

## **DISCLAIMER**

**This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof. Reference herein to any social initiative (including but not limited to Diversity, Equity, and Inclusion (DEI); Community Benefits Plans (CBP); Justice 40; etc.) is made by the Author independent of any current requirement by the United States Government and does not constitute or imply endorsement, recommendation, or support by the United States Government or any agency thereof.**

# Final Project Report

January 2021 – December 2023

Date: April 29th, 2024

Prepared for:

**U. S. Department of Energy**



Submitted by:

**Cummins, Inc.**

Columbus, IN

Unique Entity ID: E724ZMNE7E27

Prime Recipient Type: Public/For Profit



## **Connected and Learning Based Optimal Freight Management for Efficiency**

**DoE Program Award Number: DE- EE0009206**

Award Type: Cooperative Research and Development Agreement

Prepared by:

Hoseinali Borhan

Principal Investigator

Cummins Research & Technology

[hoseinali.borhan@cummins.com](mailto:hoseinali.borhan@cummins.com)

## DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

*The results presented in this report are intended to showcase the capabilities and importance of the prototyped fleet modeling and optimization tool as it pertains to the baseline fleet operations and shipment requirements. The results are based on the scenarios considered within the scope of this project and are not meant to be generalized to the other fleets or overall freight transportation system.*

## Table of Contents

---

Executive Summary .....	4
Project Objectives and Timeline .....	7
Description of Activities Performed .....	9
Summary of Technical Findings .....	13
a) Demonstration of 20% WTW GHG reduction target and sensitivity studies .....	13
b) Technology roadmap study .....	17
Conclusion .....	20
Publications .....	20
Participants and Other Collaborating Organizations.....	20

## Executive Summary

The management of the future heterogeneous fleet is a complex decision-making problem as schematically shown in Figure 1. The heterogeneous fleet is emerging as decarbonization technologies are deployed by fleets toward lowering the freight operation emissions in Medium and Heavy-duty vehicles. Traditionally, in fleets characterized by a homogeneous Diesel Internal Combustion Engine (ICE) powertrain, the process of fleet planning and operational optimization unfolds sequentially without the necessity to account for powertrain and vehicle-specific characteristics during dispatch decisions. Fleets with trucks less than 5 years old tend to maintain stable vehicle efficiency with minimal operational reliability risks for fleet managers. However, the landscape changes with the incorporation of emerging powertrain technologies, which lack extensive operational data and service experiences. This includes technologies like hybrid, Electric, Fuel Cell, or alternative fuel ICE. Operational decisions for fleets featuring heterogeneous powertrain technologies and facing limited access to alternative fueling and charging stations become intricate, requiring careful consideration and optimization at each dispatch. The difference in efficiency characteristics of emerging technologies, their range limitations, and the restricted availability of charging/alternative fueling infrastructure, coupled with sensitivity to driving conditions (e.g., EV range reduction in low temperatures) and their impact on component aging (such as batteries), become pivotal factors influencing the reliable and efficient freight transportation.

To make the path toward low emission freight transportation efficient and reliable, an AI-assisted fleet management software is developed in this project to help fleet managers in optimizing both adoption of emerging powertrain decarbonization, connected and automated technologies and also operating the fleet after such technologies are deployed as schematically shown in Figure 2. Freight transportation requirements are different depending on the cargos to be shipped, customer requirements and regions of operations. This further highlights the need for software and digital solutions to tailor deployment and operation of emerging powertrain, connectivity, and automation technologies toward the specific fleet operation requirements. The fleet management optimizer was also integrated with a model of the fleet to simulate the operation of the fleet over 1 year of the baseline fleet operation (250,000+ shipments) indicating the significance of day-to-day variations on emissions and energy consumption of a freight transportation fleet. The results demonstrate  $\geq 20\%$  improvement in freight efficiency in terms of WTW CO<sub>2</sub> per ton-mile of cargo shipments while all fleet operation constraints are enforced, and the cost (CapEx and OpEx) is minimized. A few concluding remarks are listed below.

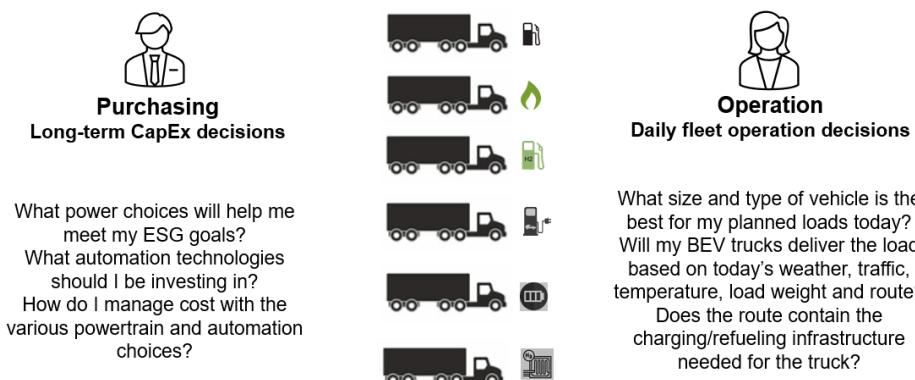


Figure 1 The fleet of the future is heterogeneous, which introduces more variables and considerations for decision making

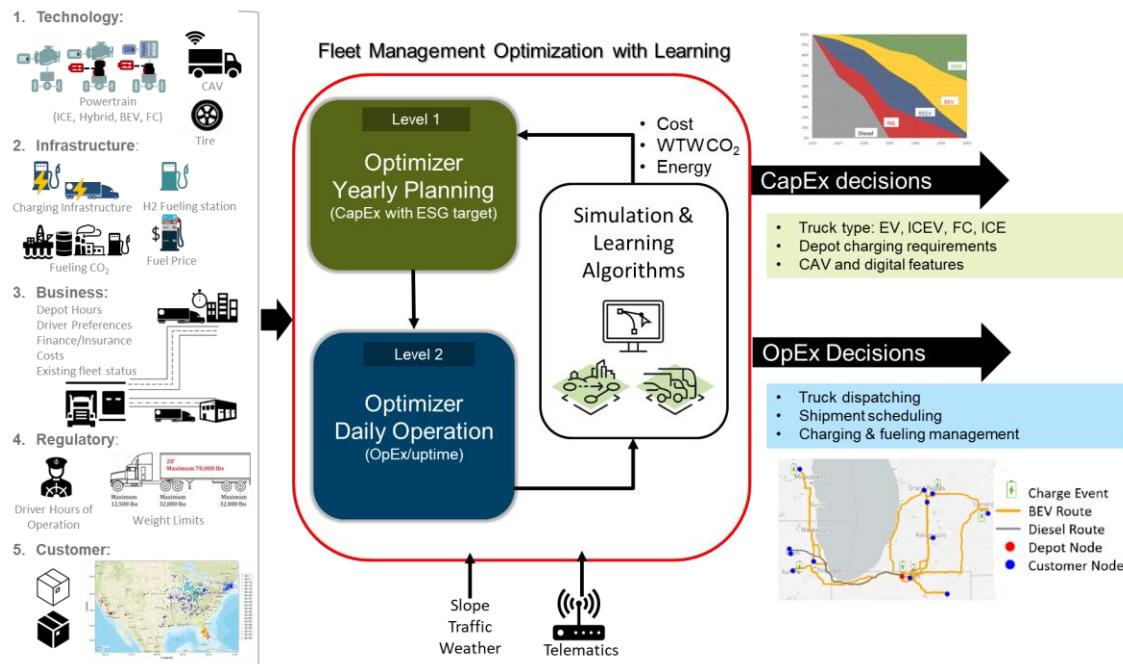


Figure 2 Fleet Optimizer Framework

- The technology adoption optimization of the project fleet partner over 2021 milestone year scenario assumptions indicates that the recommended fleet composition toward  $\geq 20\%$  improvement in fleet level WTW CO2 requires deployment of fully electric trucks, connectivity enabled eco-driving with Advanced Driver Assistance Systems (ADAS), low rolling resistance (LRR) tires, and fast chargers at depot. The project 20% WTW CO2 reduction target was further demonstrated with realistic fleet operation data by the simulation of the optimized fleet composition over real-world shipment data of the baseline fleet. Since part of the fleet is electrified with 2021 scenario toward the project target, the operation decisions of the new heterogeneous fleet turn into a more complex decision-making problem. One of the main challenges with the electric trucks is range limitations and uncertainties in driving range and energy consumption estimation. To further assess reliability, a sensitivity study to EV range uncertainties was conducted as being key for low temperature seasons in regions such as midwestern US where the baseline fleet is operating. This study indicated the risk of failed trips due to the uncertainties in EV range and energy consumption prediction. This led to the following 2 questions that are further assessed with learnings summarized:

1. *What is the impact of EV range variations on the effectiveness of EV deployment with the current battery and charging infrastructure?* The fleet operation with the recommended mixed ICE and BEV trucks was simulated for three different cases with 0%, 10% and 20% increase in average energy consumption of the BEVs. The optimizer was made aware of the impact on battery energy consumption for the three selected cases to analyze the effectiveness of BEVs toward the WTW CO2 efficiency reduction target. It was observed that by making the optimizer aware of the accurate EV energy consumption with exact EV range reduction, the trucks dispatching, and load scheduling decisions are changed accordingly to avoid failure of BEV trips. The WTW CO2

efficiency improvement however is reduced as more ICE trucks are dispatched to avoid failed trips.

2. *How do we mitigate the risk of failed trips by BEVs that are subject to inherent uncertainties in energy consumption and EV range estimation using advanced fleet management software solutions?* Through collaboration with the university of California, Berkeley, robust optimization methods along with feedback by learning the energy consumptions distribution incorporated to allow the energy consumption models to adapt to the evolving energy consumption encountered by the electric trucks to mitigate EV failed trips. While this reduced the risk of failed trips, ICE trucks are required to be deployed more comparing to the case when uncertainties in energy consumption and driving conditions are not considered. This would lead to reduction of BEV utilization due to reliability requirements.
- The technology adoption roadmap under different fuel pathway, cost and technology advancement scenarios was also developed for the baseline fleet. In this roadmap, the target is to reduce the fleet WTW CO<sub>2</sub> emissions by at least 20% with lowest TCO from baseline 2021 operation to optimized 2021, from optimized 2021 to 2025 and from optimized 2025 to 2030 scenarios. The proposed roadmap indicates the need toward major reduction in emission footprint of electricity and hydrogen generation, access to electricity/H<sub>2</sub> fueling infrastructure and advancement in reduction of cost and improvement of reliability of key components including battery and fuel cell. Under all these scenarios, connected digital and software solutions including the ones prototyped in this project are essential for efficient and reliable deployment of these emerging technologies that are subject to uncertainties in their operation and variation in their efficiency, sensitivity to driving conditions, aging behaviors, and limited access to fueling/charging infrastructure.
- Through Michelin company collaboration, dynamic low rolling resistance (LRR) tire models are developed and integrated into the vehicle models. These models consider the impact of variations in load, vehicle speed, tire temperature, pressure, and road surface conditions. The fleet planning optimizer results indicate the importance of LRR tires combined with electrification, connectivity, and automation to find a feasible and reliable low-cost path to the target.
- Through Argonne national laboratory collaboration, the baseline fleet operation simulation is extended from 3 months to 1 year. This is to assess the impact of seasonal operations and customer demand changes on the baseline fleet emissions and energy consumption calculations. Re-simulated 3 months baseline operation (more than 65,000 shipments) compared with 1 year operation (more than 250,000 shipments) indicates that the 3 months operation is representative.
- While learning from this project led to the development of advanced fleet management algorithms and IP with connectivity and AI and value demonstrated in simulation over real-world fleet operation data, testing the developed software solutions on a fleet with mixed powertrain technologies and integrated charger and possibly microgrid electricity generation at depot is recommended as the next step. Efficient, reliable, safe, and secure transition toward the future decarbonized and automated commercial fleet operation requires eco-system software and digital solutions with deployment of V2X connectivity, digital twin and AI and learning algorithms.

## Project Objectives and Timeline

---

The objective of the project was to develop, implement, and validate learning-based automated and optimal fleet simulation and management software solutions that are used to demonstrate freight operation efficiency improvement of  $\geq 20\%$  over a baseline fleet system that covers multi transportation modes including long-haul and regional-haul class 8 heavy duty trucks.

The project was conducted in 3 budget periods:

**Budget Period 1 - Technology Development (Complete):** A freight system simulation was developed in POLARIS (Argonne National Laboratory Simulation Tool), including vehicle and powertrain models, models for connected and automated technologies, deep learning and optimization algorithms, and fleet management software inputs. The freight operation was characterized, and the baseline freight operation was verified in simulation. The path to target was refined for optimal freight operational efficiency.

**Budget Period 2 - Technology Implementation and Demonstration in Simulation (Complete):** The learning and optimization algorithms were integrated with the POLARIS freight simulation models from Argonne national laboratory and the baseline fleet operation data. The freight operation scenarios were defined. A  $\geq 20\%$  freight operation efficiency was demonstrated in simulation and the specific conditions where this improvement is possible were detailed. The significance or impact on fuel savings of the various levers was determined: advanced powertrain technologies and matching with trip specific requirements, connectivity and automation, and tire adherence. Finally, path to target for freight operation optimal efficiency was refined with different levels of technology penetration.

**Budget Period 3 - Technology Validation on Fleet (Complete):** Evaluation with fleet data was completed. The utilization and refinement of algorithms and digital models, and the energy and WTW CO<sub>2</sub> savings validation on fleet was completed. The final steps were data sharing, refinement and report the path to target for freight optimal efficiency, roadmap for freight operation efficiency with advanced powertrain, connectivity and automation emerging technologies, technology to market plan and TCO analysis.

The project timeline is presented in Figure 3..

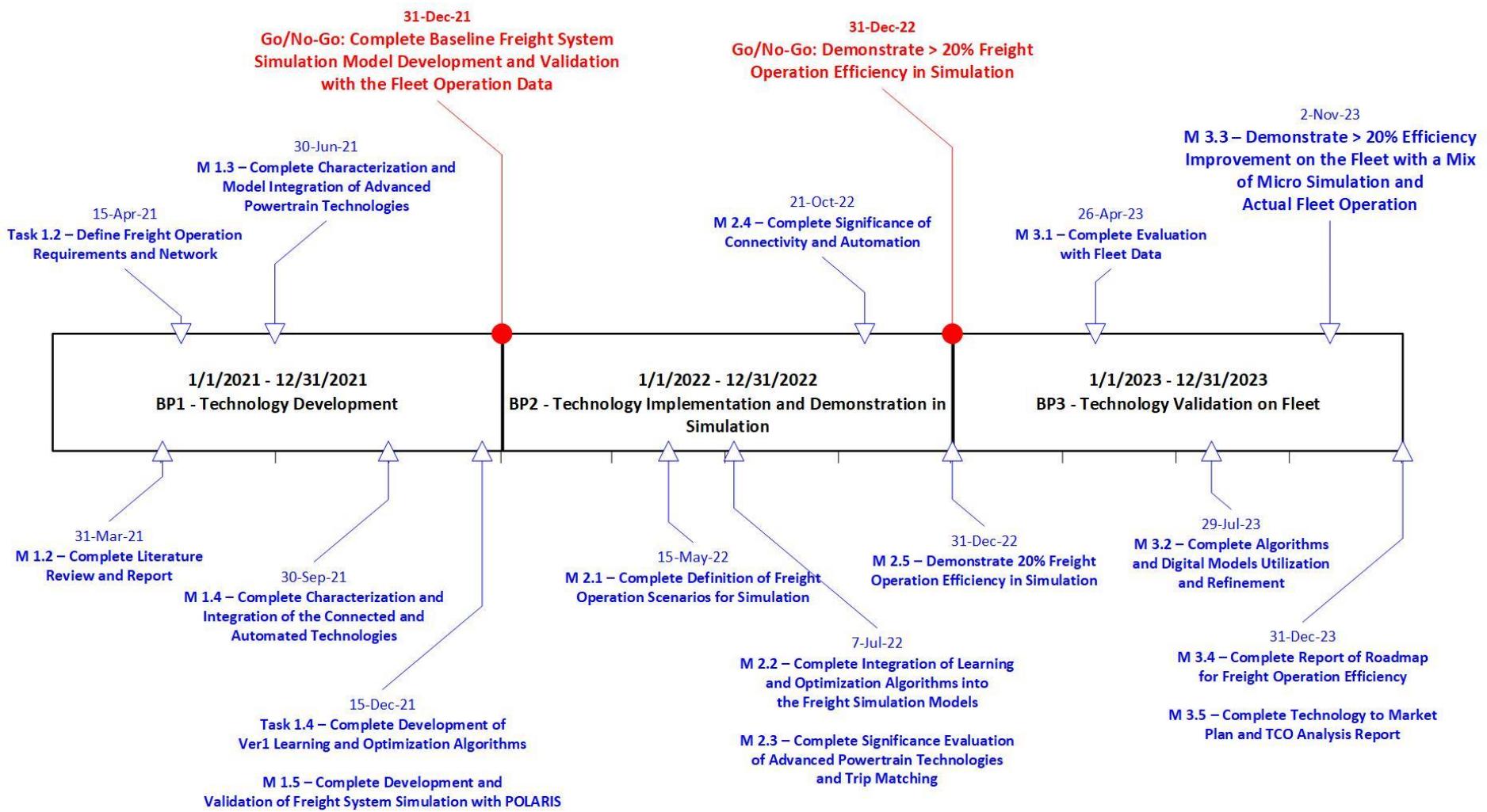


Figure 3 Project Timeline Overview

## Description of Activities Performed

---

The following tasks and milestones were completed and reported during this project.

### **Budget Period 1: Technology Development**

**Task 0.0 – Project Management and Planning:** The Recipient shall develop and maintain the Project Management Plan (PMP). The content, organization, and requirements for revision of the PMP are identified in the Federal Assistance Reporting Checklist and Instructions. The Recipient shall manage and implement the project in accordance with the PMP.

**Task 0.1 - Kick-Off Meeting:** The Recipient will participate in a project kickoff meeting with the DOE within 30 days of project initiation.

**Milestone 1.1 – Complete Kick-Off Meeting with DOE.**

**Task 0.2 – Collaboration with Argonne National Laboratory:** Achievement of overall project objectives is dependent upon tasks performed by a national laboratory funded under a separate DOE award. The recipient will coordinate and collaboratively conduct work with the national laboratory on tasks integral to the completion of the project. The results of this collaborative effort with the national laboratory will be included in all project reporting. Argonne National Laboratory will support with the POLARIS-SVTrip-Autonomie simulation system for transportation modeling. Furthermore, Argonne will be working to integrate reinforcement learning methods to aim the development of a complete optimal fleet operation system.

**Task 1.1 – Complete Literature Review and Report:** The recipient will conduct a literature survey in the state of the art of fleet management.

**Milestone 1.2 – Complete Literature Review and Report:** The literature review and report have been finalized.

**Task 1.2 – Define Freight Operation Requirements and Network:** The recipient will determine the requirements for alternative powertrains, define vehicle characterization and modeling, and perform well-to-wheels characterization. The baseline transportation fleet operation will be characterized.

**Task 1.3 – Develop Freight System Simulation in POLARIS:** The recipient will develop the building blocks for the simulation of the freight transportation system in POLARIS. It will include truck models with different powertrain technologies, CAV features, and interface to baseline fleet management software.

**Task 1.4 – Develop Learning and Optimization Algorithms for Optimal Fleet Operation:** The recipient will design stochastic optimal dispatch algorithms with learning. The recipient will develop optimal vehicle-to-route dispatch algorithms that account for uncertainty in energy and emissions and learn from data.

**Milestone 1.3 – Complete Characterization and Model Integration of Advanced Powertrain Technologies:** The characterization and model integration of advanced powertrain technologies is complete.

**Milestone 1.4 – Complete Characterization and Integration of the Connected and Automated Technologies:** The characterization and model integration of the connected and automated technologies is complete.

**Task 1.5 – Verify Baseline Freight Operation in Simulation:** The recipient will integrate the transportation fleet characteristics and the freight system simulation framework with respect to the baseline operation. This will serve as a reference for future tasks for the freight efficiency and properties of the baseline.

**Milestone 1.5 – Complete Development and Validation of Freight System Simulation:** The freight system simulation is developed and validated against the baseline freight operation.

**Task 1.6 – Refine Path to Target for Freight Operation Optimal Efficiency:** The recipient will refine the path to target of 20% improvement in freight operation efficiency to plan for the technology implementation phase.

**Go/No-Go BP1: Complete Baseline Freight System Simulation Model Development and Validation with the Fleet Operation Data:** The baseline freight operation has been successfully evaluated in the freight system simulation model. An absolute number in the appropriate units will be established as the baseline freight operation.

#### **Budget Period 2: Technology Implementation and Demonstration in Simulation**

**Task 2.1 – Define Freight Operation Scenarios for Simulation:** The recipient will determine the potential scenarios for freight operation simulation. Data from the Venture Logistics fleet will be collected, processes, and analyzed to aid in the scenario definition.

**Milestone 2.1 - Complete Definition of Freight Operation Scenarios for Simulation:** The potential scenarios for freight operation simulation have been defined.

**Task 2.2 – Integrate Learning and Optimization Algorithms with POLARIS Freight Simulation Models and Baseline Fleet Management System from Venture Logistics:** The recipient will integrate the learning and optimization algorithms with the freight simulation models and will perform optimization of the baseline freight operation.

**Milestone 2.2 - Complete Integration of Learning and Optimization Algorithms into the Freight Simulation Models:** The integration of the learning and optimization algorithms into the freight simulation models is complete and the baseline freight operation (with the current fleet of vehicles) has been optimized.

**Task 2.3 – Demonstrate 20% Freight Operation Efficiency in Simulation:** The recipient will demonstrate of  $\geq 20\%$  improvement in freight efficiency by incorporation of advanced powertrains, automation and connectivity technologies.

**Task 2.4 – Refine Path to Target for Freight Operation Optimal Efficiency with Different Levels of Technology Penetration:** The recipient will update the path to target with the inputs from the

previous tasks and subtasks to reflect the realizable benefits from optimization, alternative powertrains, connectivity, and automation.

**Milestone 2.3** - Complete Significance Evaluation of Advanced Powertrain Technologies and Matching with Trip Specific Requirements: The significance and contributions of advanced powertrain technologies and trip matching have been determined and completed.

**Milestone 2.4** - Complete Significance of Connectivity and Automation: The significance and contributions of connectivity and automation technologies have been determined and completed.

**Go/No-Go: Demonstrate  $\geq 20\%$  Freight Operation Efficiency in Simulation:** The  $\geq 20\%$  improvement in freight efficiency has been demonstrated and the conditions under which the improvement is feasible are documented. This includes quantifications of the required targets for penetration of alternative powertrains, powertrain to route matching, and automation/connectivity technologies.

### **Budget Period 3: Technology Validation on Fleet**

**Task 3.1 – Complete Evaluation with Fleet Data:** The recipient will use data collected from the fleet and evaluate on the system model.

**Milestone 3.1 – Complete Evaluation with Fleet Data:** The fleet data has been evaluated on the system model, and the models have been verified and validated under real-world conditions.

**Task 3.2 – Complete Algorithms and Digital Models Utilization and Refinement:** The recipient will use fleet data and optimization results to refine the models and optimization routines.

**Milestone 3.2 – Complete Algorithms and Digital Models Utilization and Refinement:** The models and optimization routines have been refined with fleet data and optimization results. The models' capability of learn and adapt has been demonstrated.

**Task 3.3 – Complete Energy and CO<sub>2</sub> Savings Validation on Fleet:** The recipient will estimate the energy and GHG savings under real-world fleet conditions by the aggregate of all the technologies embodied in the project.

### **Task 3.4 – Complete Data Sharing**

The recipient will provide the testing and validation data to the SMART Mobility National Lab Consortium through the Livewire Data Platform.

**Milestone 3.3 – Demonstrate  $\geq 20\%$  Efficiency Improvement on the Fleet with a Mix of Micro Simulation and Actual Fleet Operation:** A  $\geq 20\%$  improvement in freight efficiency is demonstrated under real-world fleet conditions by the aggregate of all the technologies embodied in the project.

### **Task 3.5 – Complete Refinement and Report the Path to Target for Freight Optimal Efficiency**

The recipient will update the path to target with the inputs from the previous tasks and subtasks to reflect the realizable benefits from optimization, alternative powertrains, connectivity and automation, and real-world fleet conditions.

### **Task 3.6 – Report Roadmap for Freight Operation Efficiency with Advanced Powertrain, Connectivity and Automation Emerging Technologies**

The recipient will develop the roadmap for freight operation efficiency, capturing the learnings, challenges, and achievements of the project.

**Milestone 3.4 – Complete Report of Roadmap for Freight Operation Efficiency:** The road map for freight operation efficiency improvement is complete.

**Task 3.7 – Develop Technology to Market Plan and TCO Analysis**

The recipient will develop the technology to market.

**Milestone 3.5 – Complete Technology to Market Plan and TCO Analysis Report:** The technology to market plan and techno-economic analysis are complete.

## Summary of Technical Findings

---

### a) Demonstration of 20% WTW GHG reduction target and sensitivity studies

---

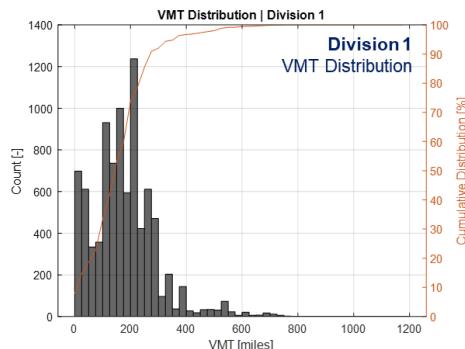
To manage the complex decision making of the emerging heterogeneous fleets and make the path toward low emission freight transportation efficient and resilient, an AI-assisted fleet optimizer is developed to optimize decisions in terms of both investment in emerging technologies and efficient and reliable utilization of these technologies in the daily operation of the fleet. The optimization is done with respect to total cost of ownership including operation cost and subject to GHG emissions reduction target, fleet operation constraints, regulatory requirements, and cargo shipments demand. Learning algorithms are integrated to utilize operation data of the fleet and update models and decisions over time as new data is collected. This model is refined and updated with actual fleet operation data. To demonstrate the target, the developed fleet optimization framework is applied on the baseline fleet with the optimized fleet composition shown in Table 1.

Table 1: Planning optimizer recommendations for the selected fleet

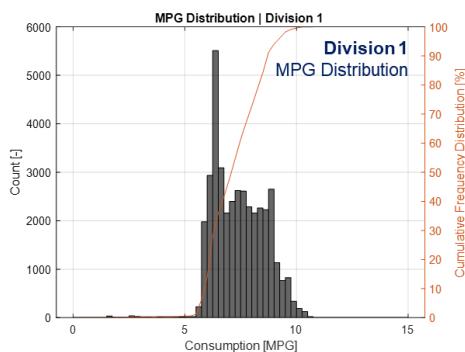
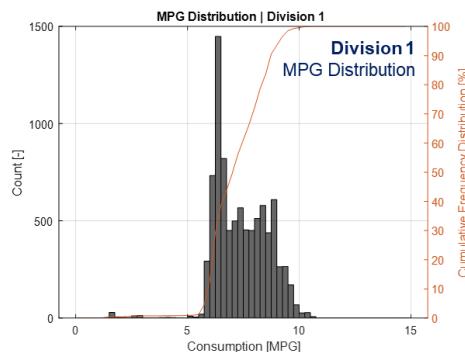
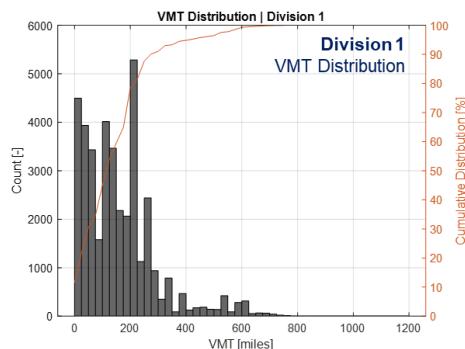
	Baseline	Optimized Fleet Composition
Fleet Composition (All Trucks Class 8 Regional Haul)	10 Conventional Diesel	7 Diesel ICE with ADAS 2 BEV with ADAS 1 BEV w/o ADAS All trucks with LRR tires Electric charger at Depot (350KW)

The fleet operation is simulated over 3 months (90 days) of baseline fleet with both the current all diesel conventional truck fleet composition and the optimized fleet composition. Through collaboration with Argonne National Laboratory team, the 3 months of operation is confirmed to be representative for 1 year of the fleet operation as shown in Figure 4. Through collaboration with Michelin company, tire models for both standard and low rolling resistance (LRR) designs are developed, and the models are integrated in the vehicle models developed in Amber Autonomie vehicle simulation tool from Argonne National Laboratory. A dynamic tire model to capture the impact of tire pressure, ambient temperature and truck duty cycle is developed by Michelin company through testing tires under different operating conditions. The daily optimizer makes the decisions of the number and types of trucks dispatched, the payload on each trip, the schedule of the trips to be assigned to each truck, and the BEV recharge events and time. Figure 5 and Figure 6 show the routing and dispatching optimal decisions for one of the days of the 3 months of the fleet operation. By running the simulation over the 3 months of fleet operation, the results shown in Figure 7 to Figure 10 are achieved. As it is demonstrated, the demand and consequently the vehicle miles travelled, energy consumption and emissions are varying in each day. More than 20% cumulative improvement in fleet level WTW GHG CO<sub>2</sub> emissions is achieved with the recommended fleet composition and operation optimization. There is also about 16.1% improvement in OpEx. Considering the increase in CapEx and improvement in OpEx, the yearly total cost of ownership is projected to increase. Please note that the results may change depending on the fleet cargo demands, cost assumptions, region of operation of the fleet, season of operation and technology improvements over time.

**Venture baseline 3-month of operation (~65k trips)**



**Venture extended 12-month of operation (~255k trips)**



**Figure 4 Comparison of selected 3 months of fleet operation versus 1 year of operation**



**Figure 5 Sample Day of Operation with the Optimized Fleet**

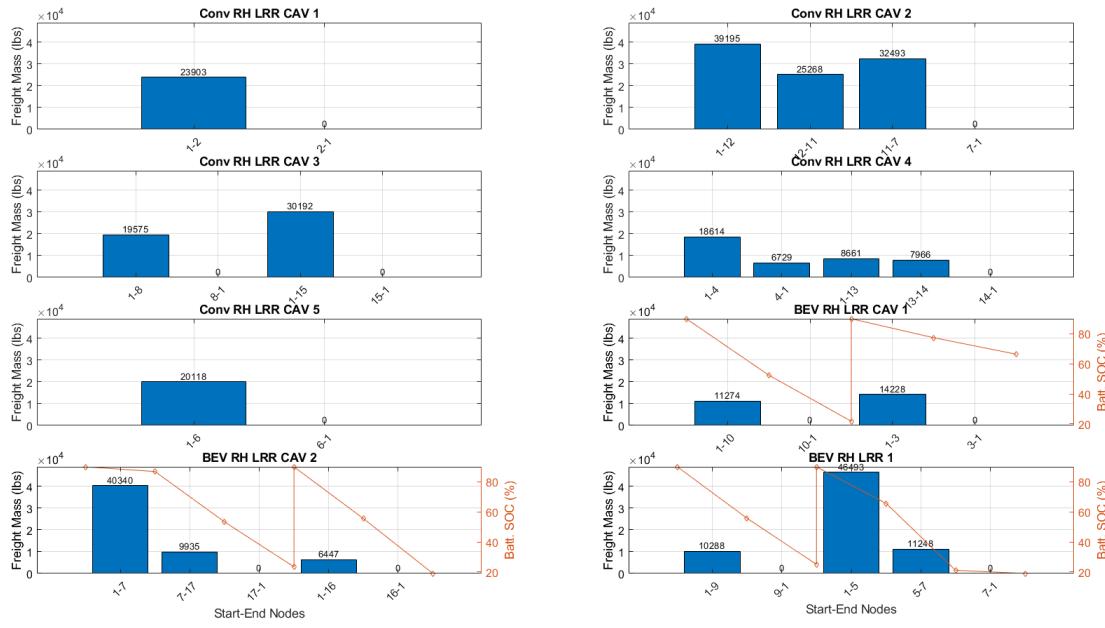


Figure 6 Sample Day of Operation with the Optimized Fleet

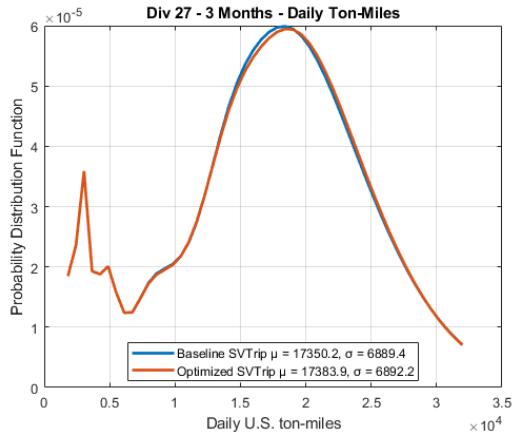


Figure 7 Distribution of daily Ton-mile

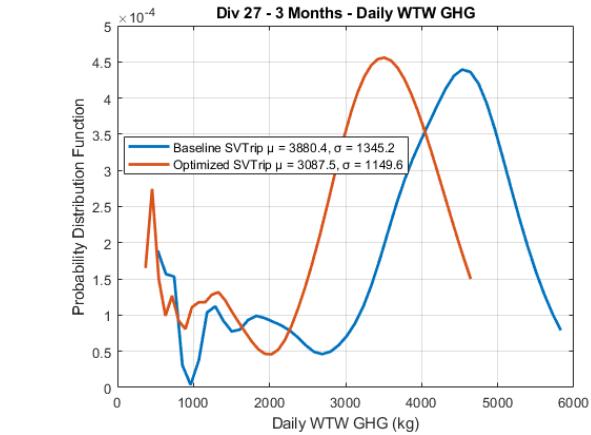


Figure 8 Distribution of freight specific WTW greenhouse gas emissions

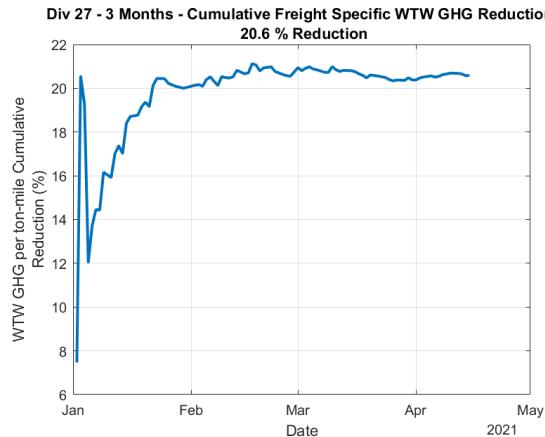


Figure 9 Cumulative freight specific WTW GHG reduction

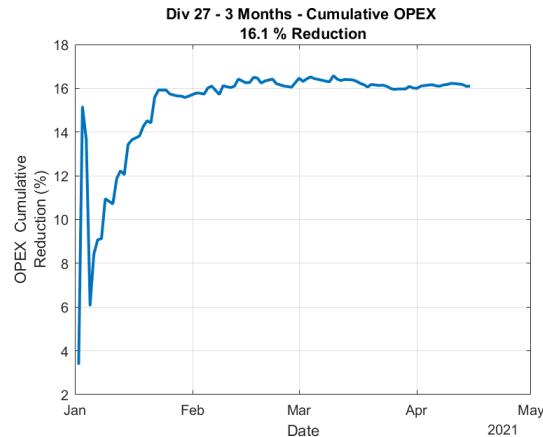


Figure 10 Cumulative OPEX reduction

To further understand the impact of fleet operation optimization over the fleet with the adopted technologies, the distribution of daily vehicle miles travelled by BEVs are compared with Diesel ICE trucks as shown in Figure 11. Out of the total vehicle miles travelled by the optimized fleet, we can see that the utilization of BEVs is maximized due to OPEX benefits of BEVs. However, since BEV operation on high milage trips is limited due to the EV range limitations, we see that the Diesel ICE trucks are dispatched more often when the daily milage goes beyond 220 miles. This emphasizes how the fleet operation optimizer reshapes the operation of the baseline fleet to maximize asset utilization toward reducing cost of operation while meeting the emissions and operation constraints.

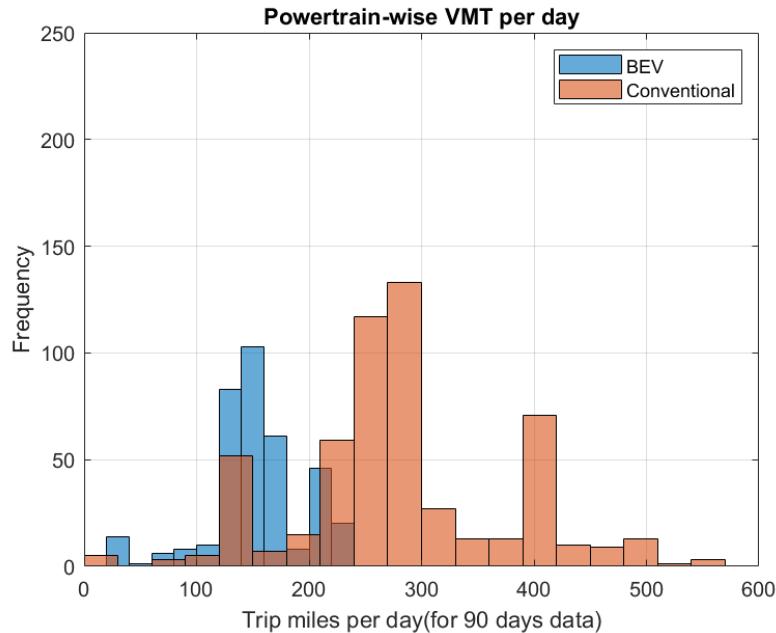
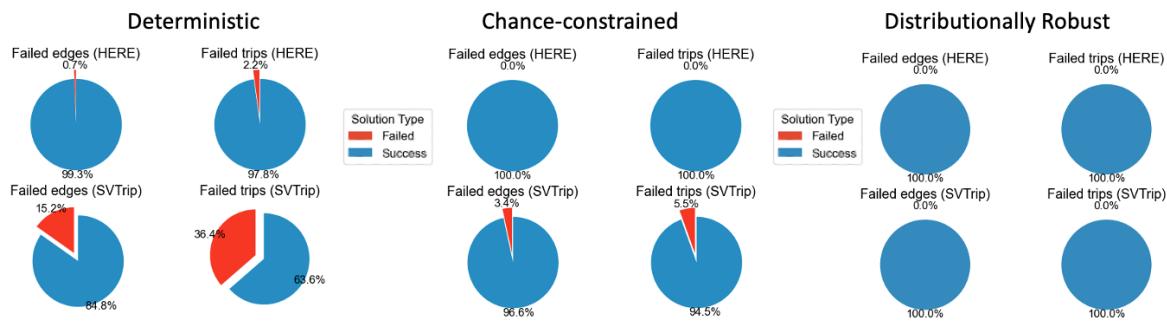


Figure 11 Powertrain-wise trip miles per day

To assess reliability, a sensitivity study to EV range uncertainties conducted as being key for low temperature seasons in regions such as midwestern US where the baseline fleet is operating. The preliminary simulation under low temperature indicated the risk of failed trips due to the uncertainties in EV range and energy consumption prediction. This led to the following 2 questions that are further evaluated:

- **What is the impact of EV range variations on the effectiveness of EV deployment with the current battery and charging infrastructure?** To address the question of the effectiveness of BEV technologies with EV range variation, the operation optimization algorithms were updated to utilize the accurate EV models with EV range reduction impacts. The fleet operation with recommended mixed ICE and BEV powertrain was simulated for three different cases with 0%, 10% and 20% increase in average energy consumption of BEVs. The results indicated that for the 10% increase in average energy consumption case, the WTW CO<sub>2</sub> reduction was 1.62% less than 20% target. For the 20% increase in average energy consumption case, the WTW CO<sub>2</sub> reduction was 4.95% less than the 20% target. This decrease in efficiency to reduce WTW CO<sub>2</sub> is due to the need for higher dispatch of ICE trucks to mitigate the EV range reduction and avoid any fail trips.
- **How do we mitigate the risk of failed trips by BEVs that are subject to inherent uncertainties in energy consumption and EV range estimation using advanced fleet management software solutions?** The BEVs have demonstrated range variation due to inherent changes in the real-world driving conditions such as duty cycle, ambient temperature, and traffic conditions. These variations are often hard to predict accurately which resulted in the need for using more complex fleet management software solutions including robust and learning optimization techniques developed

through collaboration with the University of California, Berkeley in this project. These software solutions can provide a practical and automated approach to learn uncertainties with AI methods as the fleet is operating while utilizing classical robust optimization methods to avoid failed trips. While such methods can address the risk of failed trips by BEVs due to uncertainties in EV range estimation, the effectiveness of BEV deployment is reduced due to the need for more conservative use of BEVs to mitigate the risk of BEV failed trips and meet the high priority reliability requirements of commercial vehicle fleet operation. The percentage of failed trips for each of the methods demonstrated are outlined in Figure 12.



**Figure 12** Percentage of trip failures and edge failures for (a) deterministic optimizer, (b) chance-constrained optimizer and (c) Distributionally robust optimizer.

## b) Technology roadmap study

The trajectory of improving freight efficiency in the future will be intricately linked to the evolution and integration of advanced technologies within the fleets. The advancement of technologies, such as electrified powertrains, autonomous systems, and data analytics, will be crucial in enhancing the overall efficiency of freight operations. The extent to which these technologies penetrate and integrate into diverse fleets will have a direct impact on their effectiveness in optimizing freight processes. Additionally, the shift towards decarbonized fuel pathways is expected to play a pivotal role in shaping the efficiency landscape of freight operations. The primary goal of the technology roadmap is to outline potential paths for technological development that lead to the achievement of specific targets in freight operational efficiency while considering the impact of decarbonization of fuel pathways and infrastructure availability. Roadmap considers the varying pace of technology progress and the availability of supporting infrastructure, ensuring that the proposed paths are adaptable to changes in the technological landscape. This section delves into the detailed methodology employed in the creation of the technology roadmap for the baseline fleet. It outlines the systematic approach taken to assess current technologies, project future advancements, and factor in the influence of infrastructure availability on the implementation of these technologies. To account for the uncertainties in the future, the roadmap explores different scenarios. These scenarios encompass variations in technology progress, changes in fuel pathways, and fluctuations in infrastructure development. As described in Figure 13, a total of three scenarios were considered to describe the variation in technology improvements and associated cost along with infrastructure availability. Each of these scenarios do consider Commercial Clean Vehicles Tax Credit of up to \$40,000 under Internal Revenue Code (IRC) 45W.

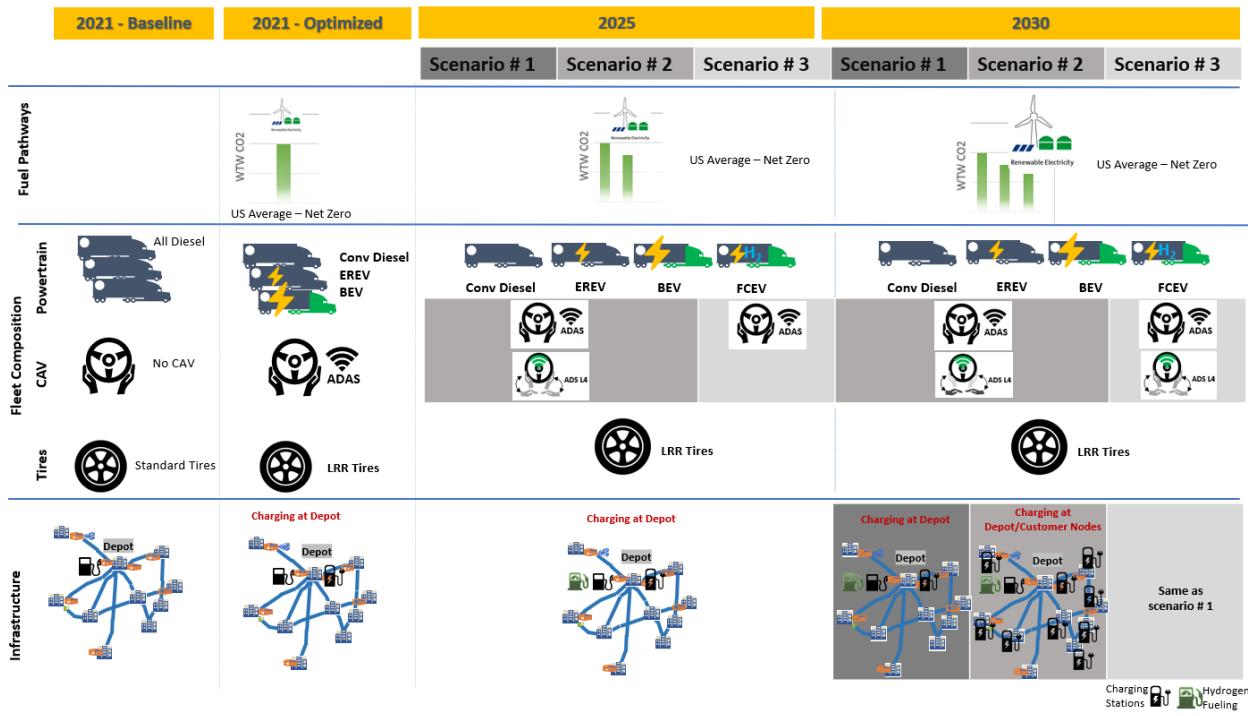


Figure 13 Scenarios for Technology Roadmap for the Baseline Fleet

**Scenario 1: Accelerated Technology Adoption (DOE Targets):** In this scenario, rapid technological advancements are expected to lead to substantial cost reductions in battery and fuel cell technologies, aligning with ambitious Department of Energy (DOE) targets for innovation and sustainability. The scenario envisions achieving these targets, making technologies more economically viable. Additionally, there is an expectation of higher penetration of Connected and Autonomous Vehicle (CAV) technologies, signaling widespread adoption of autonomous and connected vehicles. Technology trends are aligned with “low case”<sup>1</sup> from the 2022 ANL report to US Department of Energy<sup>2</sup>. For milestone year 2025, the powertrain technologies under consideration included diesel Internal Combustion Engine (ICE), Extended Range Electric Vehicle (EREV), Battery Electric Vehicle (BEV), and Fuel Cell Electric Vehicle (FCEV) with both standard and Low Rolling Resistance (LRR) tires. Each of these vehicle options offers the choice between an Advanced Driver Assistance Systems (ADAS) or a Level 4 Autonomous Driving System (ADS) package. It is assumed that a vehicle equipped with the ADS Level 4 autonomous driving system requires the driver's operation in urban areas, while the vehicle can operate autonomously on highways. This results in a 50% reduction in driver dependency for these vehicles, meaning the driver needs to operate the vehicle only 50% of the time. The capital cost associated with implementing this system is assumed to be \$50,000, accompanied by a technology service cost of \$0.32 per mile. Charging infrastructure for plug-in hybrids and Battery Electric Vehicles (BEV) is assumed to be available at the depot. The objective of the planning optimizer is to minimize the total cost of ownership (TCO) for the fleet while achieving a Well-to-Wheel (WTW) CO<sub>2</sub> reduction target of 20% compared to the 2021 baseline on the selected day of operation. The combination of powertrain technologies, vehicle technologies, and lower carbon intensities for various fuel pathways is expected to contribute to achieving this WTW CO<sub>2</sub> reduction. For milestone year 2030, powertrain technology candidates remain the same as those in 2025. Each powertrain technology includes an optional ADS Level 4 system. A

<sup>1</sup> Low case, aligned with DOE expected technology improvement based on business-as-usual case.

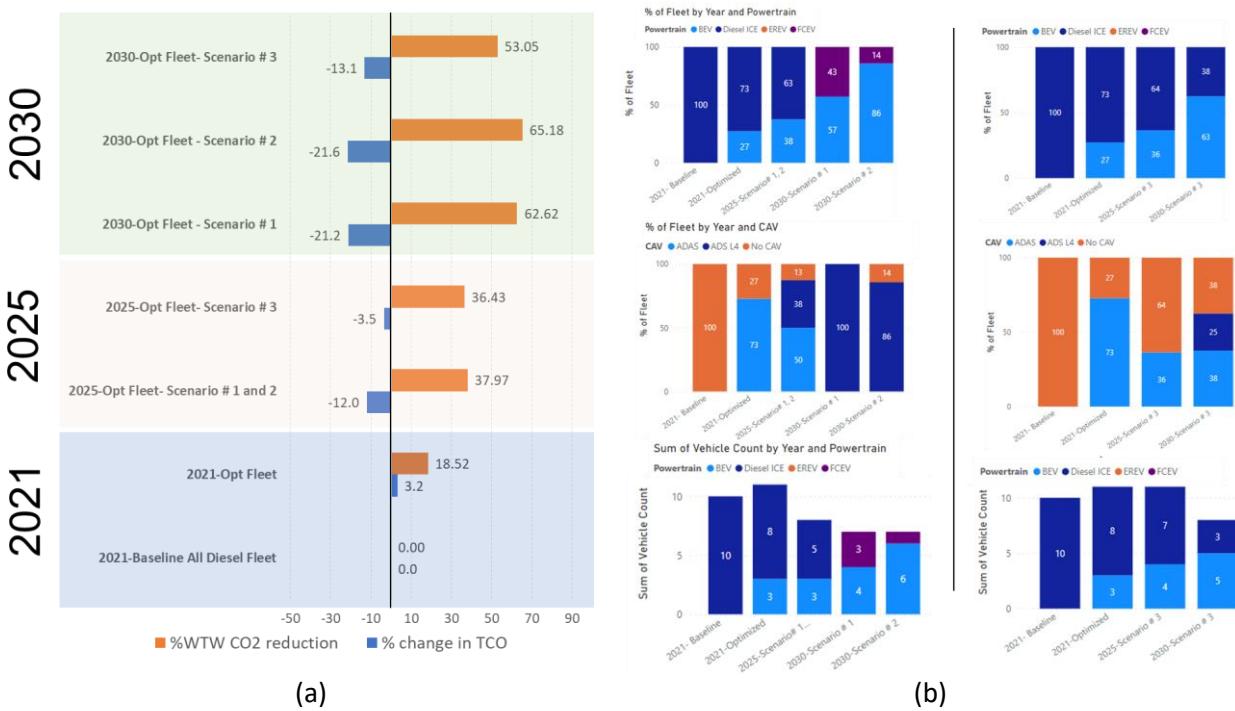
<sup>2</sup> Ehsan Sabri Islam, Ram Vijayagopal, Aymeric Rousseau. “A Comprehensive Simulation Study to Evaluate Future Vehicle Energy and Cost Reduction Potential”, Report to the US Department of Energy, Contract ANL/ESD-22/6, October 2022 (Ehsan Sabri Islam, 2022)

significant change for 2030 is the reduction in driver supervision to 20% with the ADS Level 4 system. The capital cost associated with the ADS technology remains consistent with 2025, while the technology service cost increases to \$0.45 per mile. This cost increase is attributed to a higher percentage of autonomous driving. The Well-to-Wheel (WTW) reduction target is set at 20% relative to the target value for the 2025 scenario.

**Scenario 2: Accelerated infrastructure growth:** This scenario shares the same assumptions regarding powertrain and Connected and Autonomous Vehicle (CAV) technologies as scenario #1, with one key distinction related to charging infrastructure considerations for the year 2030. This scenario incorporates a faster growth rate in public charging infrastructure for 2030. The planning optimizer considers the availability of charging infrastructure at all customer nodes for this scenario. To account for increased cost of charging at customer locations, this scenario assumes that vehicles can charge at these external locations with 75% higher cost than charging at depot.

**Scenario 3: Moderate Industry Projections:** This scenario embraces a balanced and measured approach, considering both sustainability and market dynamics. Cost reductions follow a gradual trajectory aligning with industry trends. The scenario envisions a steady but cautious decrease in battery and fuel cell costs, emphasizing sustainability without aggressive changes. The adoption of vehicle connectivity systems is approached at a measured rate, considering factors such as consumer acceptance and technological readiness. Industry projections serve as a guide, ensuring decisions align with evolving market trends. The overarching theme is to strike a balance between sustainability goals and practical considerations of the market.

The results for the technology road map study for different scenarios are outlined in Figure 14. Note that this roadmap is recommended for the baseline fleet and is not meant to be generalized for the entire freight transportation.



**Figure 14: Summary of Technology Roadmap Results towards WTW CO2 Reduction Target of the Baseline Fleet; (a) scenario-wise WTW CO2 reduction and TCO percentage changes for 2021, 2025 and 2030; (b) Scenario-wise powertrain, CAV and number of vehicles for 2021, 2025 and 2030 optimal fleet composition (Note that reduction in the number of vehicles needed in a few scenarios is due to autonomous technology adoption assumptions and related relaxation of drivers hour of operation constraints. Freight demand is assumed constant for the fleet over different milestone years and scenarios).**

## Conclusion

---

The heterogenous fleet is emerging as decarbonization technologies are deployed by fleets towards lowering the freight operation emissions in Medium and Heavy-Duty vehicles. To make the path towards low emission freight transportation efficient and reliable, an AI-assisted fleet optimizer is developed in this project to help fleet managers in making optimized decisions for efficiency and cost. The fleet management optimizer is also integrated with a model of the fleet to simulate the operation of the fleet over a given time to indicate the significance of day-to-day variations on emissions and energy consumption of a freight transportation fleet. The fleet optimizer is integrated with baseline fleet simulation models and both baseline and optimized fleet simulation results over 3 months of operation are reported. The models are further refined with real fleet operation data and updated vehicle specifications and optimization algorithms. This framework is used to demonstrate  $\geq 20\%$  improvement in freight efficiency in terms of WTW CO<sub>2</sub> GHG emissions per US ton-mile of cargo shipments while all fleet operation constraints are enforced, and the cost is minimized. The developed models and methods can be applied to different fleets and under different cost and technology readiness scenarios. Furthermore, a sensitivity analysis on EV range was conducted for low temperature cases to assess reliability of BEVs and advanced learning algorithms were developed in collaboration with University of California Berkley to make dispatches more reliable and robust.

## Publications

---

1. Ruiting Wang, Patrick Keyantuo, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Optimal Dispatch and Routing of Electrified Heavy-Duty Truck Fleets: A Case Study with Fleet Data", 2023 American Control Conference (ACC), San Diego, CA, USA, 2023, pp. 1729-1734
2. Patrick Keyantuo, Ruiting Wang, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Distributionally Robust and Data-Driven Solutions to Commercial Vehicle Routing Problems", 2023 IFAC World Congress, Volume 56, Issue 2, 2023, Pages 10497-10502, ISSN 2405-8963
3. C. Mansour, O. Sahin, N. Zuniga-Garcia, R. Vijayagopal, and H. Borhan, "From Diesel to Electric and Hydrogen: Assessing the Viability of Advanced Powertrains for Long-Haul Trucks," 103rd Transportation Research Board (TRB) Annual Meeting, TRB, 2024
4. Olcay Sahin and Charbel Mansour, "Addressing Data Gaps in Transportation Emissions Analysis: A Simulation Framework for Metropolitan Planning Organizations and Logistics Companies," 2023 Innovations in Freight Data Workshop, Washington, DC: TRB, 2023
5. Ruiting Wang, Patrick Keyantuo, Teng Zeng, Jairo Sandoval, Aashrith Vishwanath, Hoseinali Borhan, Scott Moura, "Optimal Routing of a Mixed Fleet of Heavy-Duty Trucks with Pickup and Delivery: A Case Study with Fleet Data", Under Review, IEEE Transactions on Intelligent Transportation Systems, 2023.

## Participants and Other Collaborating Organizations

---

- a) Key team members:
  - Hoseinali Borhan, Principal Investigator, Technical Project Leader, Cummins Inc., Columbus, IN
  - Aashrith Vishwanath, Technical Specialist, Cummins Inc., Columbus, IN
  - Priyank Jain, Technical Advisor - System Architecture, Cummins Inc., Columbus, IN

- David Yu, Energy Management Leader, Cummins Inc., Columbus, IN
- Sooraj Unni, Machine Integration Simulation Engineer, Cummins Inc., Columbus, IN
- Ying Huang, Sr. Research Engineer – Connected and Intelligent Systems, Cummins Inc., Columbus, IN
- Michael Hughes, Director-Advanced Connected Products and Digital Twins, Cummins Inc., Columbus, IN
- Scott Moura, Associate Professor, University of California Berkeley, Berkeley, CA
- Ruiting Wang, Graduate Student, University of California Berkeley, Berkeley, CA
- Patrick Keyantuo, Graduate Student, University of California Berkeley, Berkeley, CA
- Robert Radulescu, Executive Fellow, Michelin North America, Greenville, SC
- Gurkan Erdogan, Michelin North America, Greenville, SC
- Jeremy Trowbridge, Michelin North America, Greenville, SC
- Rajat Aggarwal, Michelin North America, Greenville, SC
- Aymeric Rousseau, Vehicle and Mobility Group Manager, Argonne National Laboratory, Lemont, IL
- Olcay Sahin, Argonne National Laboratory, Lemont, IL
- Ram Vijayagopal, Argonne National Laboratory, Lemont, IL
- Charbel Mansour, Argonne National Laboratory, Lemont, IL
- Justin Weber, Chief Operating Officer, Venture Logistics, Indianapolis, IN
- Mike Kuebler, Business Intelligence Director, Venture Logistics, Indianapolis, IN

b) Other organizations involved as partners:

- **Argonne National Laboratory**, Lemont, IL 60439  
Contribution to the project: Support with the POLARIS-SVTrip-Autonomie simulation system for transportation modeling. The knowledge, data and models that have been developed in this framework can be leveraged to adaptively transfer learning onto subsequent heavy duty and freight management modeling. Furthermore, Argonne will be working to integrate reinforcement learning methods to aim the development of a complete optimal fleet operation system.
- **Michelin North America**, Greenville, SC 29615  
Contribution to the project: Quantify the improvements in fuel savings when accounting for information about tire inflation pressure, temperature, and adherence capabilities through tire connectivity. The scope of this work will include tires for Class 3 (16" tires), Class 5&6 (19.5" tires) and Class 8 (22.5" tires) vehicles.
- **University of California Berkeley**, Berkeley, CA 94720  
Contribution to the project: Develop and integrate stochastic and learning optimal fleet management algorithms with Cummins collaboration to account for uncertainty in energy and emissions through learning algorithms. The algorithms will consider powertrain characteristics, connectivity, and automation features to be enabled when applicable.
- **Venture Logistics**, Indianapolis, IN 46217  
Contribution to the project: To support with insights on fleet logistics and operation, constraints and requirements for optimization, and data collection to characterize the fleet operation and testing of the algorithms.