Artificial Neural Networks for Emissions Modeling and Environmental Routing for Light-Duty Passenger Vehicles

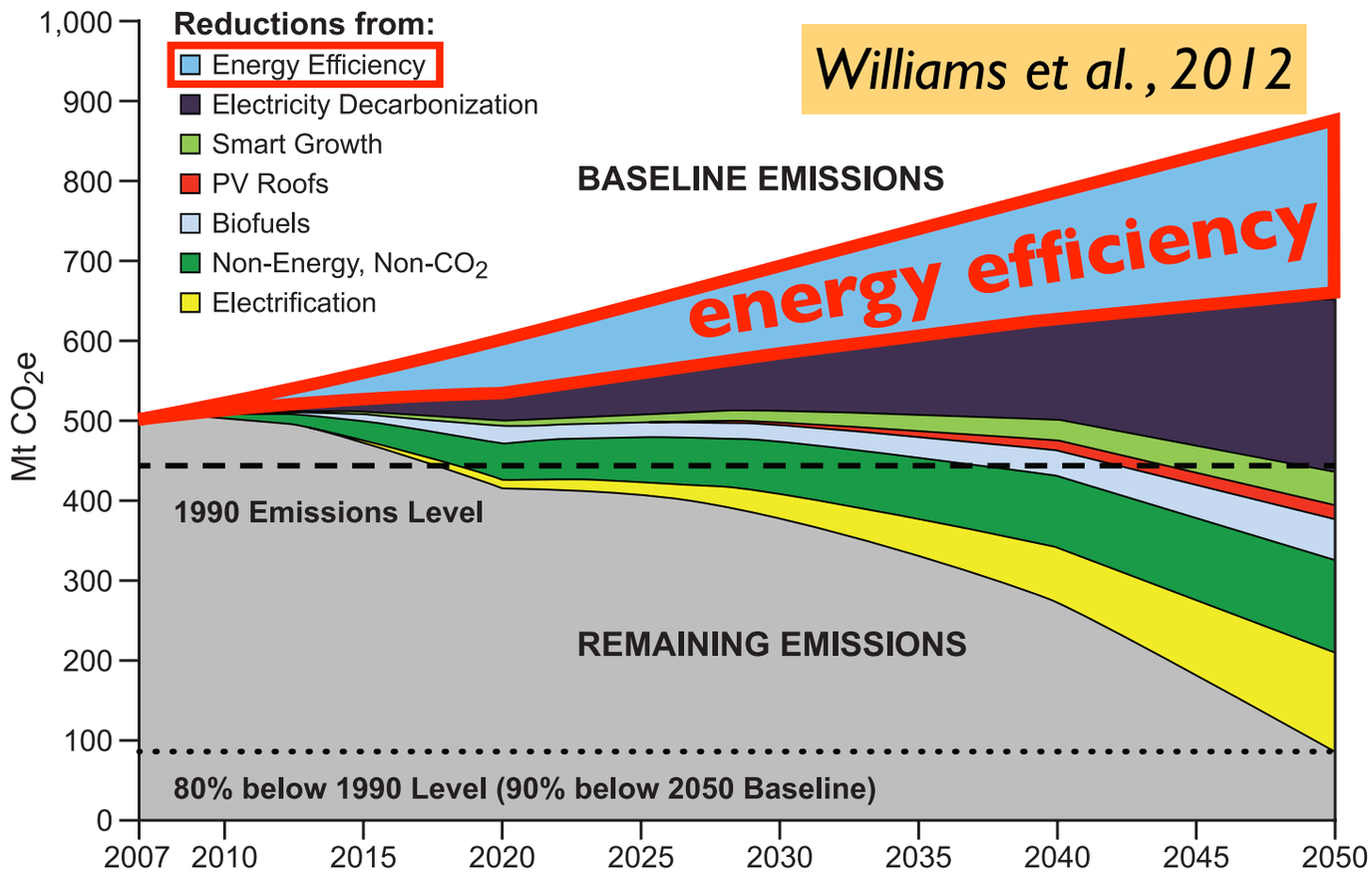
Shiva Tarun[1], Zachary Asher[2], Thomas Bradley[1], Brian Johnston[3], Chuck Anderson[4], and Shantanu Jathar[1]

[1]Mechanical Engineering, Colorado State University

[2]Mechanical and Aerospace Engineering, Western Michigan University

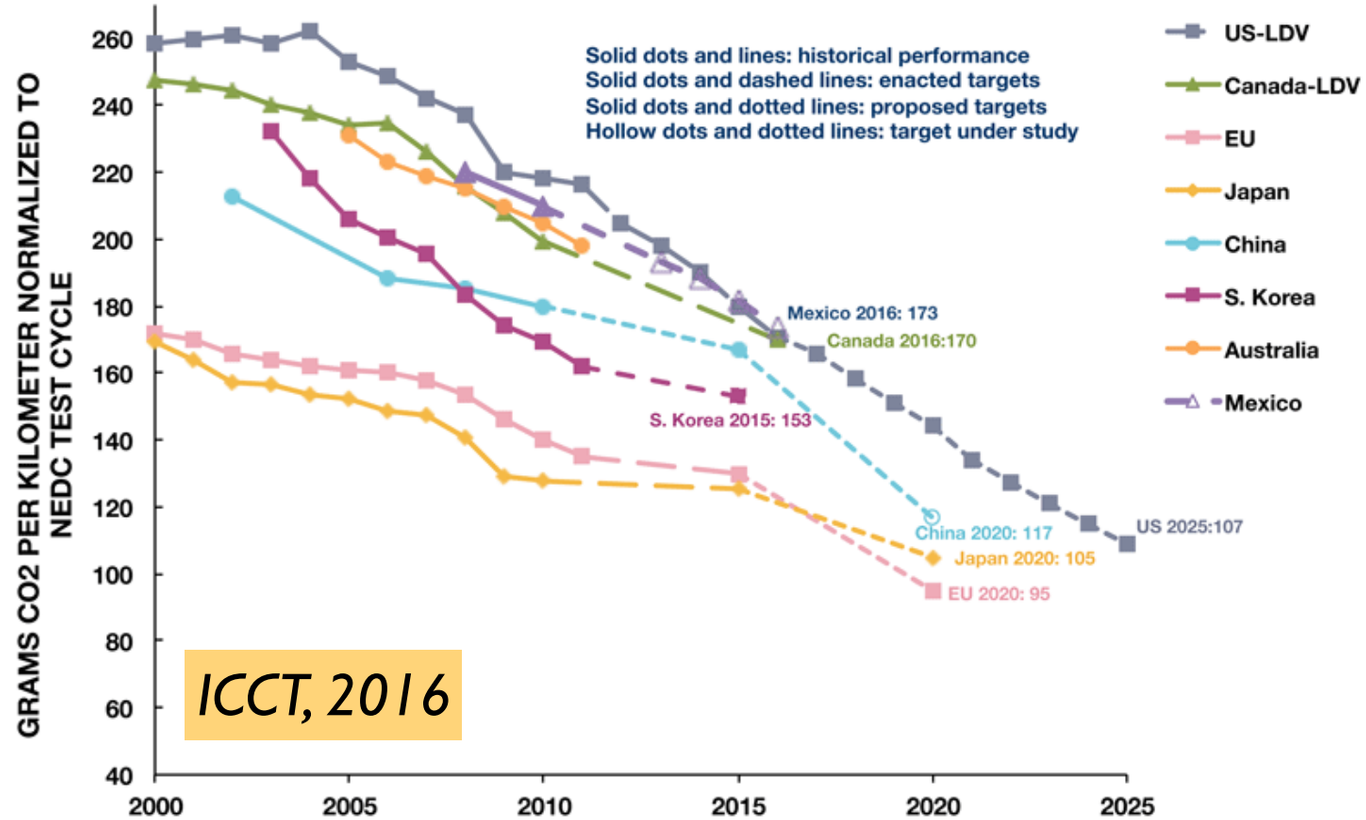
[3]Lightning Systems, Loveland CO

[4]Computer Science, Colorado State University

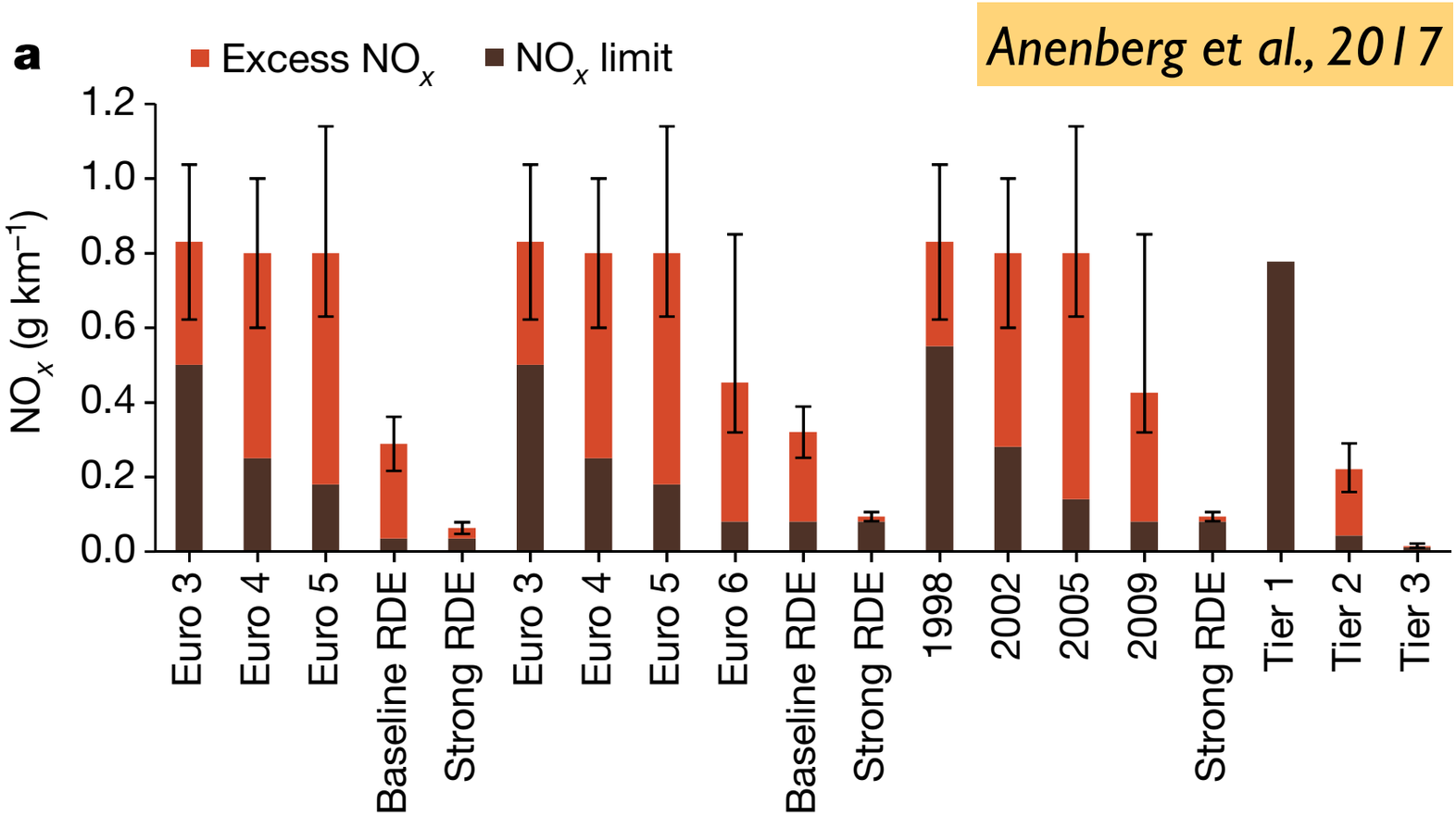


- Future Reduction in CO_{2e} emissions depends on improvements in energy efficiency (e.g., California)

- Enacted targets ***(e.g., CAFE)*** intend to nearly double fuel economy and halve CO_{2e} in the United States by 2025



[1] China's target reflects gasoline vehicles only. The target may be lower after new energy vehicles are considered.
[2] US , Canada, and Mexico light-duty vehicles include light-commercial vehicles.

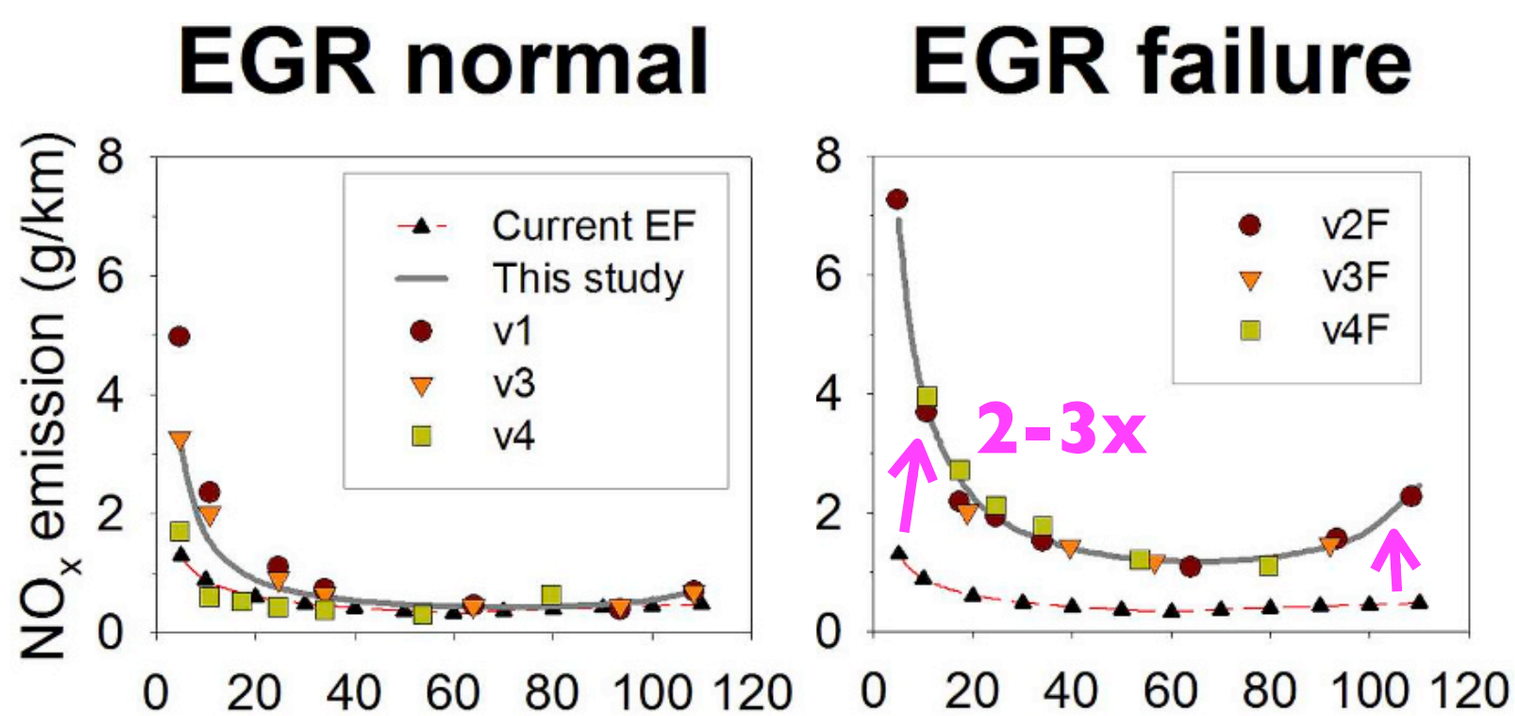


Anenberg et al., 2017

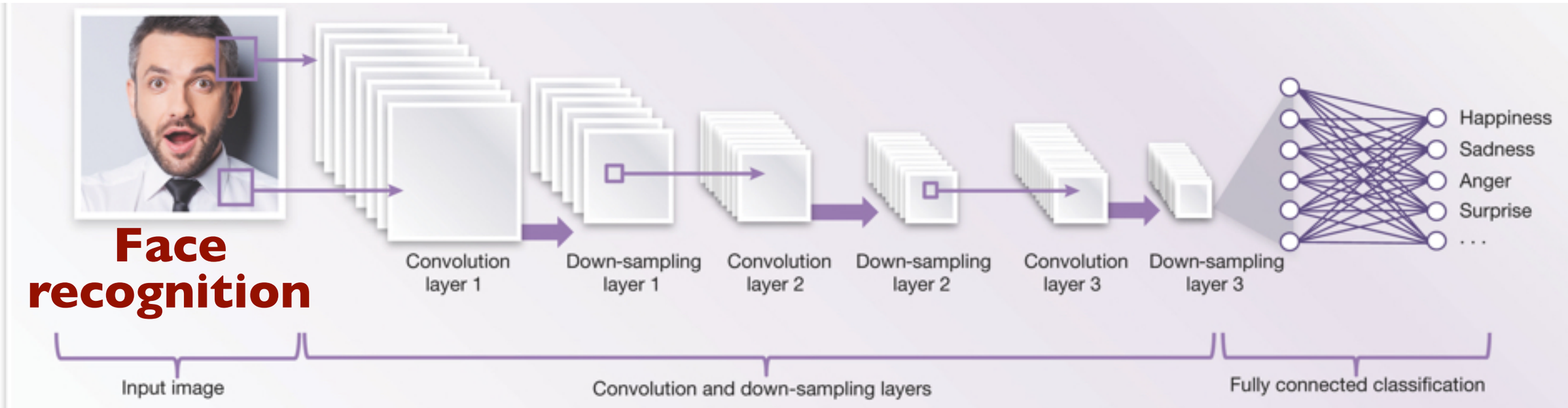
- On-road emissions have been found to ***exceed standards and dynamometer emissions*** (e.g., NOx)

Lee et al., 2018

- Emissions models (e.g., MOVES, EMFAC), trained on dynamometer tests, ***may underestimate on-road emissions***



Artificial Neural Networks



- ***Goal: Model and evaluate the fuel consumption and tailpipe emissions from light-duty vehicles using artificial neural network (ANN) models***

- Research questions:

i. How do you train and test ANNs to model fuel consumption and tailpipe emissions?

ii. Does the ANN performance vary by pollutant and how do ANNs compare to standard regression models?

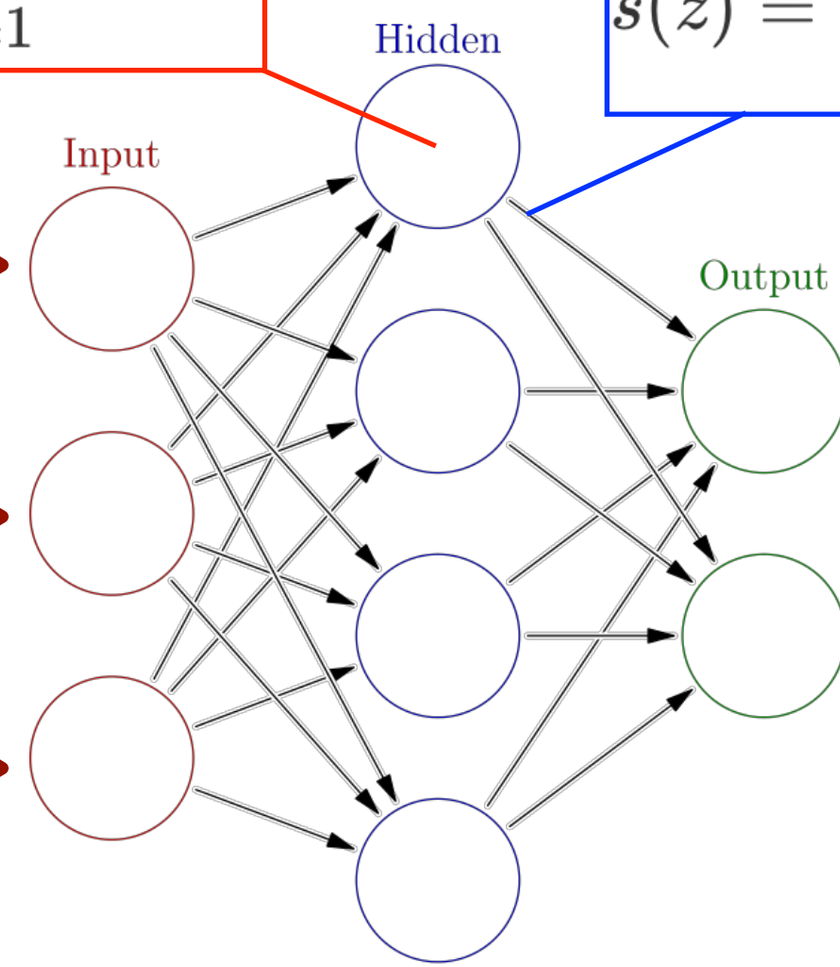
iii. How can ANNs be used for to improve on-road fuel economy?

- Artificial neural networks (ANNs) are mathematical models used for forecasting that allow complex nonlinear relationships between the input (i.e., predictors) and output (i.e., response) variables

$$z_j = b_j + \sum_{i=1}^{4} w_{i,j} x_i$$

$$s(z) = \frac{1}{1 + e^{-z}}$$

Velocity
Acceleration
Intake air temperature
Engine RPM
Time
Higher order terms (e.g., V^3)
Interaction terms (e.g., $V*a$)
…



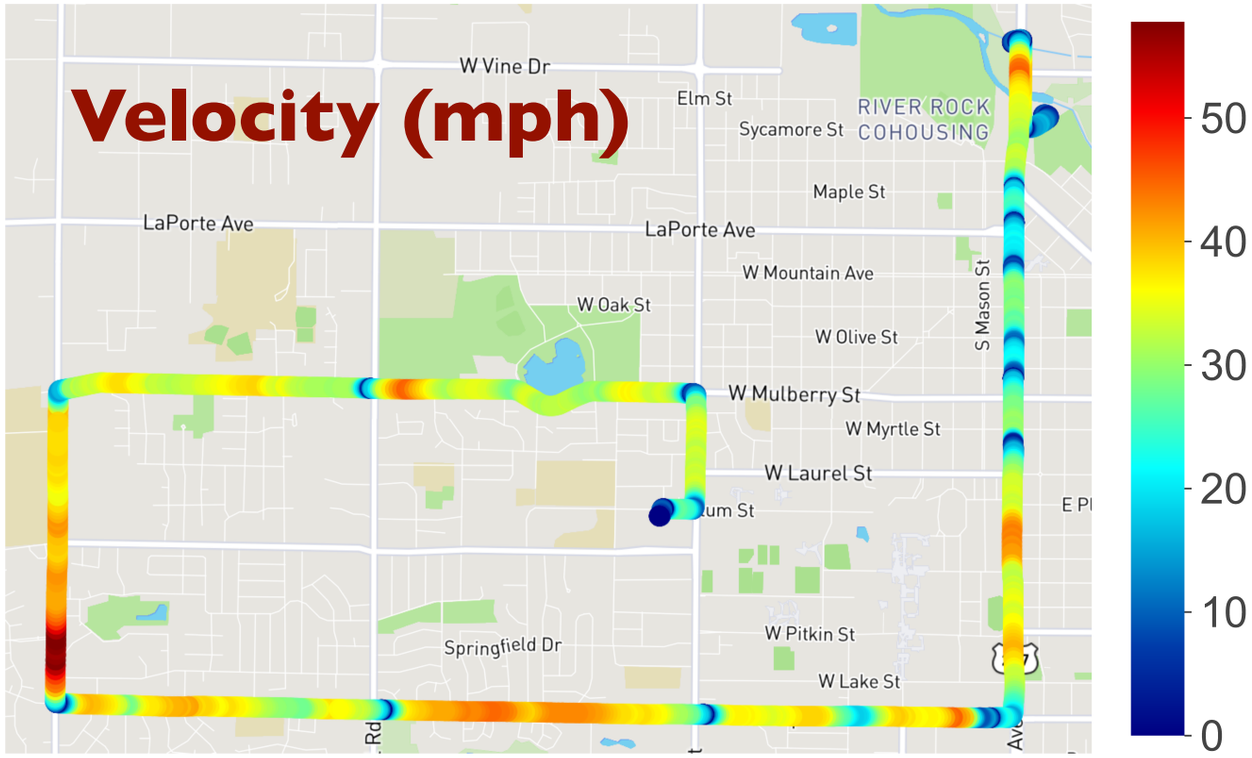
Fuel consumed
Exhaust temp.
Manifold pres.
Emissions
…

e.g., multi-layer feed-forward network

- ***Subaru Impreza gasoline '08***
  - 88,000 miles
  - Certified as LEV-II
  - Emissions control = 3-way cat.

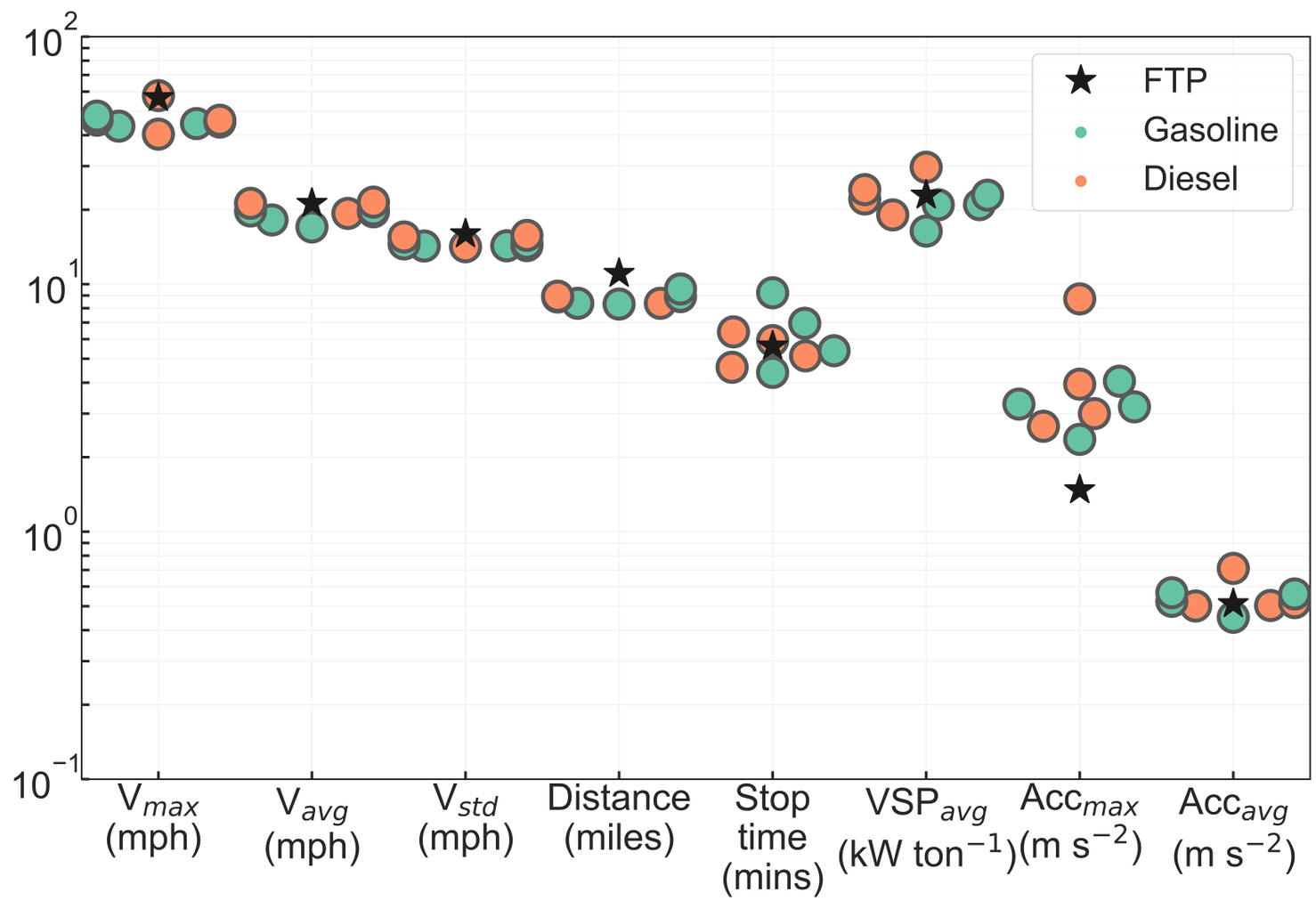
- ***VW Jetta diesel '03***
  - 120,000 miles
  - Certified as LEV-I
  - Emissions control = EGR

- ***PEMS: Global MRV AxionR/S+***
  - Measures CO_2, CO, and HC via NDIR
  - Measures NO_X and O_2 via e-chem
  - Measures PM via light scattering
  - Connects to and records OBD-II data
  - All data streams logged at 1 Hz

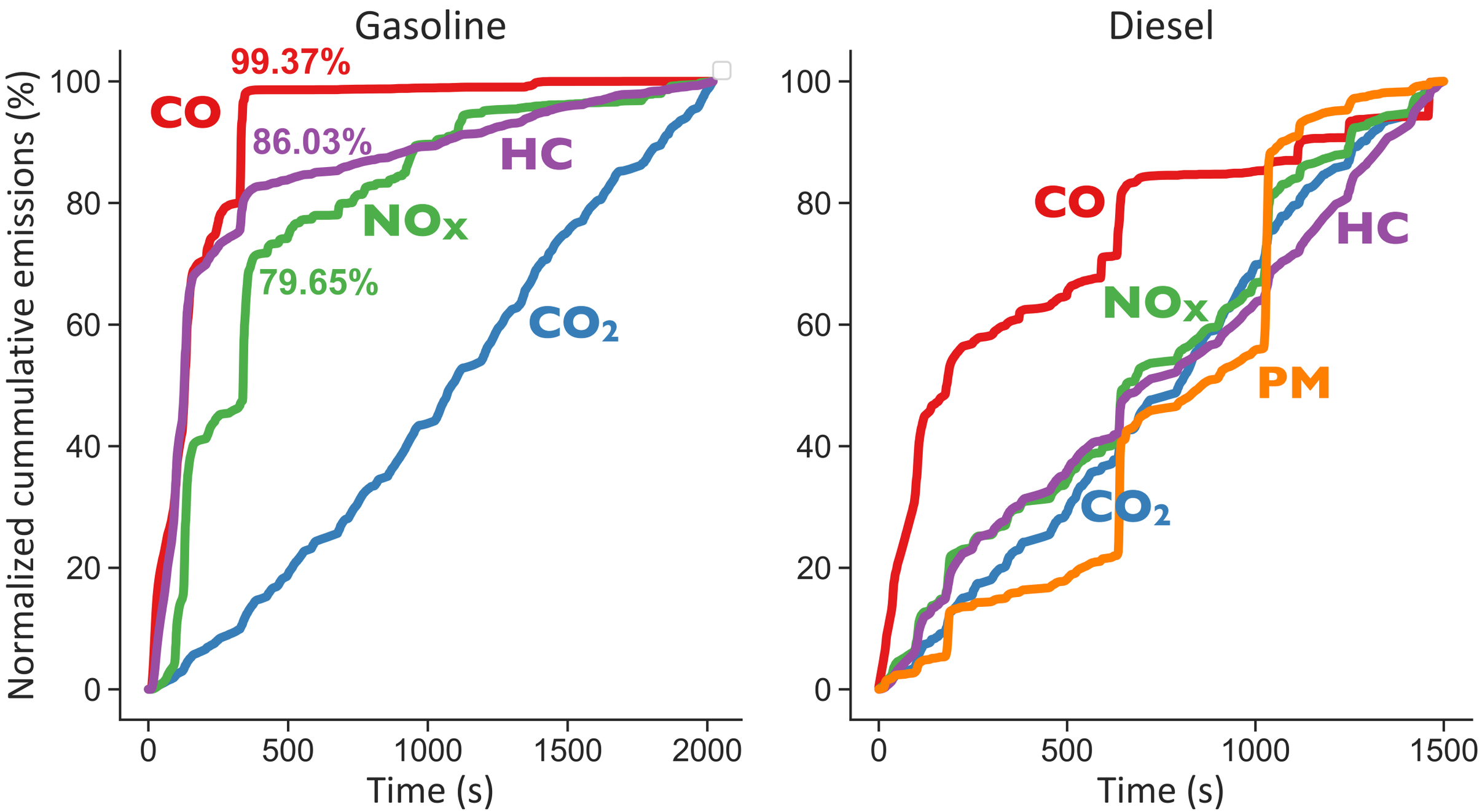


- ~10 mile urban route in Fort Collins, Colorado (population~160,000)
- 4 experiment days each for each vehicle (Spring 2018)

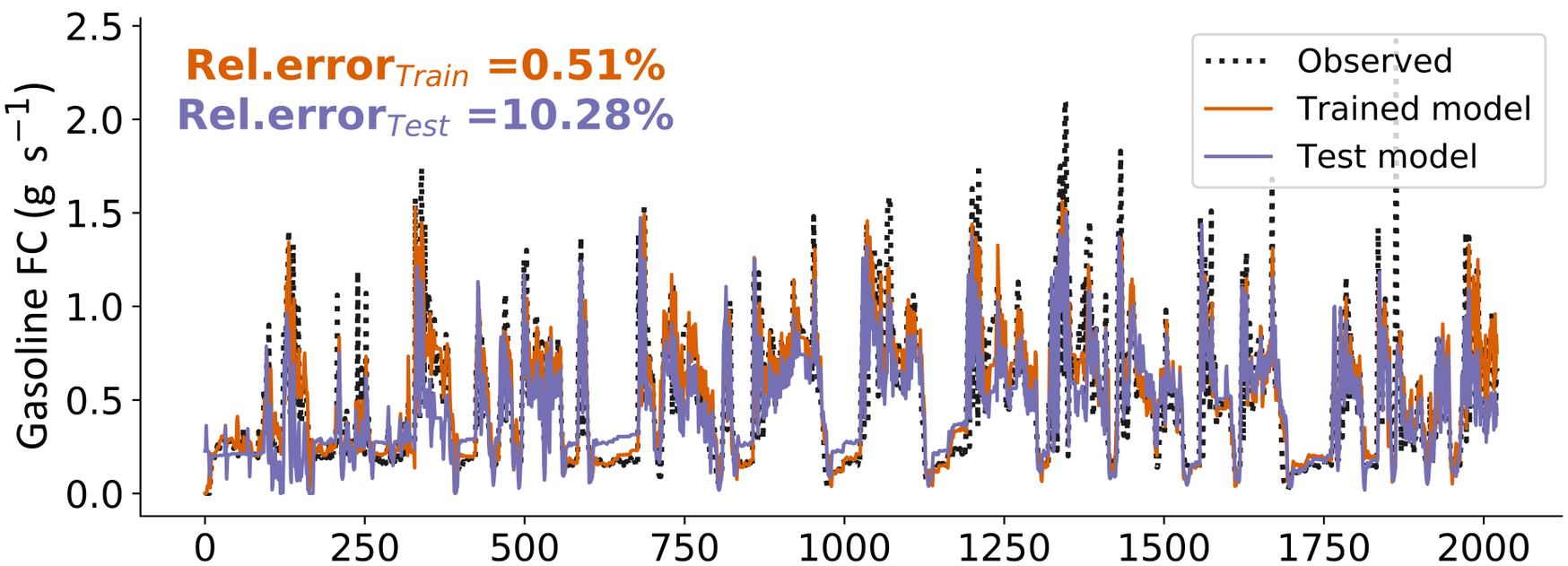
- ***Route metrics (e.g., V, VSP) were consistent with an FTP-75 cycle***

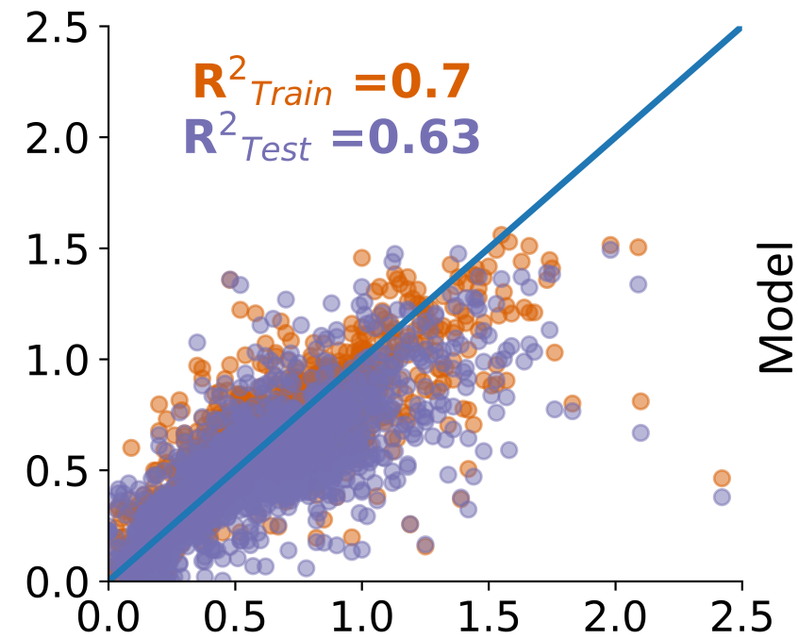


- ***>80% of the CO, HC, and NO_X were emitted in the first 8 min for gasoline vehicle ➟ cold start***
- Except CO, the diesel vehicle emissions were distributed over the entire route



- ***ANN models train and test well in predicting instantaneous and cumulative fuel consumption***
- Performance better for diesel (RE=0.55%, R^2=0.76) than gasoline (RE=10.3%, R^2=0.63)





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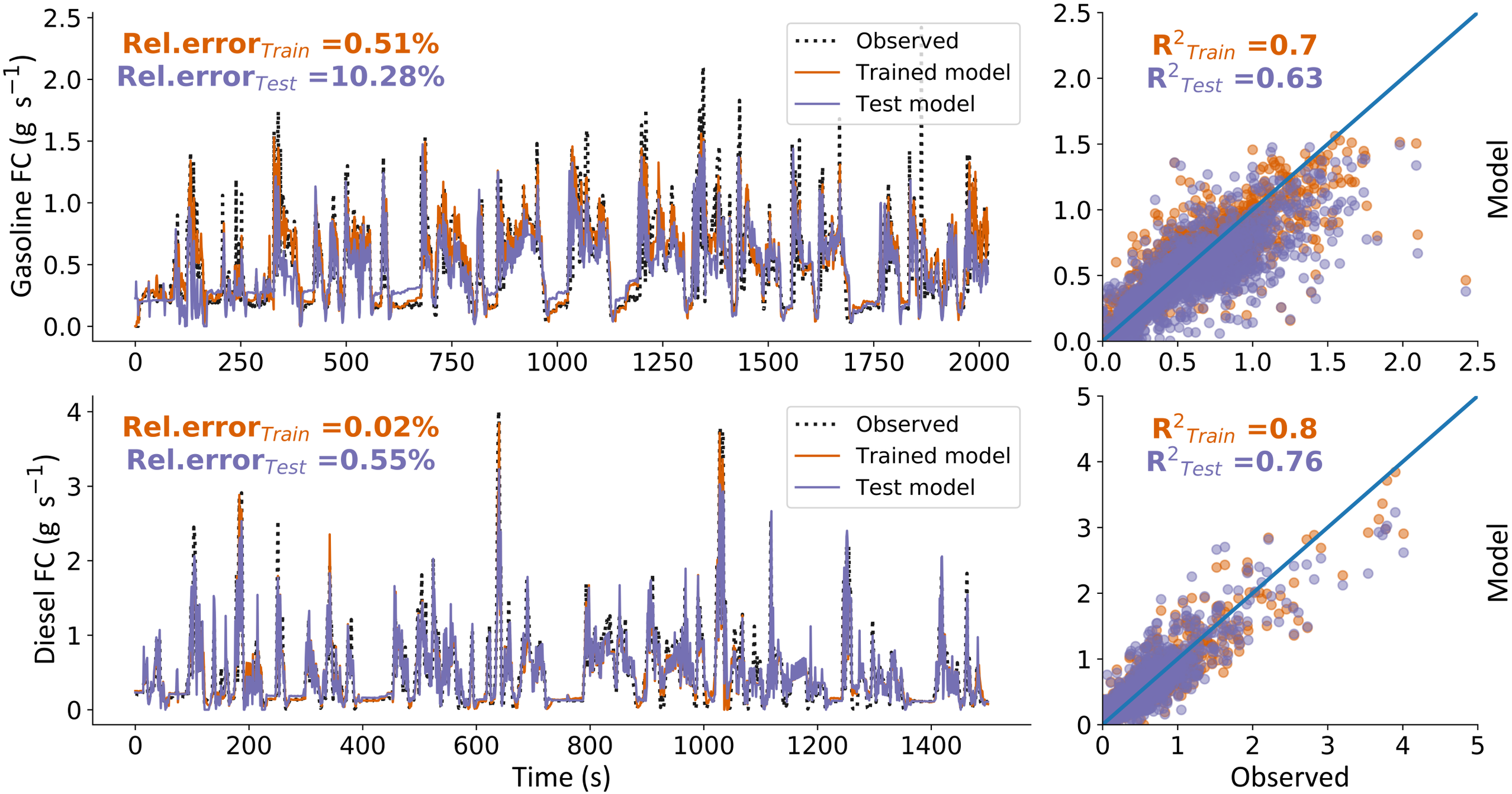
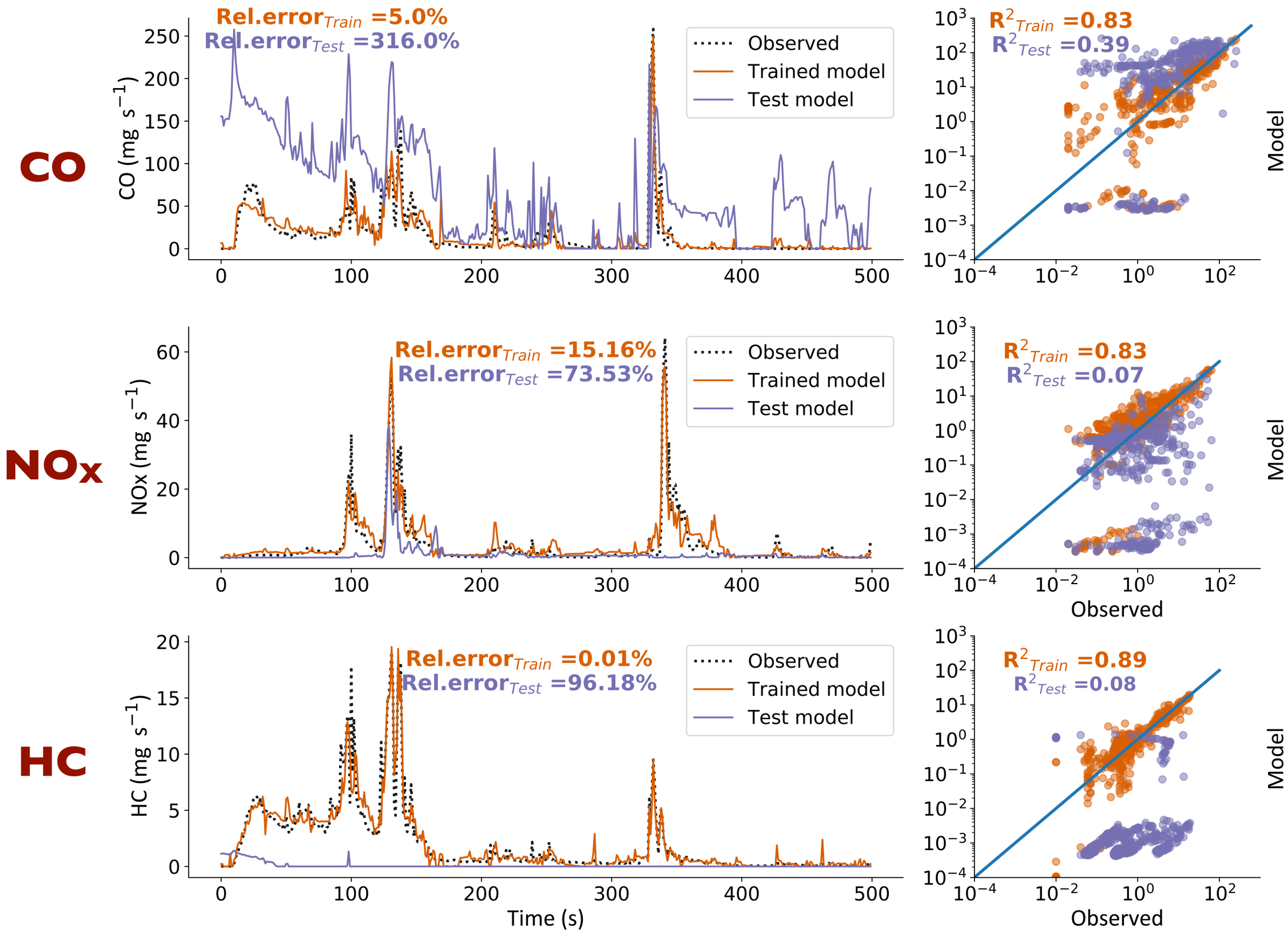
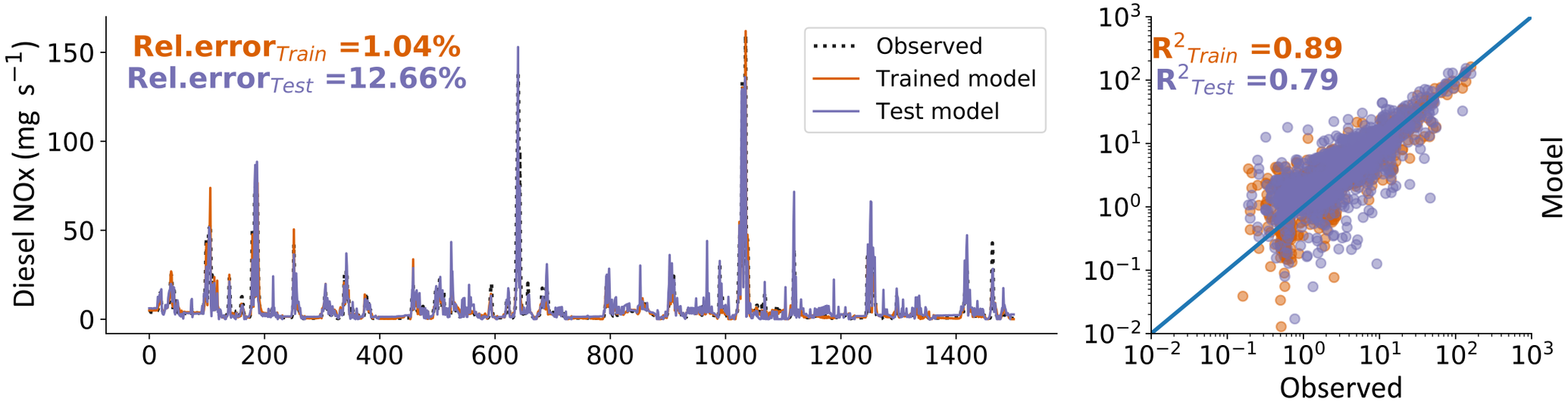


- For gasoline CO, NO_X, and PM, ANN models ***trained well but did not test well (RE>73%, R^2<0.4)***

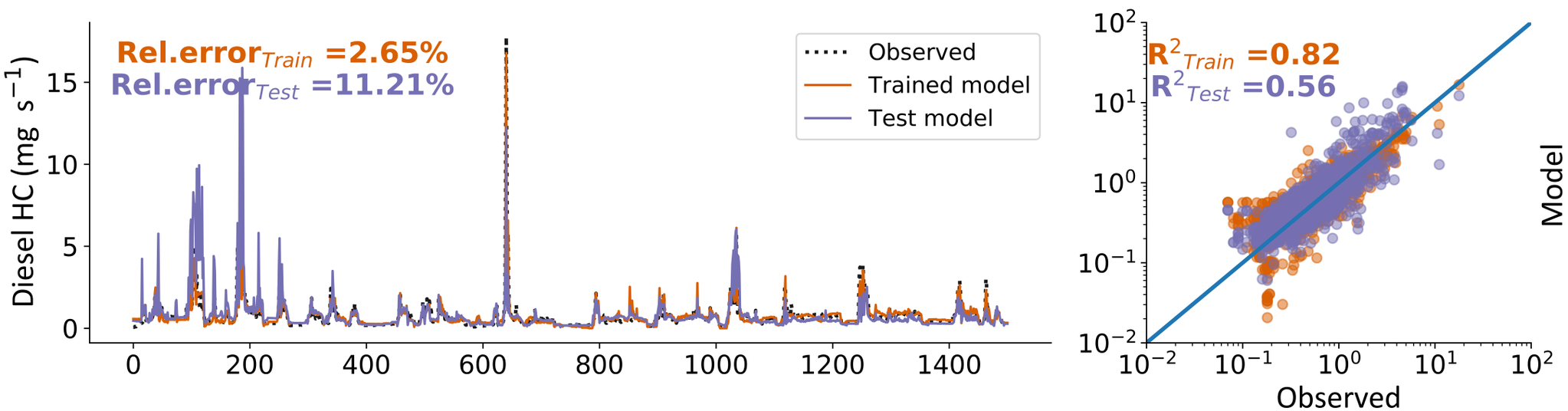


✤ In contrast, for diesel NO_X, HC, and PM, ANN models ***trained and tested well (RE<16%, R^2>0.56)***

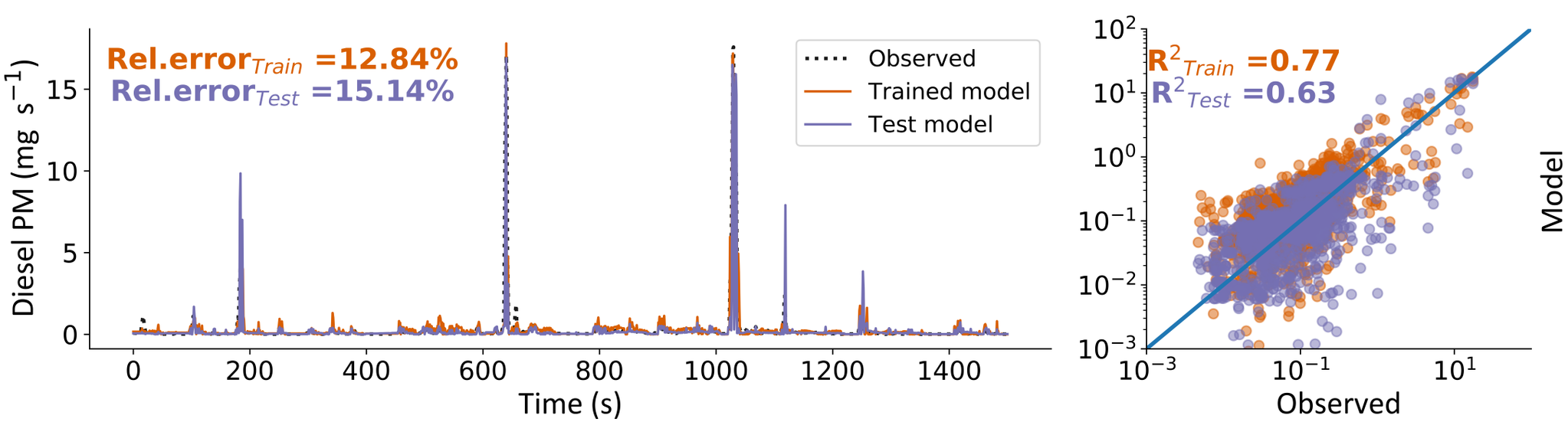
NOx



HC

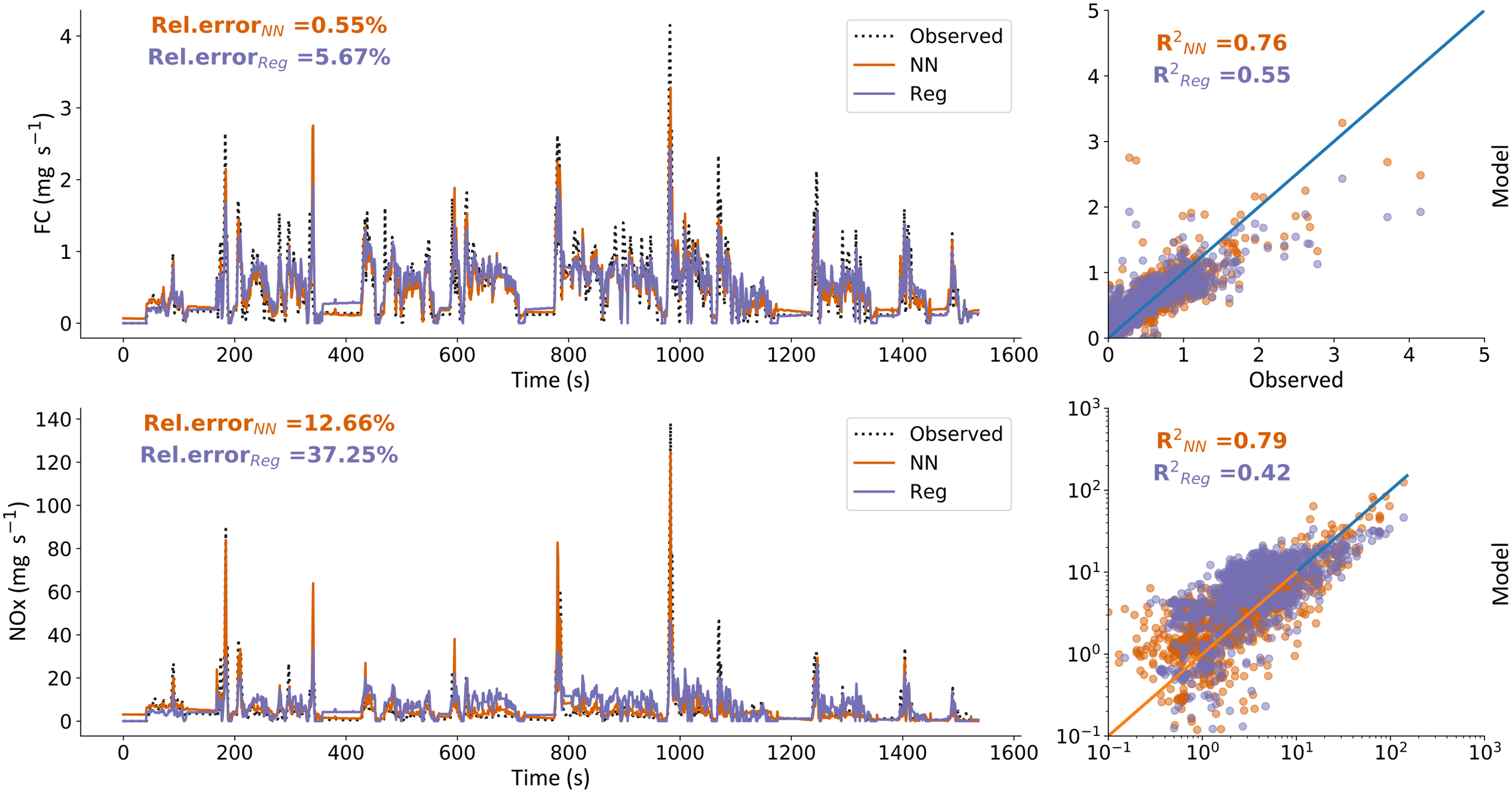


PM



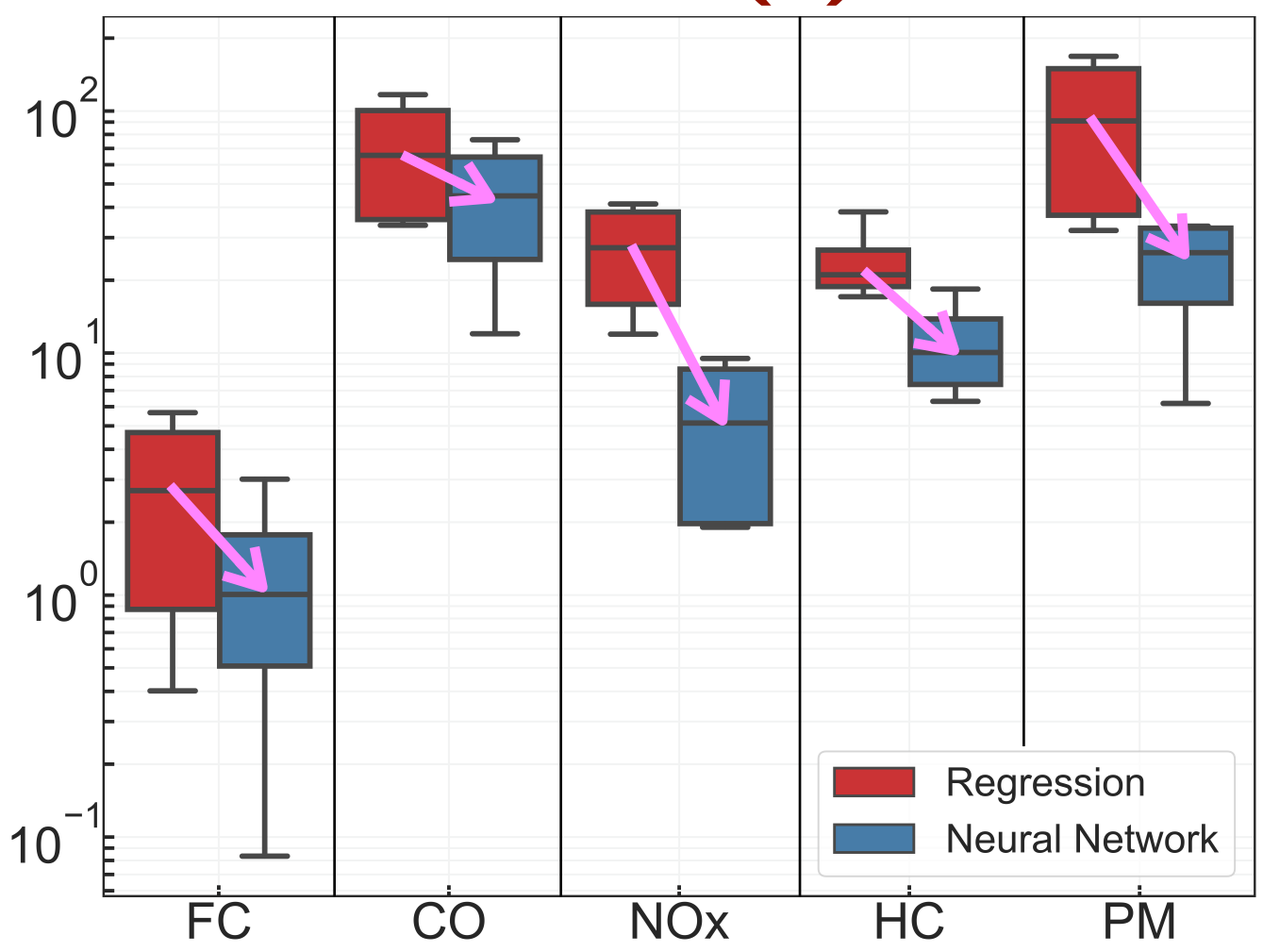
✤ANN models perform better than multivariate regression models for diesel fuel consumption (RE=0.55 vs. 5.7%) and NO_X (RE=12.7 vs. 37.2%)

Diesel FC and NOx - Regression vs NN Comparison

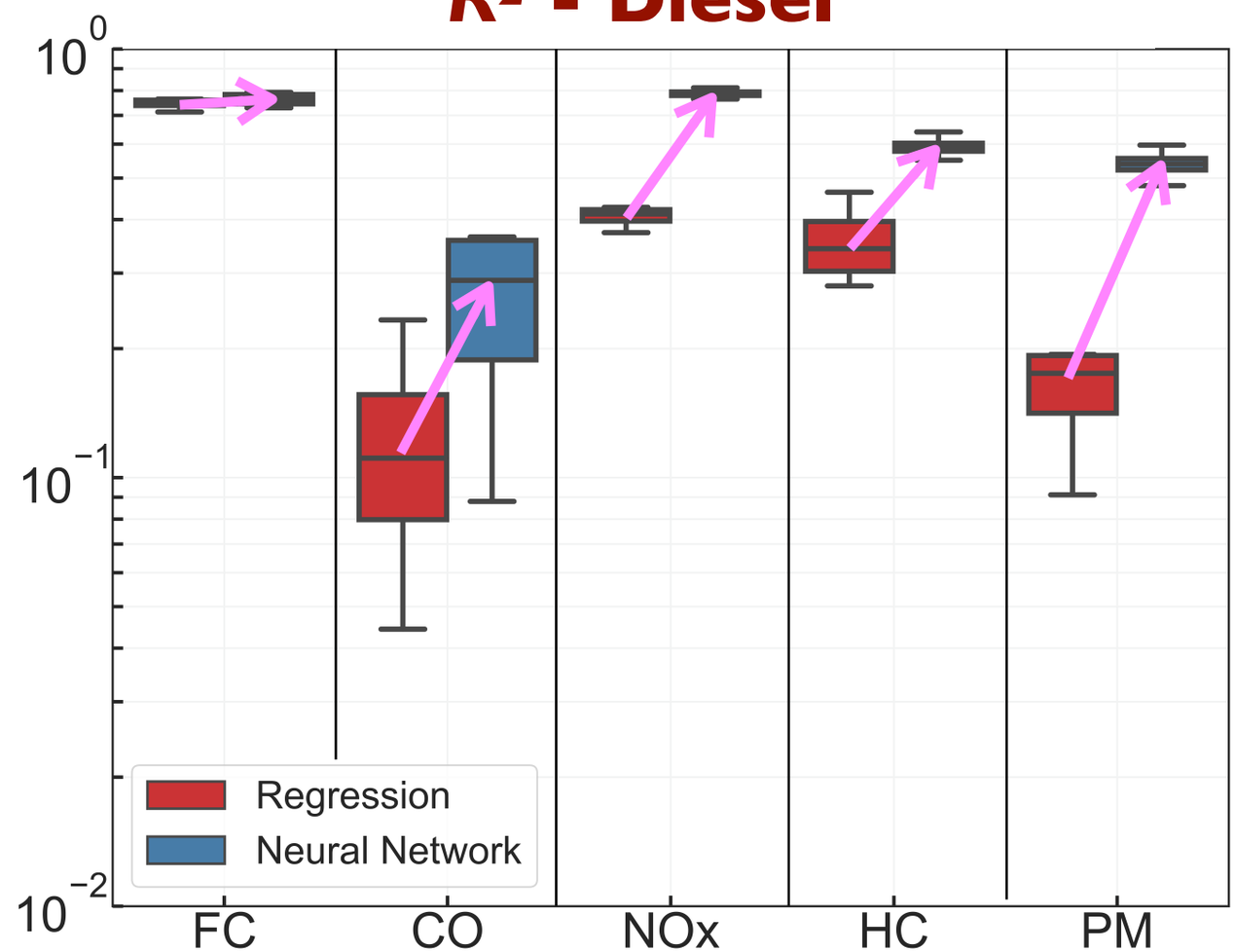


- ***Overall, ANN models perform better (lower RE, higher R^2) than multivariate regression models***
- For diesel, route fuel consumption and NO_X emissions were predicted within 3 and 10% respectively, with R^2>0.7

Relative Error (%) - Diesel



R^2 - Diesel

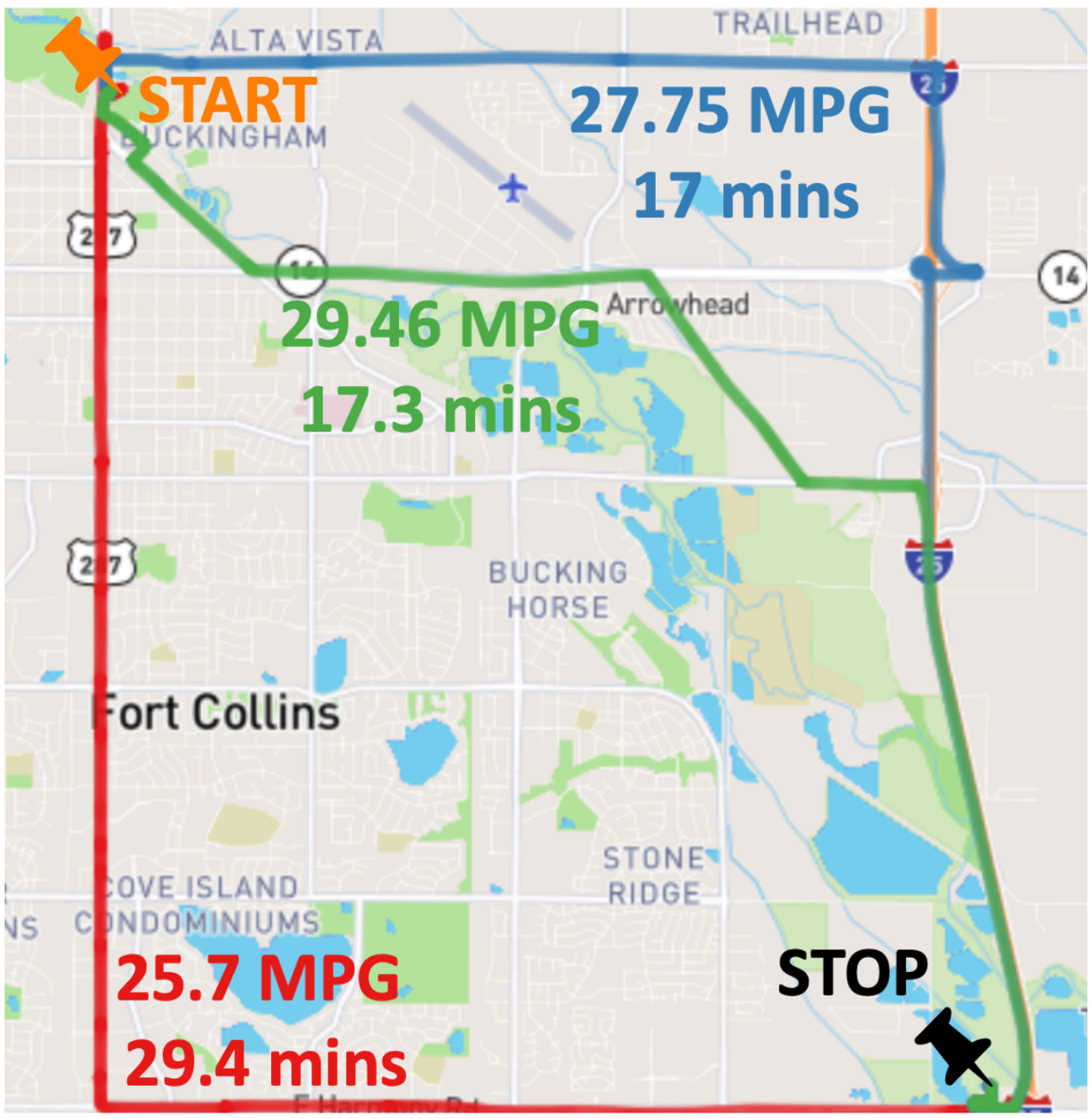


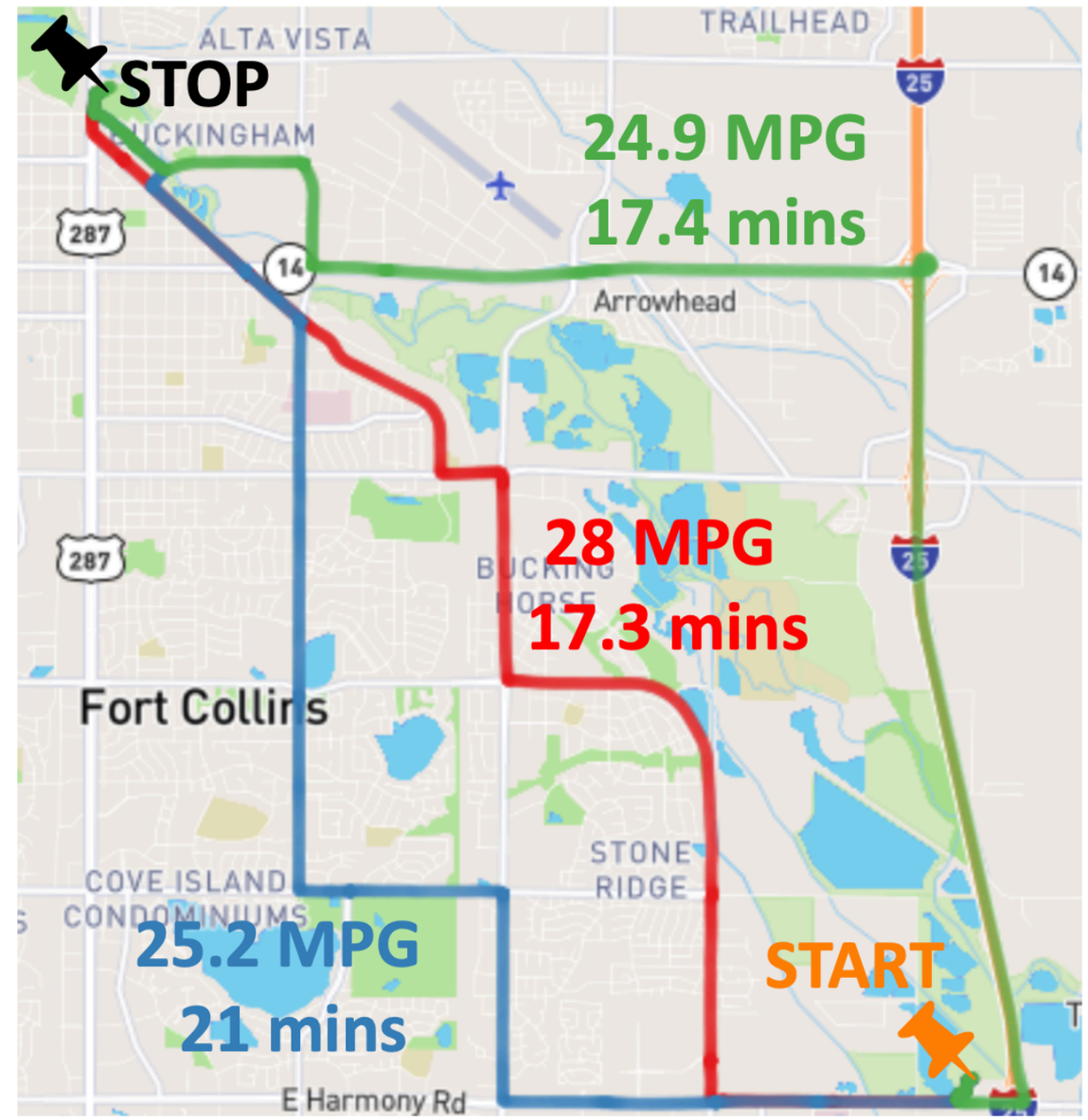
✣ *Most comprehensive model, unsurprisingly, yields the lowest RE and highest R^2*

Model Number	Model Inputs	Gasoline FC		Diesel FC	
		RE	R^2	RE	R^2
M1	V	6.52	0.19	10.03	0.17
M2	VSP	8.16	0.60	1.19	0.63
M3	VSP, t	7.54	0.60	6.95	0.65
M4	V,VSP	4.30	0.65	0.58	0.70
M5	V,ACC	6.11	0.68	0.71	0.72
M6	V,VSP, t	4.15	0.65	1.63	0.69
M7	V, RPM,VSP	3.10	0.72	3.98	0.74
M8	V,ACC, t	4.68	0.69	0.23	0.74
M9	V,V^3, t	4.57	0.20	2.03	0.20
M10	V,V^3,ACC*V, t	6.30	0.65	2.56	0.69
M11	V,V^3,ACC*V, RPM, t	3.44	0.72	3.51	0.74
M12	V,V^3,ACC*V,V*RPM, t	3.85	0.66	6.68	0.71
M13	V, RPM,ACC,ACC*V, IAT, t	7.57	0.67	4.75	0.73
M14	**V, RPM, ACC, ACC*V, IAT, VSP, t**	**3.12**	**0.73**	**1.14**	**0.76**

V=velocity, VSP=vehicle specific power, t=time from ignition, ACC=acceleration, RPM=engine speed, IAT=intake air temperature

- In a case study, we demonstrated the ability of our ANN model to choose routes that were optimized for time and fuel economy for the gasoline vehicle.





Take-aways

- ANN models were able to predict fuel consumption for the gasoline and diesel vehicle. For the diesel, the predicted route fuel consumption was always within 3% of the observed values.

- ANNs able to predict tailpipe emissions for the diesel vehicle but performance varied between pollutants, with the best predictions for NO_X (within 10%).

- ANNs seemed to do better than multivariate regression models in capturing the non-linear processes.

- With access to velocity estimates and ambient data, ANNs could help optimize routing for fuel consumption and/or tailpipe emissions.

Ongoing Work

- More PEMS tests in Spring 2019 with same vehicles
  - how well do models developed in 2018 perform for data in 2019?

- Model error propagation
  - how does uncertainty in an input (e.g., velocity) translate to an uncertainty in the output (e.g., fuel consumption)?

- Contact: ***shiva.chenna@colostate.edu* or *shantanu.jathar@colostate.edu***

Thank you | Questions?