### **Background**

As part of New York State's plan to transition to zero-emissions vehicles, the New York State Department of Environmental Conservation (NYSDEC), conducted a survey of organizations using medium- and heavy-duty vehicles throughout the state. Over a 12-month period, entities operating in the state submitted 13,213 observations of 70 variables, including organization structure, leadership, and industry, the number and types of vehicles operated, and daily use patterns. Facility information also included the types of fueling infrastructure on site, including diesel, gasoline, natural gas, electric vehicle charging, hydrogen fueling, or any other type of fueling infrastructure.

Understanding what factors impact an organization's decision to implement low emissions infrastructure may help other entities determine which is the best fueling infrastructure to adopt based on their own organization's operations. To this end, I created a multinomial regression model to predict whether a facility might install electric vehicle charging or hydrogen fuel stations.

#### Methods

The dataset downloaded from data.ny.gov was cleaned (e.g., standardizing 5 ways people entered "E85 gasoline" so each instance is considered the same value) and consolidated (e.g., simplifying variable levels from 150+ unique values to 5 most common values and "Other"). Observations with missing data were removed from the dataset, leaving 1,293 observations.

Potential explanatory variable distributions were characterized by frequency, mean, and standard deviation as appropriate. Visual inspection of graphs comparing continuous variables against low-emissions responses was used to determine whether transformations might be necessary or whether polynomial terms should be added to the maximum model.

Before variable selection, a random sample stratified by low-emissions infrastructure (electric vehicle charging, hydrogen fuel, or none) of 50% of the observations was selected as the training dataset, with the remainder as the test dataset. This operation prevents overfitting and also reduces computation time.

Due to model non-convergence, four separate "maximum" models were constructed, each with a set of 10-14 explanatory variables. Each model underwent stepwise selection with AIC as the selection criteria. Variables found to be significant in each of the four feeder models were added to the overall maximum model. Pairwise plots of each continuous variable against the other continuous variables and the outcome were inspected to determine which interaction terms

to include in the maximum model. The final maximum model was fit using the multinom() function from the nnet package, with "None" specified as the baseline response against which to compare the others. Stepwise selection with AIC criterion was conducted as above to arrive at a final "best" model.

To assess model fit, deviance residuals and Pearson residuals were plotted. ROC, AUC, and variance inflation factors were not able to be calculated for this multinomial regression model. A confusion matrix using the test dataset was constructed to assess accuracy, sensitivity, and specificity.

#### Results

Of the 1,293 observations in the final dataset, 124 (9.590%) had installed electric vehicle charging infrastructure, and 7 (0.5414%) had installed hydrogen fuel infrastructure. The remaining 1,162 facilities did not have any type of low-emissions infrastructure. Overall, 29.47% of facilities were equipped with some type of fossil fuel infrastructure, including 22.29% of facilities without low-emissions infrastructure, 93% of those with electric charging stations, and 100% of those with hydrogen fueling stations (**Table 1**).

Main effects in the final model include the following: industry type (as classified by the North American Industry Classification System), whether the organization has a sustainability plan, facility type (such as truck yards, warehouses, factories, or retail locations), whether their facility is owned or leased, the presence of fossil fuel emissions infrastructures (gasoline, diesel, natural gas, or other), the fuel type most commonly used at the facility, the number of mediumto heavy-duty vehicles operated by the organization, the number of vehicles that travel certain distances in a day (<100 miles, 100-150 miles, 150-200 miles, 200-300 miles, >300 miles), the average annual miles traveled by a vehicle, the number of vehicles that return to their home base at the end of each work day, the number of vehicles that are parked for at least 8 hours at their home base each day, the number of vehicles that have a predicable usage pattern most days, the number of vehicles that fuel primarily at their home base, the number of vehicles that operate at their weight limit most days, the number of vehicles equipped with GPS or another mileage tracking device (other than an odometer), the number of vehicles equipped with all wheel drive, and the number of vehicles designated as backup equipment. There are also 80 interaction terms included in the model. These effects are summarized in **Table 2**.

Variables found *not* to be significant for model creation include organization type (public, private, or government agency), the organization's revenue in 2021, government jurisdiction, whether the organization's sustainability plan specifically addressed transportation emissions, the type of trailers hauled by the organization's medium- to heavy-duty vehicles, the body type and weight class of the vehicles, how many vehicles towed trailers more than 100 miles per day, how many vehicles were model year 2010 or older, how many vehicles had been retrofitted or repowered, the average number of years a vehicle was kept after purchase, and

whether most vehicles operated by the organization were owned or brokered. Additionally, some variables could not be included in model creation due to preventing model convergence. This includes the number of contracted entities to which the organization makes deliveries, the number of subhaulers contracted by the organization, and the number of vehicles operated by subhaulers.

As shown in the confusion matrix and associated statistics in **Table 3**, the model's overall prediction accuracy was 92.11%. The sensitivities for electric charging, hydrogen fuel, or no infrastructure were 92.77%, 87.10%, and 66.67%, respectively; the specificities, 87.69%, 95.38%, and 97.51%.

#### Discussion

This multinomial regression model is meant to predict whether an organization installs low-emissions infrastructure at facilities where the medium- to heavy-duty vehicles they operate are based. In terms of model utility, the overall accuracy of 92.11% and specificities for each outcome above 87.5% suggest that the model is adequate in achieving this aim. The model distinguishes between hydrogen vs electric infrastructure very well – of the 57 organizations with low-emissions infrastructure in the testing dataset, only 1 organization (1.754%) was predicted to have the incorrect type of infrastructure. However, the model does overestimate the probability of organizations that do not have low-emissions infrastructure opting for hydrogen or electric infrastructure. Therefore, its predictive capabilities may be better suited for individual organizations deciding which type of infrastructure may suit their needs, rather than being used by NYSDEC to plan public infrastructure, as the current model would overestimate the prevalence of organizations who install their own.

The effects of some variables on low-emissions infrastructure installation were expected (holding all other variables constant, the odds that an organization whose vehicles mainly use electricity having electric vehicle charging instead of no low-emissions infrastructure are 2.190 times higher than organizations whose vehicles mainly use natural gas), but others were less intuitive. For instance, for each additional vehicle operated with a predictable usage pattern, the odds that the organization had electric vehicle charging *decreased* by a factor of 0.75 compared to those without low-emissions infrastructure, holding all other variables constant. Another surprising effect was that of other fossil fuel infrastructures: the odds of an organization having hydrogen infrastructure significantly increase when their facility also has *any of* diesel, gasoline, or natural gas infrastructure.

More variables than expected were incorporated into the final model, which could make it more tedious for the layperson to use. However, the type of information captured in these variables should be easy to find – organizational leadership *should* have access to the number of medium- to heavy-duty vehicles they operate and their typical usage patterns. Consulting with

subject matter experts and potential end users may help refine the variable list into something more widely accessible, even if the overall accuracy of the model decreases somewhat.

Strengths of the model include its overall accuracy and efforts to minimize bias by including as many variables and interactions in the maximum model as was computationally feasible for this project. Objective criteria (AIC) were specified before model building to avoid bias in variable selection. To avoid overfitting, the dataset was randomly divided into training and validation sets. To increase predictive power, continuous and ordinal data were prioritized whenever possible. However, due to limited computing time and power, nominal variables with many levels had to be considerably condensed so that no non-ordinal nominal variable had more than 5 levels, which could obscure the effects of other levels that were consolidated into a single "Other" level. Additionally, most of the dataset could not be used for model creation due to missing values. This may introduce bias, as there could be systemic reasons that certain organizations did not report certain covariates. Future work using this dataset might investigate the role of these discarded levels in nominal variables to explore these possibilities.

**Table 1**. Overlap of fossil fuel infrastructure (gasoline, diesel, natural gas, or other) and lowemissions fuel infrastructure (electric vehicle charging or hydrogen fuel) availability

LEM	None		Elec	tric	Hydrogen		
Variable	N	Percent	N	Percent	N	Percent	
GasolineInfrastructure	1162		124		7		
0	1019	88%	13	10%	7	100%	
1	143	12%	111	90%	0	0%	
DieselInfrastructure	1162		124		7		
0	910	78%	9	7%	0	0%	
1	252	22%	115	93%	7	100%	
NGInfrastructure	1162		124		7		
0	1158	100%	37	30%	7	100%	
1	4	0%	87	70%	0	0%	
OtherInfrastructure	1162		124		7		
0	1162	100%	124	100%	7	100%	
1	0	0%	0	0%	0	0%	
FF_Infrastructure	1162		124		7		
0	903	78%	9	7%	0	0%	
1	259	22%	115	93%	7	100%	

FF: Fossil fuels; LEM: Low-Emissions; NG: Natural Gas

**Table 2**. Odds ratios for multinomial regression model predicting the installation of lowemissions infrastructure, comparing response (electric charging or hydrogen fueling) to baseline of no low emissions infrastructure

				12		
		LEM			LEM	
Predictors	Odds Ratios	р	Response	Odds Ratios	s p	Response
(Intercept)	0.17	<0.001	Electric	0.15	<0.001	Hydrogen
NAICS Name [Construction]	0.18	<0.001	Electric	0.70	<0.001	Hydrogen
NAICS Name [Other]	0.84	<0.001	Electric	0.66	<0.001	Hydrogen
NAICS Name [PublicAdministration]	0.51	<0.001	Electric	0.25	<0.001	Hydrogen
NAICS Name [TransportationWarehousing]	0.91	<0.001	Electric	0.49	<0.001	Hydrogen
SustainabilityPlan [No]	0.52	<0.001	Electric	0.22	<0.001	Hydrogen
SustainabilityPlan [Yes]	0.83	<0.001	Electric	0.65	<0.001	Hydrogen
FacilityType [Factory]	0.57	<0.001	Electric	0.56	<0.001	Hydrogen
FacilityType [Multi-building campus/base]	0.23	<0.001	Electric	0.73	<0.001	Hydrogen
FacilityType [Other]	0.09	<0.001	Electric	0.61	<0.001	Hydrogen
FacilityType [ServiceCenter]	3.35	<0.001	Electric	0.45	<0.001	Hydrogen
FacilityType [Store]	5.46	<0.001	Electric	1.00	<0.001	Hydrogen
FacilityType [TruckYard]	1.09	<0.001	Electric	0.81	<0.001	Hydrogen
FacilityType [Warehouse]	0.70	<0.001	Electric	2.52	<0.001	Hydrogen
OwnedLeased [Owned]	2.13	<0.001	Electric	1.15	<0.001	Hydrogen
DieselInfrastructure [1]	0.63	<0.001	Electric	2.62	<0.001	Hydrogen
GasolineInfrastructure [1]	10.30	<0.001	Electric	1.27	<0.001	Hydrogen
NGInfrastructure [1]	70.75	<0.001	Electric	4.64	<0.001	Hydrogen
OtherInfrastructure1	1.00	1.000	Electric			

Table 2., cont.

	LEM			LEM			
Predictors	Odds Ra		Response	Odds Ro		Response	
FuelType [Diesel]	0.33	<0.001	Electric	0.58	<0.001	Hydrogen	
FuelType [Electricity]	3.19	<0.001	Electric	0.59	<0.001	Hydrogen	
FuelType [Gasoline]	0.47	<0.001	Electric	0.73	<0.001	Hydrogen	
FuelType [Natural Gas]	1.00	<0.001	Electric	1.00	<0.001	Hydrogen	
FuelType [Other]	0.34	<0.001	Electric	0.60	<0.001	Hydrogen	
NumberOfVehicles	0.90	<0.001	Electric	1.24	<0.001	Hydrogen	
NumberBelow100mi	1.49	<0.001	Electric	0.95	<0.001	Hydrogen	
NumberBetween100and150mi	1.67	< 0.001	Electric	0.48	< 0.001	Hydrogen	
NumberBetween150and200mi	1.12	<0.001	Electric	2.07	<0.001	Hydrogen	
NumberBetween200and300mi	1.67	<0.001	Electric	0.75	<0.001	Hydrogen	
NumberMoreThan300mi	1.05	<0.001	Electric	2.20	<0.001	Hydrogen	
AverageAnnualMiles	1.00	0.511	Electric	1.00	0.179	Hydrogen	
PredictableUsagePattern	0.25	<0.001	Electric	0.37	<0.001	Hydrogen	
FuelAtHome	1.26	<0.001	Electric	0.89	< 0.001	Hydrogen	
ReturnToHome	1.90	< 0.001	Electric	0.58	<0.001	Hydrogen	
Within50mi	1.20	< 0.001	Electric	2.27	<0.001	Hydrogen	
Parked8Hours	1.35	< 0.001	Electric	1.75	<0.001	Hydrogen	
AtWeightLimit	0.96	< 0.001	Electric	0.97	< 0.001	Hydrogen	
GPSMileageTracking	0.72	<0.001	Electric	0.82	<0.001	Hydrogen	
AllWheelDrive	0.75	<0.001	Electric	1.01	<0.001	Hydrogen	
Backup	0.96	<0.001	Electric	1.13	<0.001	Hydrogen	
NumberOfVehicles × NumberBelow100mi	0.88	<0.001	Electric	0.92	<0.001	Hydrogen	
NumberOfVehicles × NumberBetween100and150mi	1.88	<0.001	Electric	1.23	<0.001	Hydrogen	
NumberOfVehicles × NumberBetween150and200mi	1.29	<0.001	Electric	1.16	<0.001	Hydrogen	

Table 2., cont.

	LEM			LEM		
Predictors	Odds Rat	ios p	Response	Odds .	Ratios	p Response
NumberOfVehicles × NumberBetween200and300mi	1.74	<0.001	Electric	1.09	<0.001	Hydrogen
NumberOfVehicles × NumberMoreThan300mi	1.49	<0.001	Electric	0.97	<0.001	Hydrogen
NumberOfVehicles × AverageAnnualMiles	1.00	<0.001	Electric	1.00	0.339	Hydrogen
NumberOfVehicles × PredictableUsagePattern	1.24	<0.001	Electric	1.19	<0.001	Hydrogen
NumberOfVehicles × FuelAtHome	1.05	<0.001	Electric	0.86	<0.001	Hydrogen
NumberOfVehicles × ReturnToHome	0.25	<0.001	Electric	0.93	<0.001	Hydrogen
NumberOfVehicles × Within50mi	1.58	<0.001	Electric	0.99	<0.001	Hydrogen
NumberOfVehicles × Parked8Hours	1.19	<0.001	Electric	0.94	<0.001	Hydrogen
NumberOfVehicles × AtWeightLimit	1.41	<0.001	Electric	0.67	<0.001	Hydrogen
NumberOfVehicles × GPSMileageTracking	0.65	<0.001	Electric	0.80	<0.001	Hydrogen
NumberOfVehicles × AllWheelDrive	1.19	<0.001	Electric	1.04	<0.001	Hydrogen
NumberOfVehicles × Backup	0.76	<0.001	Electric	0.94	< 0.001	Hydrogen
NumberBelow100mi × NumberBetween100and150mi	1.62	<0.001	Electric	1.75	<0.001	Hydrogen
NumberBelow100mi × NumberBetween150and200mi	0.90	<0.001	Electric	0.88	<0.001	Hydrogen
NumberBelow100mi × AverageAnnualMiles	1.00	0.003	Electric	1.00	0.361	Hydrogen
NumberBelow100mi × PredictableUsagePattern	0.89	<0.001	Electric	0.88	<0.001	Hydrogen
NumberBelow100mi × FuelAtHome	1.16	<0.001	Electric	0.94	<0.001	Hydrogen

Table 2., cont.

		LEM			LEM	
Predictors	Odds Ratios	s p	Response	Odds Ratios	p	Response
NumberBelow100mi × ReturnToHome	0.92	<0.001	Electric	0.82	<0.001	Hydrogen
NumberBelow100mi × Within50mi	1.10	<0.001	Electric	1.13	<0.001	Hydrogen
NumberBelow100mi × Parked8Hours	0.82	<0.001	Electric	1.78	<0.001	Hydrogen
NumberBelow100mi × GPSMileageTracking	1.90	<0.001	Electric	1.20	<0.001	Hydrogen
NumberBelow100mi × AllWheelDrive	0.90	<0.001	Electric	1.46	<0.001	Hydrogen
NumberBelow100mi × Backup	0.84	<0.001	Electric	0.99	<0.001	Hydrogen
NumberBetween100and150mi ×	1.01	<0.001	Electric	0.80	<0.001	Hydrogen
NumberBetween150and200mi						
NumberBetween100and150mi × AverageAnnualMiles	1.00	0.266	Electric	1.00	0.103	Hydrogen
NumberBetween100and150mi × Parked8Hours	0.62	<0.001	Electric	0.91	<0.001	Hydrogen
NumberBetween100and150mi × AtWeightLimit	1.17	<0.001	Electric	0.74	<0.001	Hydrogen
NumberBetween100and150mi × Backup	0.77	<0.001	Electric	1.66	<0.001	Hydrogen
NumberBetween150and200mi × NumberMoreThan300mi	0.82	<0.001	Electric	1.05	<0.001	Hydrogen
NumberBetween150and200mi × Parked8Hours	1.34	<0.001	Electric	0.99	<0.001	Hydrogen
NumberBetween150and200mi × AtWeightLimit	0.76	<0.001	Electric	1.01	<0.001	Hydrogen
NumberBetween150and200mi × GPSMileageTracking	0.89	<0.001	Electric	1.40	<0.001	Hydrogen
NumberBetween150and200mi × Backup	1.15	<0.001	Electric	0.96	<0.001	Hydrogen

Table 2., cont.

	LEM			LEM		
Predictors	Odds Ra	itios p	Response	Odds Ratios	s p	Response
NumberBetween200and300mi × AtWeightLimit	1.20	<0.001	Electric	0.74	<0.001	Hydrogen
NumberBetween200and300mi × Backup	0.75	<0.001	Electric	1.95	<0.001	Hydrogen
NumberBetween200and300mi × NumberMoreThan300mi	0.82	<0.001	Electric	0.83	<0.001	Hydrogen
NumberBetween200and300mi × AverageAnnualMiles	1.00	0.056	Electric	1.00	0.016	Hydrogen
NumberBetween200and300mi × PredictableUsagePattern	0.89	<0.001	Electric	1.17	<0.001	Hydrogen
NumberBetween200and300mi × FuelAtHome	0.86	<0.001	Electric	1.38	<0.001	Hydrogen
NumberBetween200and300mi × ReturnToHome	0.45	<0.001	Electric	1.22	<0.001	Hydrogen
NumberBetween200and300mi × Within50mi	1.05	<0.001	Electric	1.00	<0.001	Hydrogen
NumberBetween200and300mi × Parked8Hours	1.79	<0.001	Electric	1.21	<0.001	Hydrogen
NumberMoreThan300mi × PredictableUsagePattern	0.66	<0.001	Electric	0.99	<0.001	Hydrogen
NumberMoreThan300mi × FuelAtHome	0.67	<0.001	Electric	0.84	<0.001	Hydrogen
NumberMoreThan300mi × ReturnToHome	1.33	<0.001	Electric	1.12	<0.001	Hydrogen
NumberMoreThan300mi × AtWeightLimit	0.79	<0.001	Electric	1.32	<0.001	Hydrogen
NumberMoreThan300mi × GPSMileageTracking	1.49	<0.001	Electric	0.97	<0.001	Hydrogen
PredictableUsagePattern × FuelAtHome	0.65	<0.001	Electric	1.10	<0.001	Hydrogen
PredictableUsagePattern × ReturnToHome	1.49	<0.001	Electric	0.73	<0.001	Hydrogen
PredictableUsagePattern × Within50mi	1.57	<0.001	Electric	1.09	<0.001	Hydrogen

Table 2., cont.

		LEM			LEM	
Predictors	Odds Ratios	p	Response	Odds Ratios	p	Response
PredictableUsagePattern × Parked8Hours	0.77	<0.001	Electric	1.39	<0.001	Hydrogen
PredictableUsagePattern × GPSMileageTracking	0.84	<0.001	Electric	0.92	<0.001	Hydrogen
$Fuel At Home \times Return To Home$	1.02	<0.001	Electric	1.39	<0.001	Hydrogen
FuelAtHome × Within50mi	0.82	<0.001	Electric	1.05	<0.001	Hydrogen
FuelAtHome × Parked8Hours	1.49	<0.001	Electric	0.77	<0.001	Hydrogen
FuelAtHome × GPSMileageTracking	1.07	<0.001	Electric	1.00	<0.001	Hydrogen
FuelAtHome × AllWheelDrive	0.95	<0.001	Electric	1.05	<0.001	Hydrogen
FuelAtHome × Backup	0.82	<0.001	Electric	1.11	<0.001	Hydrogen
ReturnToHome × Parked8Hours	1.38	<0.001	Electric	0.79	<0.001	Hydrogen
ReturnToHome × GPSMileageTracking	4.10	<0.001	Electric	1.13	<0.001	Hydrogen
ReturnToHome × AllWheelDrive	0.65	<0.001	Electric	0.99	<0.001	Hydrogen
ReturnToHome × Backup	0.44	<0.001	Electric	1.14	<0.001	Hydrogen
ReturnToHome × Within50mi	0.84	<0.001	Electric	1.00	<0.001	Hydrogen
Within50mi × Parked8Hours	1.29	<0.001	Electric	0.82	<0.001	Hydrogen
Within50mi × AtWeightLimit	0.85	<0.001	Electric	0.93	<0.001	Hydrogen
Within50mi × GPSMileageTracking	0.45	<0.001	Electric	0.86	<0.001	Hydrogen
Within50mi × AllWheelDrive	1.09	<0.001	Electric	1.02	<0.001	Hydrogen
Within50mi × Backup	1.41	<0.001	Electric	1.22	<0.001	Hydrogen
Parked8Hours × AtWeightLimit	0.92	<0.001	Electric	1.10	<0.001	Hydrogen

Table 2., cont.

	LEM			LEM			
Predictors	Odds Ratios	p	Response	Odds Ratios	s p	Response	
Parked8Hours × GPSMileageTracking	0.49	<0.001	Electric	1.26	<0.001	Hydrogen	
Parked8Hours × AllWheelDrive	1.40	<0.001	Electric	0.63	<0.001	Hydrogen	
Parked8Hours × Backup	2.50	<0.001	Electric	0.77	<0.001	Hydrogen	
AtWeightLimit × GPSMileageTracking	0.90	<0.001	Electric	1.41	<0.001	Hydrogen	
AtWeightLimit × AllWheelDrive	1.40	<0.001	Electric	0.89	<0.001	Hydrogen	
AtWeightLimit × Backup	1.02	<0.001	Electric	0.92	<0.001	Hydrogen	
GPSMileageTracking × AllWheelDrive	0.70	<0.001	Electric	1.04	<0.001	Hydrogen	
GPSMileageTracking × Backup	1.27	<0.001	Electric	1.12	<0.001	Hydrogen	

LEM: low-emissions; NG: natural gas

**Table 3**. Confusion matrix and statistics

# Reference

Prediction	None	Electric	Hydrogen
None	539	7	1
Electric	27	54	0
Hydrogen	15	1	2

## Overall Statistics

Accuracy: 0.9211 95% CI: (0.8975, 0.9407)

No Information Rate : 0.8994 P-Value [Acc > NIR] : 0.03537

Kappa : 0.6511

Mcnemar's Test P-Value: 1.533e-05

# Statistics by Class:

	Class: None Class:	Electric Class:	Hydrogen
Sensitivity	0.9277	0.87097	0.666667
Specificity	0.8769	0.95377	0.975117
Pos Pred Value	0.9854	0.66667	0.111111
Neg Pred Value	0.5758	0.98584	0.998408
Prevalence	0.8994	0.09598	0.004644
Detection Rate	0.8344	0.08359	0.003096
Detection Prevalence	0.8467	0.12539	0.027864
Balanced Accuracy	0.9023	0.91237	0.820892