insights to consider in the deployment of alternative fuel technologies as well as in the development of the user-oriented tool.

WBS	Milestone Title	Summary
M8.2	Stakeholder engagement	**Milestone:** Industry Advisory Board briefing and engagement for feedback on scenarios is carried out. Relevant information on data needs defined in M1.2 are collected. Stakeholder engagement covers value proposition, adoption barriers, and criteria for uptake, with model structure, functionality, tech demonstration of planned capabilities, and IP strategy for open-source determined. Continued railroad engagement is maintained for testing and utilization of the optimization framework. Any data sharing and testing objectives are defined. Railroad data are used to test and validate the optimization framework. Results are analyzed for insights and feedback from the railroad is obtained. **Actual Performance:** Stakeholder engagement tasks involving meetings with executives from the BNSF and shortline railroads is continued. Insights are gained through meetings and presentations of NUFRIEND Dashboard, including the presentation at the NUTC Business Advisory Council meeting on Nov. 9. Engagement with ARPA-E scientists working on energy-related research for the decarbonization of freight decarbonization helped to improve the functionality of the NUFRIEND Dashboard.
M8.3	First iteration of T2M plan	**Milestone:** The initial T2M plan is reviewed, with industry advisory board briefing and input on methodology and scenario data. Document is submitted to PD for approval. **Actual Performance:** First iteration of T2M plan included and in place. Features presentation of current work to optimize the time-dependent deployment of charging/refueling facilities on rail networks to the Industry Advisory Board members at the NUTC BAC meeting on Nov. 9. Includes goals for continued feedback and communication from stakeholders in the rail industry.
M8.4	Levelized cost of ES technology	**Milestone:** This task develops estimates for a fair baseline comparison of the cost components to establish a firmer basis for costs such as capital cost, maintenance and repair, depreciation, and operating costs for rail for the different ES technologies considered. Document is submitted for PD approval. **Actual Performance:** Full suite of technologies for comparison is completed, including hybrid diesel/battery locomotives. Comparison of technologies, utilizing the updated NUFRIEND Dashboard is underway, with results summarized in material to be published along with release of public dashboard access and final reporting.
M8.5	Release Open-Source Code	**Milestone:** The open-source software code is prepared and publicly released on GitHub. Documentation of the code is

WBS	Milestone Title	Summary
		provided. A getting started tutorial will guide new users through setting up and running an optimization simulation. A set of example assumptions, that reflect the most current public information, are provided with example results. **Actual Performance:** Code documented and packaged for use by multiple stakeholders. Updates to underlying models and NUFRIEND Dashboard user interaction included in most recent version. Open-source code to be released with final report.

Section C - Project Activities and Background

The goal of this project was to develop a tool to aid railroads and other stakeholders assess and approach the decarbonization of freight rail operations. The NUFRIEND framework was developed to address the project goals as a network-level optimization and scenario simulation and evaluation tool. Following the initial phase of work, this report details the updates and expansions made to improve the NUFRIEND framework's applicability and functionality for a broader range of stakeholders and use cases. The resulting suite of tools present users with a comprehensive industry-oriented tool for simulating the deployment of new energy technologies across the U.S. freight rail network over time. In it, scenario-specific simulation and optimization modules provide estimates for carbon reduction, capital investments, cost of carbon reduction, as well as operational impacts for any given deployment profile. The NUFRIEND Framework code package and Dashboard, along with supporting documentation and reports have been made publicly available.[1]

Section C.1 - Introduction

The transportation sector is the largest contributor to greenhouse gas (GHG) emissions in the US, contributing 27% of the emissions in 2020 [1]. Many transportation modes, particularly in the freight sector, have been difficult to decarbonize due to their massive energy requirements and the associated investments that would be necessary for that purpose. However, recent advances in lower-carbon fuels, battery technology, and hydrogen fuels have provided potentially viable alternatives to diesel for these traditionally hard-to-decarbonize modes.

In 2019, the US freight rail sector accounted for approximately 40% of the national freight ton-miles and emitted nearly 40 megatons of CO_2 into the atmosphere in the process, an amount equivalent to the emissions of all the passenger vehicles in Texas alone [2], [3]. Though freight rail offers about four times greater energy efficiency than trucking [4], recent strides in the electrification of trucks [5] may significantly reduce rail's environmental advantage and cause freight demand to shift away to less energy efficient modes. As rail freight's importance in the overall supply chain continues to grow in the era of e-commerce [6], freight demand is forecast to grow rapidly in the coming decades [7], which may counteract railroads' investments in engine efficiency improvements. External pressures have also been mounting to decarbonize freight rail as local governments have considered regulations on locomotive idling in urban areas [8] and large shippers such as Amazon and IKEA have committed to net-zero carbon emissions by 2040 which include those produced by the shipment of their goods [9].

Diesel-electric locomotives have dominated US freight rail operations since the 1960's [10] and have seen significant improvements in powertrain efficiencies since that time [11]. With the exception of a few corridors in the Northeast, track electrification has been limited to passenger rail as it would place a significant economic burden on private freight railroads to deploy electrical infrastructure in mostly rural stretches of the country and upgrade the many track segments that cannot accommodate overhead rail due to height constraints [12]. Advancements in alternative energy storage technologies in recent decades—particularly in lower-carbon drop-in fuels, battery chemistries, and cleaner hydrogen pathways—offer a practical alternative to track electrification

[1] https://www.transportation.northwestern.edu/research/featured-reports/locomotives.html

for decarbonization. Railroads and fuel chemists now have a larger portfolio of lower-carbon diesel replacements (e.g., biodiesel, electric-fuels, renewable-diesels) than they did a decade ago [11]. Innovations in battery chemistry have led to increased volumetric and gravimetric energy densities, while reducing their overall cost per energy storage capacity [13], making this technology sufficiently mature to power electric locomotives [14]. Hydrogen combustion and fuel cell experimentation has made the technology viable for locomotive applications [11], while experimentation in fuel production has yielded many different kinds of hydrogen fuel pathways (e.g., steam-methane reforming, electric, nuclear, renewable), each with differences in their environmental impacts and costs of production [15]. Each of these alternative technologies provide distinct benefits and challenges to their implementation and must be compared on the economic, environmental, and operational impacts of their deployment to appropriately assess their value.

Several high-profile pilot studies have been conducted in partnership between multiple railroads, locomotive manufacturers, and local and state governments to test the viability of alternative technologies on revenue service [11], [16], [17]. The 2019 BNSF-Wabtec battery-electric pilot ran a battery-electric locomotive in a diesel-hybrid consist on revenue service between the 300-mile Stockton-Barstow route in California, showing emissions reductions of approximately 15% [16]. In partnership between the Pacific Harbor Line and Progress Rail, a battery-electric switcher locomotive was run in the Port of Los Angeles and Long Beach to investigate its performance while reducing carbon emissions and eliminating all localized pollutant emissions [17]. The Union Pacific Railroad has purchased 20 battery-electric locomotives for use as yard switchers, making it the largest commercial investment in the technology to date [18]. After running a hydrogen fuel cell locomotive pilot, Canadian Pacific has committed to expanding its fleet of hydrogen locomotives and constructing two hydrogen production facilities to supply their operations [19].

Picking the right mix and schedules to invest and deploy the next-generation of energy technologies is a challenging process. Technological uncertainties, network effects, regional economics, and economies of scale all render mathematical optimization formulations of the problem essentially intractable. Decarbonization decisions will no-doubt have far-reaching environmental, operational, and financial impacts on railroads, shippers, regulators, and other stakeholders in the greater supply chain. While previous research focused on conventional fuel types and highly simplified railroad networks, there is a significant research gap in developing optimization models to support the deployment of infrastructure to support rail decarbonization.

Section C.2 - NUFRIEND Framework

The Northwestern University Freight Rail Infrastructure & Energy Network Decarbonization (NUFRIEND) Framework was developed to assist the rail industry in planning and evaluating the adoption of alternative fuels for decarbonization efforts. Scenario-specific simulation and optimization modules provide estimates for emissions reduction, capital investments, cost of carbon reduction, and operational impacts for any deployment profile. For further information on the initial development of the NUFRIEND Framework and Dashboard, readers are referred to the Final Technical Report produced as a result of the first project phase [20].

Section D - Updates and Expansions to NUFRIEND Framework

Section D.1 - NUFRIEND Optimization Framework Models

In this section we detail the updates and expansions made to the NUFRIEND Optimization Framework's models. More specifically, we provide information on the updates made to the Static Optimization Framework, the development of a new Rollout Optimization Framework, and the expansion of existing life-cycle, techno-economic, and operational analysis tools.

Section D.1.1 - Static Optimization

The joint facility location and sizing problem is a combinatorial problem to solve [21], especially over networks, where potential facility locations have many degrees of interconnectivity. To simplify the problem in the first iteration of the NUFRIEND Framework, therefore, we decoupled and formulated variations of the facility location and sizing problems that capture important managerial concerns [20].

Among the subsequent updates to the NUFRIEND Framework outlined in this report, we improve the facility location optimization model. More specifically, we expand on models in the literature to simultaneously optimize facility location and route selection decisions (instead of doing these in sequence, as in the first phase) [22], [23], [24]. The resulting impact on the NUFRIEND Framework structure is captured in Figure 1; we note that the facility sizing optimization and deployment evaluation steps remain as in the prior version [20]. This approach provides solutions that are jointly optimized for network construction and O-D routing concerns. Moreover, we present two alternative facility location and flow selection models: (1) maximize total flow capture subject to a facility deployment budget constraint (Max Flow) and (2) minimize total facility deployment costs subject to meeting a target flow capture (Min Cost). These alternative formulations provide users of the NUFRIEND Framework with significant modeling flexibility in representing the objectives and constraints they find most relevant. For example, the Max Flow formulation can be used by a railroad/stakeholder that wants to make the most of a fixed budget directed at decarbonizing their operations. Similarly, the Min Cost formulation can be used by a railroad/stakeholder that wants to test the network and economic impacts of setting decarbonization targets. These updates to the static facility location optimization model also serve as the basis for the dynamic facility location optimization models used in the new rollout optimization framework discussed in Section D.1.2 - Rollout Optimization.

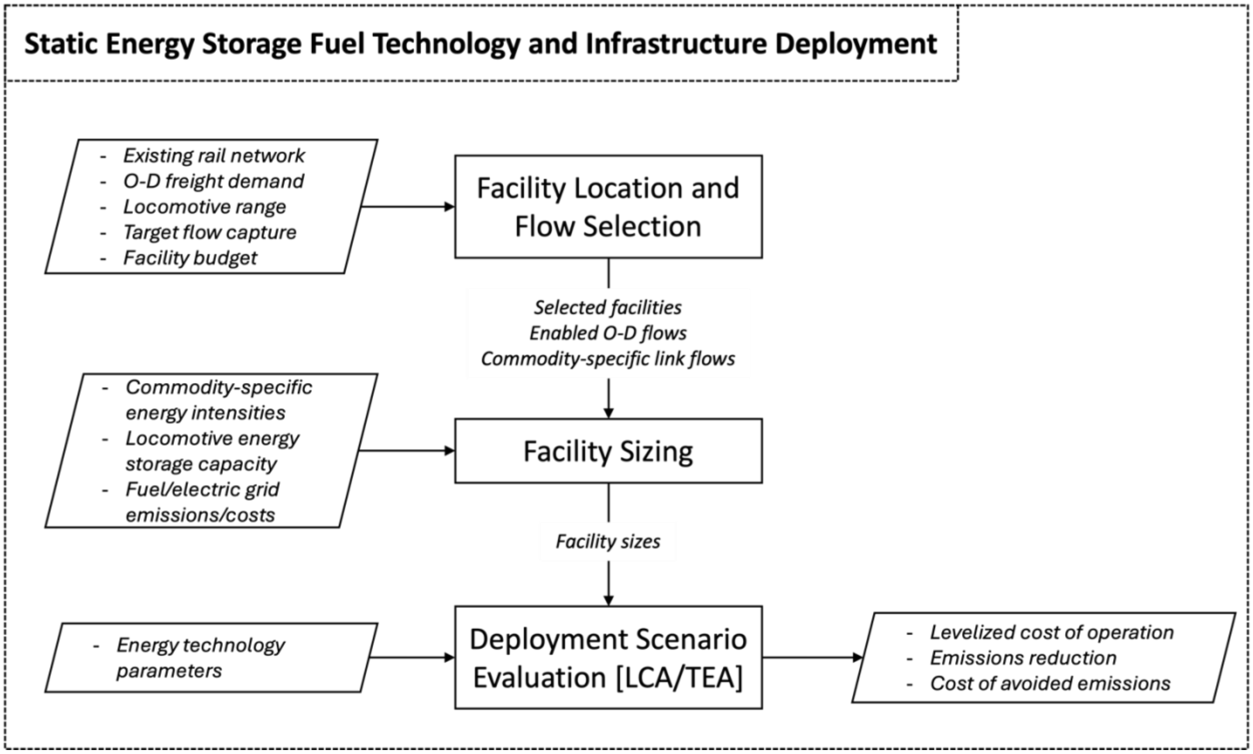

Figure 1 - Flowchart of updated optimization framework to support the deployment of refueling/charging infrastructure for hydrogen and battery-electric technologies.

Section D.1.2 - Rollout Optimization

Time plays a critical role in the deployment of alternative fuel technologies. More specifically, assuming we can use the static NUFRIEND Framework to determine what an optimal future alternative technology support network should look like, we can ask three questions: (a) In what order do we deploy specific facilities to enable specific flows on the network? (b) How do we size the selected facilities over time? (c) How would variations in time-dependent inputs such as freight demand, facility costs, facility budgets, flow capture targets, etc. affect our decisions? Therefore, a significant update to the NUFRIEND Framework is the development of a Rollout Optimization Framework, which aims to optimize the spatiotemporal decisions on facility location, flow selection, and facility sizing subject to time-varying inputs. In other words, this framework optimizes the time-dependent nature of these decisions, taking into consideration variations in freight demand, facility costs and budgets, and flow capture targets, among other parameters. The facility location and flow selection optimization models used add time-dependent decision variables and constraints to the models presented in the static framework. Similarly, we extend the facility sizing and deployment evaluation models to handle multi-period optimization and analysis. The framework, with its critical inputs and outputs is represented in the flowchart in Figure 2.

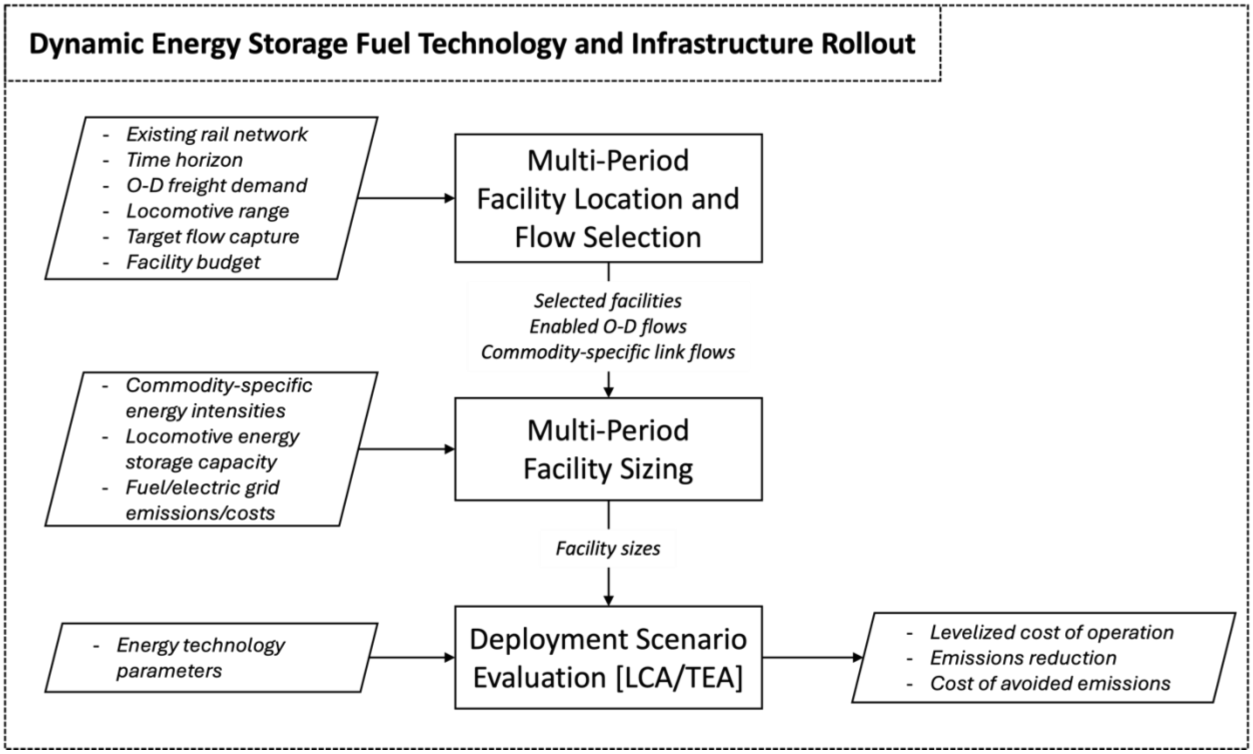

Figure 2 - Flowchart of dynamic optimization framework to support the deployment of refueling/charging infrastructure for hydrogen and battery-electric technologies over time.

The optimization of multi-period scenarios requires time-dependent inputs for a number of parameters including the specification of:

- Time horizon: planning period for consideration of technology deployment and operation.
- Energy technologies: variations in emissions, cost, and technological parameters over time.
- Electric grid: costs and emissions over time.
- Hydrogen: costs over time.
- Diesel (baseline): costs over time.
- Freight demand: market-specific projections of freight demand for different growth cases.
- Baseline network: state of the network (tracks and facilities) that are active over time.
- Discount rate: tool for fair valuation of future costs/flows.

We note the computation required to optimize time-dependent scenarios takes considerably longer than the static optimization.[2] For this reason, the optimization tool and executable files have been made available on the public NUFRIEND GitHub repository with an accompanying user guide and sample data sets, as discussed in Section F - Project Outputs.

Section D.1.3 - Life-cycle Analysis (LCA) of Energy Technologies

As in the prior work on the static NUFRIEND Framework, we examine the GHG emissions of different energy technologies with a system boundary covering both the well-to-pump (WTP) and pump-to-wheel (PTW) stages, which together comprise well-to-wheel (WTW) analysis. The

[2] Though they are still often very tractable, taking on the order of 5 minutes.

functional unit for the emissions is set as gCO_2/ton-mile. We use ANL's GREET model [15]—updated annually with the most up-to-date and detailed energy use and emissions data for petroleum refineries and electric power plants—to conduct the WTW analysis. The R-1 report published by Surface Transportation Board (STB) provides the annual diesel usage and associated revenue ton-miles for each of the Class I railroads [25]. Combining these values with the emissions factors from GREET, we estimate the railroad-specific WTW GHG emissions in gCO_2/ton-mile using Equation (1).

$$
\begin{aligned}
GHG\ emissions \left[\frac{gram\ CO_2}{ton-mile}\right] &= \frac{Total\ Diesel\ Use\ [gallons]}{Total\ Revenue\ Ton-Miles\ [ton-mile]} \\
&\times \quad Emission\ Factor\ from\ GREET \left[\frac{gram\ CO_2}{Btu}\right] \\
&\times Lower\ Heating\ Value\ of\ Diesel \left[\frac{Btu}{gallons}\right]
\end{aligned} \tag{1}
$$

The WTW analyses in the prior report have been extended using time-dependent emissions data for the relevant fuel technology pathways. In recent updates, we assume electric grid emissions vary over time as efforts to decarbonize electricity generation are expected to change the energy source's WTP emissions [26]. Though the framework has the flexibility to accommodate time-varying emissions estimates for any fuel pathway, the remaining fuel pathways (i.e., diesel, hydrogen, e-fuel, and biodiesel) are assumed to be time-invariant with respect to their emissions. The estimation of WTW emissions for hybrid diesel-battery locomotive technologies is discussed in greater detail in Section D.2 - Hybrid Locomotive Energy Technology Deployment.

Section D.1.4 - Techno-economic Analysis (TEA)

As in the static NUFRIEND Framework, we assume the deployment of conventional diesel, biodiesel, and e-fuels, incur only levelized cost of refueling, as these energy technologies do not require additional infrastructure investments. For technologies requiring the deployment of charging/refueling infrastructure (i.e., battery-electric, hydrogen, and hybrid diesel-battery), we consider the charging/refueling infrastructure cost in addition to the battery/hydrogen tender car capital investment and refueling costs. We extend prior work in static techno-economic analysis to the time-dependent case where cost estimates for different fuel technologies may vary over time.

We apply ANL's bottom-up TEA tools, Heavy-duty Electric Vehicle Infrastructure Scenario Analysis Model (HEVISAM) for battery-electric, and Hydrogen Delivery Scenario Analysis Model (HDSAM) for hydrogen [27], to estimate the levelized cost of charging/refueling for a given locomotive demand and facility specification. The levelized costs of operation are estimated in terms of cost per quantity of energy (e.g., \$/kWh) for battery, as in Equation (2), or fuel (e.g., \$/kgH_2, \$/gallon) for hydrogen, as in Equation (3). These estimates are converted to cost per revenue ton-mile using commodity-specific energy intensity parameters. The levelized cost of operation per ton-mile is a fair metric for comparing alternative fuel technology costs based on their operational impacts.

$$\begin{aligned}&\mathit{Levelized\ cost\ of\ operation}\left[\frac{\$}{kWh}\right]\\&= \mathit{levelized\ cost\ of\ battery}\ (\mathit{ammortized\ capital\ cost\ of\ battery})\\&+ \mathit{levelized\ cost\ of\ charging}\ (\mathit{charging\ station\ contribution\ from\ HEVISAM}\\&+ \mathit{electricity\ price\ by\ state}\end{aligned} \tag{2}$$

$$\begin{aligned}&\mathit{Levelized\ cost\ of\ operation}\left[\frac{\$}{kgH_2}\right]\\&= \mathit{levelized\ cost\ of\ hydrogen\ tender\ car}\ (\mathit{ammortized\ capital\ cost\ of\ tender}\\&+ \mathit{levelized\ cost\ of\ refueling}\begin{pmatrix}\mathit{delivery\ and\ refueling\ station\ capital\ cost}\\ \mathit{contribution\ from\ HDSAM}\end{pmatrix}\\&+ \mathit{hydrogen\ fuel\ price}\ (\mathit{production})\end{aligned} \tag{3}$$

Importantly, we extend prior work to include time-varying cost estimates in the estimation of the levelized cost of operation of different fuel technologies. These include temporal electricity generation costs [26] and hydrogen fuel procurement costs [28]. The framework can also be applied to consider temporal variations in battery or hydrogen tender costs as well as time-dependent capital infrastructure costs for locating new (or expanding existing) charging/refueling facilities.

To facilitate cross-technology and scenario comparison, the WTW GHG emissions and the levelized cost of operation metrics are combined into a single metric: the cost of avoided emissions (CAE). The CAE for a given scenario is defined as the ratio of the levelized cost of operations (in $/ton-mile) and the WTW GHG emissions intensity (in kgCO2/ton-mile), relative to the baseline diesel operations, as represented in Equation (4). The CAE is a measure of the cost per unit of reduced carbon emissions for a specific technology deployment and is a key policy metric that can be compared with the social cost of carbon. Since both the WTW GHG emissions and levelized cost of operations metrics are time-dependent, the resulting CAE metrics also vary over time, capturing the economics of future investments in decarbonization technologies and future carbon credit/tax schemes.

$$\begin{aligned}&\mathit{Cost\ of\ avoided\ emissions}\left[\frac{\$}{kgCO_2}\right]\\&= \frac{\mathit{LCO\ alternative\ technology} - \mathit{LCO\ diesel}}{\mathit{WTW\ GHG\ alternative\ technology} - \mathit{WTW\ GHG\ diesel}}\end{aligned} \tag{4}$$

Section D.1.5 - Operational Implications

As in the static NUFRIEND Framework, operational performance metrics feature heavily in the dynamic NUFRIEND Framework and in the impact analyses for different deployment scenarios. More specifically, we compute the average charging/refueling delay associated with a particular deployment strategy (over time) and model potential congestion at charging/refueling facilities. We also continue to model flows as commodity-specific, particularly as freight demand forecasts indicate significant variability by O-D pair and commodity group. This consideration is critical for railroads and other stakeholders as different commodities have different values of time, operational requirements, and spatiotemporal distributions. The queuing models and delay estimation used in the dynamic NUFRIEND framework follow those presented in the initial static framework [20].

Section D.2 - Hybrid Locomotive Energy Technology Deployment

We build on available locomotive simulation tools to include two hybrid diesel-battery locomotive configurations in the set of available energy technologies for simulation within the NUFRIEND Framework and Dashboard. The OneTrain locomotive simulation tool, which comprises a part of the A-STEP tool funded by the US DOE ARPA-E LOCOMOTIVES project, was used to simulate the energy intensities and fuel/electricity consumption of two different train configurations: (1) diesel to battery locomotive ratio of 2:1 and (2) diesel to battery locomotive ratio of 1:1. The relevant assumptions were made to match with those taken in the NUFRIEND Framework, such as assuming a train with 6 locomotives (the configurations of which matched the two cases modeled) and 75 cars.[3] The simulation was run on 9 different regions, as described in the OneTrain tool. The region-specific energy intensities and fuel/energy consumption values are show in Figure 3Figure 4, respectively, for the two train configurations considered (including the baseline 100% diesel and 100% battery configurations). The resulting regional energy intensity values (in btu/ton-mile) were assigned to each of the corresponding links (to match the region they lie in) for use in the facility sizing model. These values are critical in estimating the regional energy consumption values for serving the assigned freight flows.

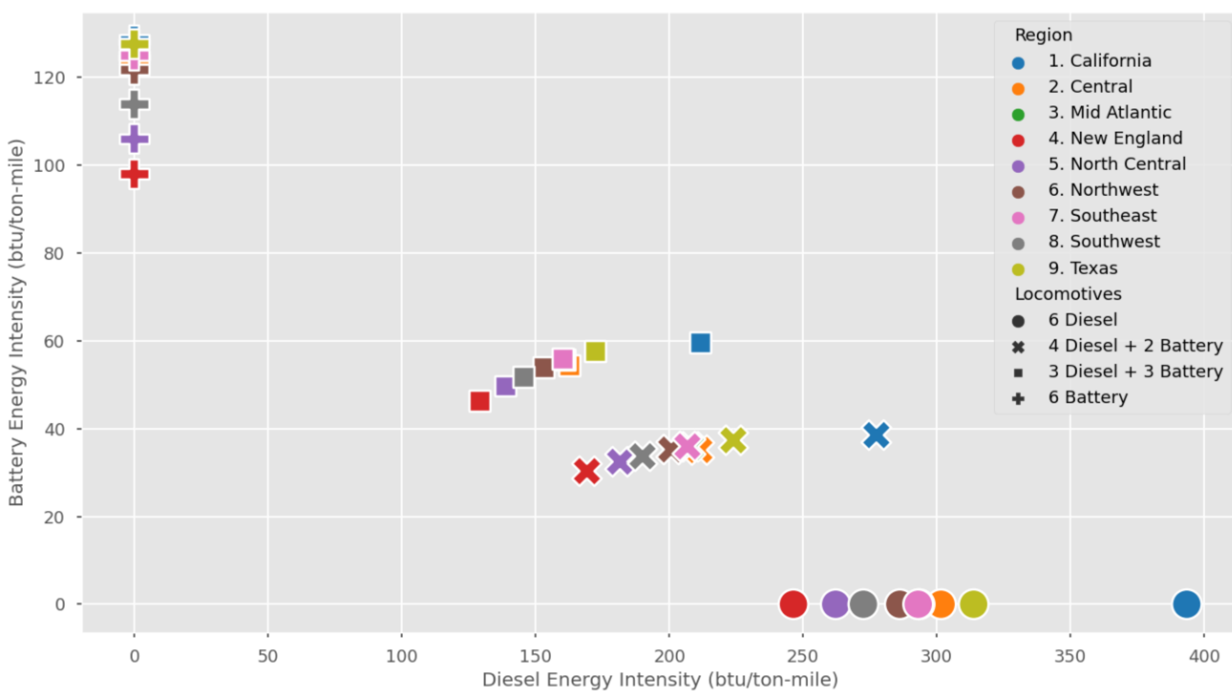

Figure 3 - Simulated hybrid diesel-battery locomotive energy intensities for different regions and train configurations from OneTrain [29]

[3] Assuming 6 locomotives per train, the 2:1 diesel-battery configuration is 1 train with 4 diesel and 2 battery locomotives, while the 1:1 diesel-battery configuration is 1 train with 3 diesel and 3 battery locomotives.

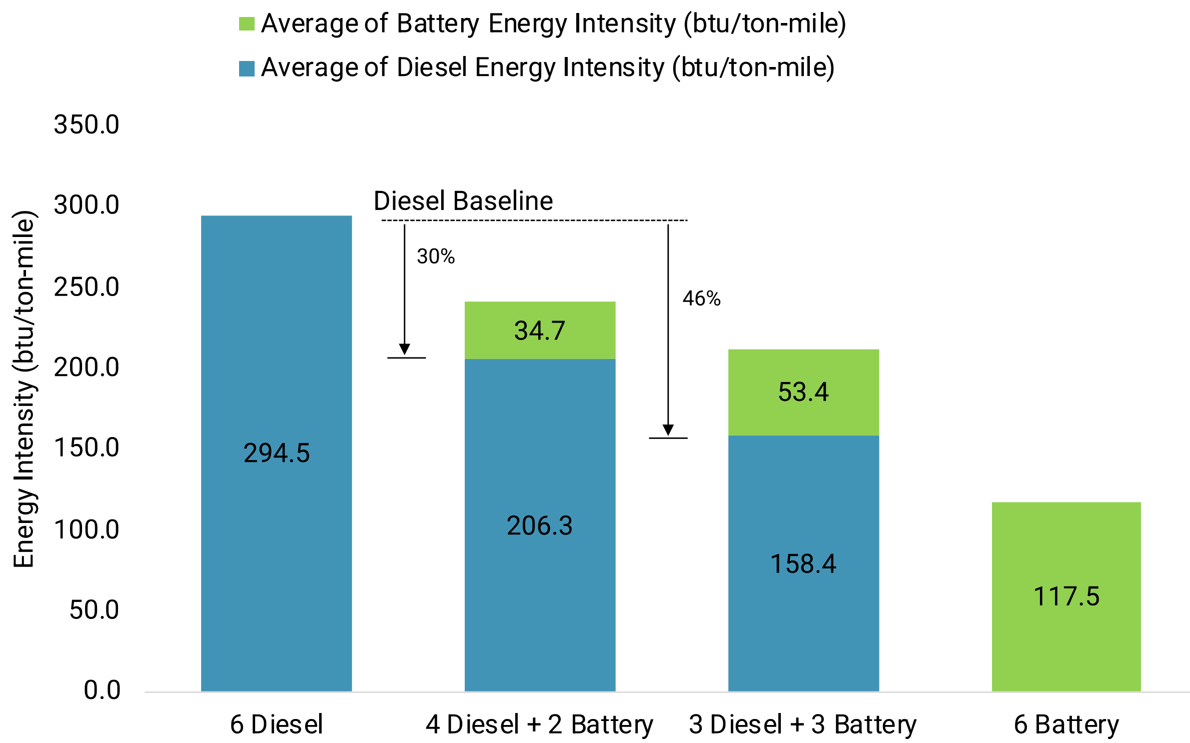

Figure 4 - Simulated average hybrid diesel-battery locomotive energy intensities for different train configurations from OneTrain [29]

Section E - Project Findings

In this section, the updates and extensions to the NUFRIEND Framework are illustrated through several scenarios. The primary focus is on the updates pertaining to the rollout optimization framework and the inclusion of the hybrid diesel-battery locomotive technologies.

Section E.1 - Compiled Data and Parameters

The data used build on those used in the static NUFRIEND Framework, an can be seen in greater detail in the initial final report [20]. Here, we describe the new data used for any relevant time-dependent parameters. For details on the underlying data used in the hybrid diesel-battery technology simulation, we refer the reader to the OneTrain simulation tool documentation [29]. We assume the US Class I railroads network is constant over the assumed time horizon. The multi-period scenarios considered assume the following time-dependent inputs:[4]

- Time horizon: 2025 through 2050 (in 5-year increments).
- Energy technologies: variations in emissions, cost, and technological parameters over time.
    - Diesel (baseline): fuel cost variations [26].
    - Biodiesel: fixed fuel cost assumed.
    - E-fuel: fuel cost variations.

[4] The non-confidential relevant data files have been made available in the public GitHub repository. Any data originating from confidential sources have been replaced with randomly generated data showing the required format for running the program.

    - Hydrogen: fuel cost variations [28].
    - Battery-electric: electricity cost and emissions variations [26], [28].
- Freight demand: market-specific projections of freight demand for different growth cases.

Section E.1.1 - Freight Demand

Freight rail demand for 2019 was estimated from the Surface Transportation Board's (STB) annually compiled Carload Waybill Sample (CWS) [30], which samples a subset of all rail movements in the U.S. and provides movement-specific data on railroad, routing, and costs. To produce a forecast, the Bureau of Transportation Statistic's (BTS) Freight Analysis Framework 5 (FAF5) [31] is used to apply market-specific growth rates to the sampled waybills in the STB's 2019 CWS data [30]. Importantly, the growth factors computed from the FAF5 data for the 5-year periods in 2025-2050 (relative to 2019) are matched to the corresponding O-D pairs and commodity groups from the STB's CWS data.[5]

Section E.2 - Roullout Optimization Scenario Analysis

This section presents scenario results and visualizations that highlight the updates and expansions made to the dynamic NUFRIEND Framework.

Section E.2.1 – Optimal vs. Myopic Facility Deployment Strategies

To motivate the impact of optimizing the temporal deployment of charging/refueling facilities, we compare the optimal facility rollout strategy with a (sub-optimal) myopic facility rollout strategy for battery-electric locomotive deployment on a (composite) national rail network. The scenario considered seeks to maximize total freight flow served by battery-electric locomotives over the 5-year increments from 2025 through 2050, with per period budget of 5 facilities (for a cumulative budget of 30 facilities by 2050). A fixed locomotive range of 1000 miles (1600 km) is selected. The freight demand is time-varying and taken from the projected data discussed in Section E.1.1 - Freight Demand. Finally, we assume the final set of 30 facilities to be activated by 2050 is pre-determined; this allows for the fair comparison of the optimal and myopic facility location strategies.[6] In this context, the myopic rollout strategy selects the 5 facilities that increase the total flow capture at each time period and does not account for network effects, nor how future demands change. We contrast this with the developed rollout optimization model that optimally selects the facilities for each period such that the total flow capture is maximized, considering network effects and future variations in freight demand. Figure 5Figure 6 show how the solutions differ in the order in which facilities are deployed, even when the final solutions are constrained to be the same for both solutions. The order in which facilities are deployed has significant consequences on the planning period's carbon emissions reductions, with the optimal solution reducing cumulative

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[5] Though this framework can be applied to any individual railroad, the CWS data was aggregated to the three-railroad level in accordance with STB policy to preserve confidentiality in the illustration of results that follow. All operational parameters were also aggregated in a similar manner.
[6] This is set by solving the static facility location and flow selection optimization model with the 2050 demand data and relevant parameters.

emissions by 11% more than the myopic solution by 2050, emphasizing the benefits of optimizing facility rollout strategies.

Figure 5 - Optimal facility rollout strategy.

Figure 6 - Myopic (sub-optimal) facility rollout strategy.

Section E.2.2 - Battery-electric Rollout Optimization

In this section we show the rollout optimization framework applied to two battery-electric deployment scenarios. We consider rollout strategies to maximize total (discounted) flow capture over all periods, subject to facility budget constraints (Figure 7-Figure 12) and rollout strategies to minimize total facility deployment costs, subject to meeting minimum flow capture targets over all periods (Figure 13-Figure 18). The results show the emissions reduction, levelized cost of operations, and cost of avoided emissions metrics for each time period. We assume a battery-electric locomotive range of 600 miles (approximately 1000 km) deployed on a national (aggregate) rail network over the 5-year periods from 2025 through 2050. For the maximum flow capture scenario, we fix the budget to be 5 facilities per period (for a total of 30 facilities by 2050). For the minimized facility deployment cost scenario, we set the flow capture targets to [20%, 40%, 60%, 80%, 90%, 95%] for the 6 periods from 2025 through 2050.

In the results we observe that for the Max Flow solution, as we increase the number of facilities deployed (from none to 30 by 2050), the growing emissions reductions result in a lower CAE in each resulting period. This shows there are economies of scale and network effects at play as a result of the facility deployment strategies, emphasizing the need to optimize these rollout schedules. Moreover, we see that though there is an initial increase in the CAE metric the Min Cost case, the value in 2050 is the lowest CAE of all in the planning horizon.

Variable	Value
Time Step	2025
Cumulative Budget	5.0
Max Flow Capture %	9.98%
Emissions Reduction	4.2%
Levelized Cost of Operations	¢0.51/ton-mi
Cost of Avoided Emissions	\$163/ton CO_2

Figure 7 - Solution from Max Flow problem for battery-electric locomotives in 2025.

Variable	Value
Time Step	2030
Cumulative Budget	10.0
Max Flow Capture %	21.04%
Emissions Reduction	14.18%
Levelized Cost of Operations	¢0.5/ton-mi
Cost of Avoided Emissions	\$145/ton CO_2

Figure 8 - Solution from Max Flow problem for battery-electric locomotives in 2030.

Variable	Value
Time Step	2035
Cumulative Budget	15.0
Max Flow Capture %	30.23%
Emissions Reduction	17.61%
Levelized Cost of Operations	¢0.52/ton-mi
Cost of Avoided Emissions	$138/ton CO_2

Figure 9 - Solution from Max Flow problem for battery-electric locomotives in 2035.

Variable	Value
Time Step	2040
Cumulative Budget	20.0
Max Flow Capture %	37.39%
Emissions Reduction	21.47%
Levelized Cost of Operations	¢0.53/ton-mi
Cost of Avoided Emissions	$132/ton CO_2

Figure 10 - Solution from Max Flow problem for battery-electric locomotives in 2040.

Variable	Value
Time Step	2045
Cumulative Budget	25.0
Max Flow Capture %	44.77%
Emissions Reduction	29.35%
Levelized Cost of Operations	¢0.55/ton-mi
Cost of Avoided Emissions	$114/ton CO_2

Figure 11 - Solution from Max Flow problem for battery-electric locomotives in 2045.

Variable	Value
Time Step	2050
Cumulative Budget	30.0
Max Flow Capture %	51.29%
Emissions Reduction	44.46%
Levelized Cost of Operations	¢0.58/ton-mi
Cost of Avoided Emissions	$93/ton CO_2

Figure 12 - Solution from Max Flow problem for battery-electric locomotives in 2050.

Variable	Value
Time Step	2025
Number of Facilities	11
Flow Threshold %	20.0
Flow Capture %	20.73%
Emissions Reduction %	14.88%
Levelized Cost of Operations	¢0.53/ton-mi
Cost of Avoided Emissions	$116/ton CO_2

Figure 13 - Solution from Min Cost problem for battery-electric locomotives in 2025.

Variable	Value
Time Step	2030
Number of Facilities	23
Flow Threshold %	40.0
Flow Capture %	40.6%
Emissions Reduction %	21.31%
Levelized Cost of Operations	¢0.53/ton-mi
Cost of Avoided Emissions	$153/ton CO_2

Figure 14 - Solution from Min Cost problem for battery-electric locomotives in 2030.

Variable	Value
Time Step	2035
Number of Facilities	42
Flow Threshold %	60.0
Flow Capture %	60.39%
Emissions Reduction %	36.81%
Levelized Cost of Operations	¢0.59/ton-mi
Cost of Avoided Emissions	\$153/ton CO_2

Figure 15 - Solution from Min Cost problem for battery-electric locomotives in 2035.

Variable	Value
Time Step	2040
Number of Facilities	63
Flow Threshold %	80.0
Flow Capture %	80.5%
Emissions Reduction %	50.61%
Levelized Cost of Operations	¢0.63/ton-mi
Cost of Avoided Emissions	\$137/ton CO_2

Figure 16 - Solution from Min Cost problem for battery-electric locomotives in 2040.

Variable	Value
Time Step	2045
Number of Facilities	85
Flow Threshold %	90.0
Flow Capture %	90.02%
Emissions Reduction %	60.12%
Levelized Cost of Operations	¢0.65/ton-mi
Cost of Avoided Emissions	\$125/ton CO_2

Figure 17 - Solution from Min Cost problem for battery-electric locomotives in 2045.

Variable	Value
Time Step	2050
Number of Facilities	104
Flow Threshold %	95.0
Flow Capture %	95.0%
Emissions Reduction %	68.99%
Levelized Cost of Operations	¢0.65/ton-mi
Cost of Avoided Emissions	$101/ton CO_2

Figure 18 - Solution from Min Cost problem for battery-electric locomotives in 2050.

Section E.2.3 - Hydrogen Rollout Optimization

In this section, we display how the rollout optimization framework can be applied to optimize hydrogen locomotive deployment. More specifically, we consider the deployment of cryogenically pumped hydrogen fuel for pathways utilizing nuclear power for PEM electrolysis on an (aggregate) Eastern rail network. We aim to maximize the flows served by hydrogen locomotives over a time horizon of the 5-year periods from 2025 through 2040, with per period facility budgets of [5, 5, 5, 10] for a cumulative budget of 25 facilities by 2040. The results are shown in Figure 19-Figure 22.

The results show that with clean fuel pathways, the emissions reductions may actually exceed the percentage of ton-miles captured, as shifting those commodity flows with higher energy intensities can result in above average emissions reductions per ton-mile.

Variable	Value
Time Step	2025
Cumulative Budget	5.0
Max Flow Capture %	31.99%
Emissions Reduction	39.69%
Levelized Cost of Operations	¢0.7/ton-mi
Cost of Avoided Emissions	$170/ton CO_2

Figure 19 - Solution from Max Flow problem for hydrogen locomotives in 2025.

Variable	Value
Time Step	2030
Cumulative Budget	10.0
Max Flow Capture %	46.76%
Emissions Reduction	52.16%
Levelized Cost of Operations	¢0.75/ton-mi
Cost of Avoided Emissions	$202/ton CO_2

Figure 20 - Solution from Max Flow problem for hydrogen locomotives in 2030.

Variable	Value
Time Step	2035
Cumulative Budget	15.0
Max Flow Capture %	58.34%
Emissions Reduction	61.04%
Levelized Cost of Operations	¢0.81/ton-mi
Cost of Avoided Emissions	$206/ton CO_2

Figure 21 - Solution from Max Flow problem for hydrogen locomotives in 2035.

Variable	Value
Time Step	2040
Cumulative Budget	25.0
Max Flow Capture %	73.51%
Emissions Reduction	74.3%
Levelized Cost of Operations	¢0.89/ton-mi
Cost of Avoided Emissions	$208/ton CO_2

Figure 22 - Solution from Max Flow problem for hydrogen locomotives in 2040.

Section E.3 - Hybrid Diesel-Battery Locomotive Scenario Analysis

In this section, we present results from the updates to the NUFRIEND Framework to include hybrid diesel-battery locomotive technologies in the suite of considered alternative fuels. We consider the static deployment of two hybrid technology configurations on the national rail network. We specify that charging facilities should be spaced at most 1000 miles (1600 km) apart, and assume the objective is to minimize the total facility deployment cost. Facilities are also sized accordingly to supply the sufficient energy demand, as calculated from the hybrid simulation computed by applying OneTrain [29]. The results for the hybrid locomotive 2:1 diesel-battery configuration are shown in Figure 23, while Figure 24 shows the results for the 1:1 diesel-battery hybrid locomotive configuration. We see that a 2:1 diesel-battery configuration (a single train with 4 diesel locomotives and 2 battery locomotives) provides approximately 20% emissions reduction, while a 1:1 diesel-battery configuration (a single train with 3 diesel locomotives and 3 battery locomotives) provides reduces emissions by 30% relative to the baseline diesel operations.

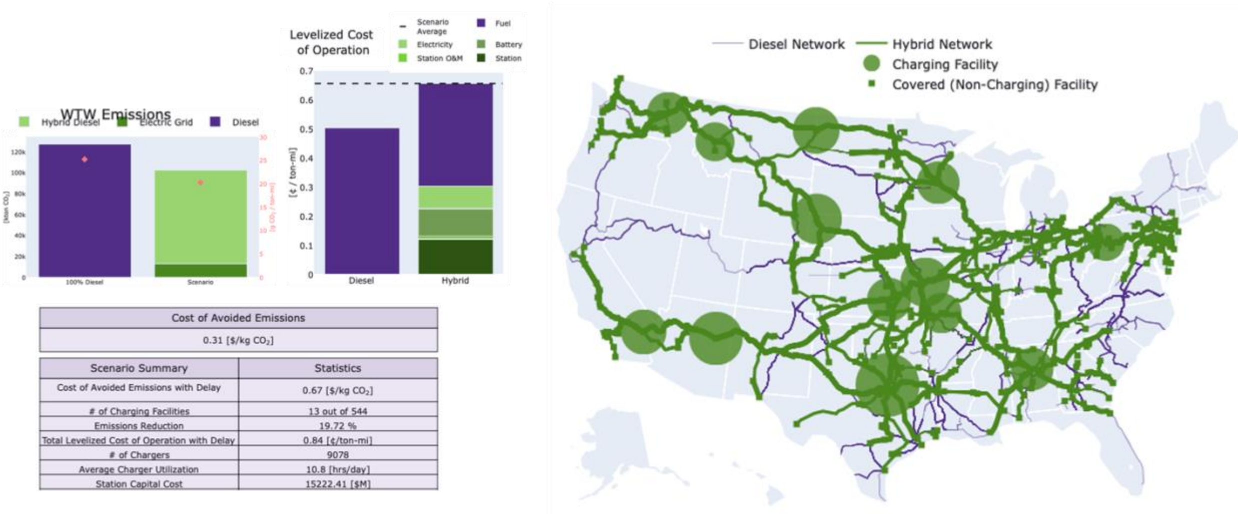

Figure 23 - Deployment of hybrid locomotives in a 2:1 diesel-battery configuration.

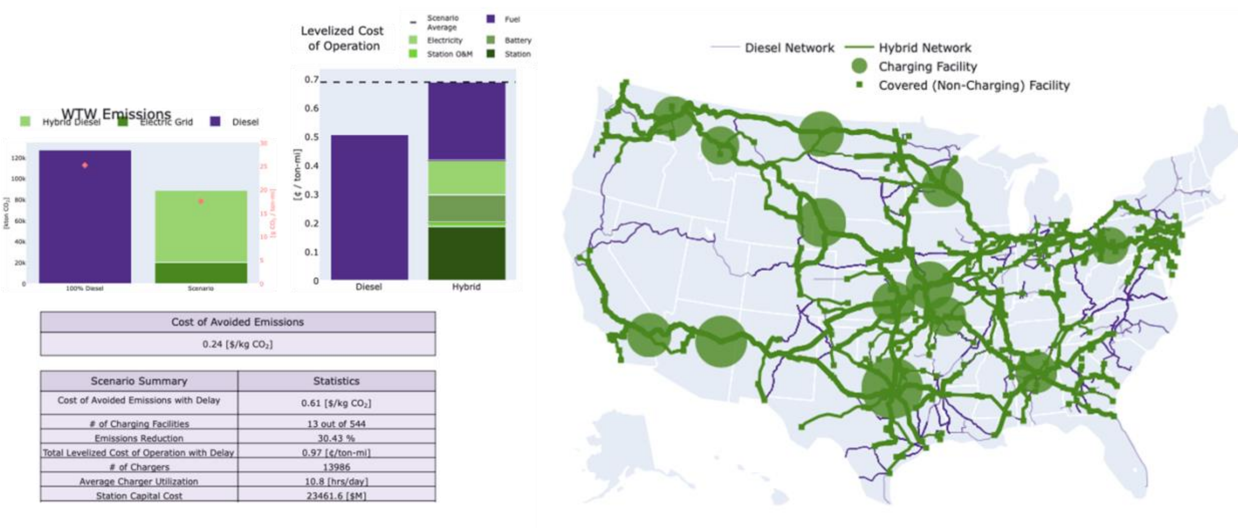

Figure 24 - Deployment of hybrid locomotives in a 1:1 diesel-battery configuration.

Section F - Project Outputs

Technology-to-Market

With the development of the NUFRIEND Rollout Optimization Framework and updates to the existing NUFRIEND Dashboard, continual user engagement and feedback from industry and government stakeholders allowed for the refinement of a fully functioning simulation framework. The members of the project's Industry Advisory Board (IAB), shown in Table 3, have provided critical feedback and guidance on achieving project goals and updating existing tools. In addition to meetings with the IAB and its members, meetings were held with specific railroad companies and executives on the value of the suite of NUFRIEND tools.

In February 2023, The Northwestern University Transportation Center hosted Dr. April Kuo from the BNSF. Dr. Kuo presented her team's work on developing optimization models for intermodal operations at the BNSF. The team met with her and presented the NUFRIEND Dashboard along with current project milestones.

We also presented our NUFRIEND framework and dashboard at the ARPA-E Energy Innovation Summit on March 22-24, 2023, in Washington, D.C. Industry participants, including railroads and OEMs, government officials, and researchers expressed enthusiasm and interest in integrating the framework into their investment decision-making and planning processes.

An opportunity to improve the NUFRIEND dashboard's functionality and expand its applications to broader innovative technology analyses was initiated by an ARPA-E intern, Eli Schulman, and Dr. Apoorv Agarwal in May 2023. The NUFRIEND Dashboard was updated to enable greater user interaction, allowing inputs for battery technology costs, diesel fuel costs, and energy densities to be input and/or extracted more easily.

More recently, presentations of updates to the NUFRIEND Framework and Dashboard have been made to the NUTC Business Advisory Council on Nov. 9, 2023. This presentation was followed by a more in-depth presentation at the NUTC Executive Education Course on Freight and Logistics on Nov. 15, 2023, where railroad executives from the BNSF, UP, GATX, and Telegraph participated and provided valuable feedback for improving the tool to better meet their needs. Work to analyze and compare different ES technologies was presented at the 103rd Annual Meeting of the Transportation Research Board (TRB) on Jan. 7-11, 2024. Finally, at the 2024 TRB Annual Meeting, the NUFRIEND Dashboard and its applications were presented at the Intermodal Freight Terminal Design and Operations, AT045(1) Subcommittee.

Journal Articles

1. Hernandez, A., Ng, M.T.M., Siddique, N., Durango-Cohen, P.L., Elgowainy, A., Mahmassani, H.S., Wang, M., Zhou, Y. (Joann), 2024. Evaluation of Rail Decarbonization Alternatives: Framework and Application. Transportation Research Record: Journal of the Transportation Research Board 2678, 102–121.
2. Ng, M.T.M., Hernandez, A., Durango-Cohen, P.L., Mahmassani, Hani S., 2023. Trading off energy storage and payload – an analytical model for freight train configuration. *Under review at Transportation Research Part E: Logistics and Transportation Review.*

3. Hernandez, A., Ng, M.T.M., Choudhury, S., Durango-Cohen, P., Mahmassani, H., Elgowainy, A., Wang, M., Zhou, Y. (Joann), 2024. Abatement Cost Curve Analysis of Freight Rail Decarbonization Alternatives. *Submitted to Transportation Research Part D: Transport and Environment.*
4. Hernandez, A., Ng, M.T.M., Durango-Cohen, P., Mahmassani, H., 2024. Optimizing service networks to support freight rail decarbonization: Flow selection, facility location, and energy sourcing. *Under review at the European Journal of Operational Research.*

Presentations

Our work has been presented at various conferences throughout the course of the project. Presentations have covered the technical framework, analysis of findings, and live dashboard demonstrations, as listed in Table 2.

Table 2 - List of Presentations

Date	**Event**	**Location**
May 23-25, 2022	2022 ARPA-E Summit	Denver, CO
Jun 5, 2022	4th International Symposium on Infrastructure Asset Management	Evanston, IL
Aug 30, 2022	Meeting with short line railroad (Anacostia) representative	Evanston, IL
Oct 16, 2022	2022 INFORMS Annual Meeting	Indianapolis, IN
Nov 2, 2022	Railroad Environmental Conference	Champaign, IL
Nov 16-17, 2022	Northwestern University Transportation Center Business Advisory Council Meeting	Evanston, IL
Jan. 8-12, 2023	Transportation Research Board 102nd Annual Meeting	Washington, D.C.
Jan. 30, 2023	Virtual Interuniversity Symposium on Infrastructure Management	Virtual
Feb. 23, 2023	NUFRIEND Presentation with Dr. April Kuo, Director of Data Science, BNSF	Evanston, IL
Mar. 22 - 24, 2023	ARPA-E Energy Innovation Summit	National Harbor, MD
Apr. 24, 2023	Virtual Interuniversity Symposium on Infrastructure Management	Virtual
Apr. 27-28, 2023	Transportation Research Forum 64th Annual Meeting	Chicago, IL
Jul. 17-21, 2023	World Conference on Transport Research	Montreal, Canada
Jul. 23-26, 2023	INFORMS Transportation Science and Logistics Society Conference	Chicago, IL
Oct. 15-18, 2023	INFORMS Annual Meeting	Phoenix, AZ

Nov. 9, 2023	Northwestern University Transportation Center Business Advisory Council Meeting	Evanston, IL
Nov. 15, 2023	Northwestern University Transportation Center Executive Education Program	Evanston, IL
Jan 7-11, 2024	Transportation Research Board 103rd Annual Meeting	Washington, D.C.

Status Reports

Quarterly reports have been submitted to the project sponsor from the start of the project through the effective end date.

Media Reports

We have expanded our NUFRIEND Insights pieces to include topics facility rollout optimization and hybrid diesel-battery technology deployment.[7] Additionally, a user guide for the NUFRIEND Framework code package has been produced and made available for public access to supplement the open-source GitHub repository.

Collaborations Fostered

To assist with the project's technology-to-market initiatives, the Northwestern University Transportation Center leveraged its existing Business Advisory Council and industry connections to put together an Industry Advisory Board (IAB) for the project, the members of which are shown in Table 3. The IAB members represent individuals across multiple companies and entities that operate in the rail sector, providing valuable perspectives on the challenges and opportunities to decarbonize freight rail. Several group and individual meetings were held with IAB members to gain valuable insights and showcase the dashboard and framework for feedback, to ensure its value for all stakeholders, as shown in Table 3.

Table 3 - Members of Industry Advisory Board

Member	**Title**	**Organization**	**Information**
John Gray	Senior VP – Policy & Economics	AAR	Policy; relevant AAR working groups and data
John Friedmann	VP – Network Planning & Optimization	NSC	Rail Operations and scheduling
April Kuo	Director – Data Science Intermodal Analytics	BNSF	Rail Operations and scheduling
Adam Longson	VP – Energy	CSXT	Energy source impacts
John Lovenburg	VP – Environmental	BNSF	Wabtec battery pilot; Technology deployment considerations
Roger Nober	*Former* EVP – Law & Corporate Affairs, CLO	*Formerly at* BNSF	Regulations

[7] https://www.transportation.northwestern.edu/research/featured-reports/locomotives.html

Barbara W. Wilson	*Former* CEO & President	*Formerly at* RailUSA	Perspectives of shortline railroad
Norman Carlson	Vice Chair	Metra	Passenger rail interest

Websites Featuring Project Work Results

The NUFRIEND Dashboard has been made available for public use online.[8] Additionally, information on the project and objectives, informational reports on key findings, a list of related publications, and a demo video and user guides are hosted on a dedicated NUTC webpage.[9] Information on the developed framework and results is also linked on Argonne National Library's GREET model webpage.[10]

Release Open-Source Code

Interest from both Class I and shortline railroads has motivated a user-friendly coding architecture in the program source code, so that future users can interact the core tools with as few barriers as possible. The complete software code in Python 3.10 of the NUFRIEND Framework has been published on GitHub with full documentation regarding the workflow and data input and output.[11] A user guide shows users how to setup, use, and test the program using the provided datasets.

[8] https://nufriend.transportation.northwestern.edu
[9] https://www.transportation.northwestern.edu/research/featured-reports/locomotives.html
[10] https://greet.es.anl.gov/other.models
[11] https://github.com/NUTransport/NUFRIEND

Section G - References

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