Connected Commercial Electric Vehicle Research for Intelligent Energy Management and Emissions Reductions

Will Northrop

Associate Professor – Mechanical Engineering

Director, Thomas E Murphy Engine Research Lab

wnorthro@umn.edu

CTS Transportation Environment and Energy (E&E) in Transportation Research Council October 27, 2020



Vehicle Transport and CO₂ Emissions

2018 U.S. GHG Emissions by Sector

2



2018 U.S. Transportation Sector GHG Emissions by Source

https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions

Medium and heavy duty trucks account for only ~4% of the vehicle population



Electrification can lower net CO₂ emissions



https://www.carbonbrief.org/fact check-how-electric-vehicleshelp-to-tackle-climate-change

However, due to lifecycle energy use, it is not a panacea



Telematics and Data Analysis

- Commercial truck sales down significantly in 2020
- Telematics market is growing
 - 29.3 million vehicles in 2020
 - 10% annual increase
 - \$17.1B market in the US
- Reductions in fuel use proportional to CO₂ – reductions



https://www.forbes.com/sites/sarwantsingh/2020/06/03/commercial-vehicle-sales-are-ailing-so-why-is-the-connected-truck-telematics-market-still-in-good-health/#2daa316f7e12

Telematics: Part of the Connectivity Landscape



Vehicles will use greater levels of connectivity in the future V2V, V2I, V2C, V2X



Vehicle Data Vision

- Collect more and diverse datasets
- Data can be used for:
 - 1. Analysis for design feedback
 - 2. Predictive diagnostics
 - 3. In-use powertrain improvement
- Develop rule-based data approaches to:
 - Improve fuel economy for PHEVs
 - Optimize on-route fast charging
 - Predict EV range on-route
 - Adjust shifting control to minimize energy use



https://www.magzter.com/article/Autom otive/Commercial-Vehicle/Safe-Drive-With-Telematics

Connectivity Enables Vehicle Electrification

- Range in EVs is limited
- Depends heavily on:
 - Ambient temperature
 - HVAC loads
 - Mass
 - Driving behavior



- Connectivity can
 provide range
 confidence
- Charge optimization
- Route planning and load distribution



Technology Description



8

Portfolio of Connected Vehicle Projects



DOE/Exergi Predictive **EV Delivery Truck Range Prediction**

Cloud-Connected Last Mile Delivery Vehicles

- <u>Aim:</u> Improve the fuel economy of range extender (REx)-equipped electric delivery vehicles through real-time powertrain optimization using two-way vehicle-to-cloud (V2C) connectivity
- <u>Goal</u>: Greater than 20% energy efficiency improvement of a baseline 2016 E-Gen delivery vehicle integrating routing, V2C and physics-aware data analytics







Connected Energy Management

- **Two Interventions:** C-EMS and Energy Efficient Routing (EER)
- EER Reduced energy use between set origin-dest. pairs with time penalty
- C-EMS Minimized fuel consumption through practical rulebased algorithms



Workhorse E-Gen Vehicle

- E-GEN Vehicles are rangeextended PHEVs
 - 20 kW BMW I-3 REx
 - 60 kW-hr battery
 - 1 kW-hr/mile average energy use
 - ~ 60 mile all electric range
- UPS Fleet
 - Currently 125 vehicles
 - Desired end SOC = 10%
 - Driver sets route distance (L_{set})





Rule-Based Control for SOC Minimization

- Vehicle data mined at 0.2 Hz for 16 months from >100 in-use UPS E-GEN vehicles
- Varied locations
- Different route types

Goal: Vehicle returns to depot each day with 10% battery state of charge (SOC), <u>minimize REx</u> <u>use</u>







Truck Energy Use



Vehicles above green line use more fuel than desired



Connected Energy Management

- Implemented energy management strategy using reinforcement learning [1,2]
- Enabled over 20% MPGe improvement on actual routes





[1] Wang, Pengyue, Yan Li, Shashi Shekhar, and William F. Northrop. 2019. "A Deep Reinforcement Learning Framework for Energy Management of Extended Range Electric Delivery Vehicles." In *Proceedings of the 2019 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, 1837–42. Hong Kong, China.

[2] Wang, Pengyue and William Northrop. 2020. "Reinforcement Learning Based Energy Management of Multi-Mode Plug-in Hybrid Electric Vehicles for Commuter Route." *SAE Technical Papers* 2020-April (April): 1–9.

15



Rule-Based State of Charge Control

Two rules:

- 1. If the real-time SOC is lower than the SOC_{ref} , turn engine on
- 2. If the calculated SOC_{ref} is higher than 60%, set it as 60%

$$SOC_{ref} = 100\% \times \left(1 - 0.9 \times \frac{d}{L_{set}}\right)$$

• SOC_{ref} = energy in battery when the vehicle has travelled *d* miles given the parameter L_{set} (energy-compensated expected trips distance)





Physics-informed strategy for rule-based control with reinforcement learning



(Richard Sutton, Reinforcement learning: An Introduction)

Agent: The computer algorithm

Environment: low-order physics based model + historical trips

State: Available information for current trip

Reward: A function that rewards low fuel use but penalizes SOC<10% **Action:** Change the L_{set} variable

In-Use Example Trip





Trajectories of two UPS delivery trips



Date: 3/6/19 Distance: 40.59 mile MPGe: 13.75 Fuel use: 5.67 L

Date: 3/7/19 Distance: 39.14 mile MPGe: 17.40 Fuel use: 3.48 L

15 trips in total



Savings found over all tested in-use driving days



Average MPGe Improvement = 21.8%



Energy Efficient Routing

Scenario-based energy consumption estimation [1,2]

Predicted

14 min

17 min

Fastest

21

 Trajectory-aware path selection algorithm developed

Time

 Led to estimated 12% energy use reduction with moderate time increase



5 09

Energy-efficient	17 min	16 min 30 sec	5.43	5.09	
[1] Li, Yan, Shashi Shekhar, Pengyue Wang, and William Northrop. "Physics-guided energy-efficient path selection: a summary of results." In Proceedings of the					
26th ACM SIGS	SPATIAL International Co	onference on Advances in	Geographic Informatic	on Systems, pp. 99-108. A	CM, 2018.
[2] Li, Yan, Prat	ik Kotwal, Pengyue Wan	g, Shashi Shekhar, and W	/illiam Northrop. "Traje	ctory-aware Lowest-cost F	Path Selection: A Summary of Results."

5 4 3

In Proceedings of the 16th International Symposium on Spatial and Temporal Databases, pp. 61-69. ACM, 2019.

Actual (average)

14 min 23 sec

16 min 30 sec

Intelligent Energy Management System for Class 8 Regional Delivery





VEHICLE TECHNOLOGIES OFFICE





- Physics-based model + data (vehicle + exogenous)
- Predictive charging strategy for given route
- Energy efficient routing to save energy
- Optimal charger location for a fleet of EV trucks





Development of a Heavy-Duty Electric Vehicle Integration and Implementation (HEVII) Tool



- Analysis of two regional Class 6-8 commercial vehicle fleets.
- Novel mass prediction algorithm using fleet trajectory data to estimate EV range

STUDIES

- Develop an integrated charger location estimation tool
- ²³ Validate the developed tool

Summary

- Medium and heavy vehicles have high carbon impact
- Electrification can significantly reduce emissions
- Telematics and connectivity is growing
- Connectivity can be used to enable electrification
- Research is using data to lower energy use, improve range confidence for commercial EVs



Thank You!

Contact: Will Northrop Associate Professor Director, T.E. Murphy Engine Research Lab wnorthro@umn.edu (612) 625 6854





UNIVERSITY OF MINNESOTA Driven to Discover®

Crookston Duluth Morris Rochester Twin Cities

The University of Minnesota is an equal opportunity educator and employer.