Investigation of NO_X Sensor Measurement Errors and Potential Methods of Correction

SOUTHWEST RESEARCH INSTITUTE®

Christopher Sharp

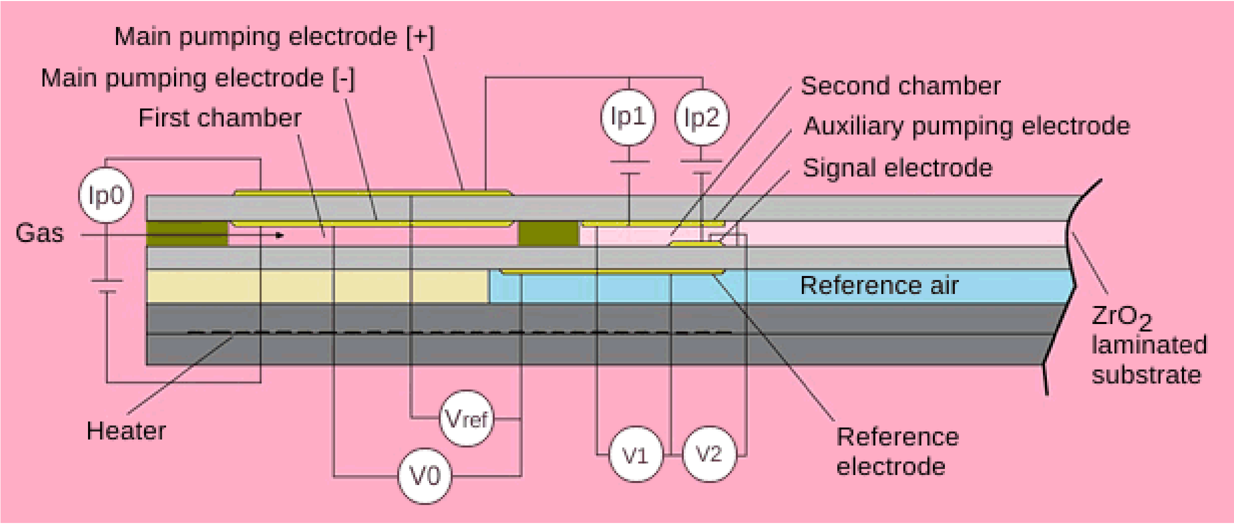
April 17, 2025

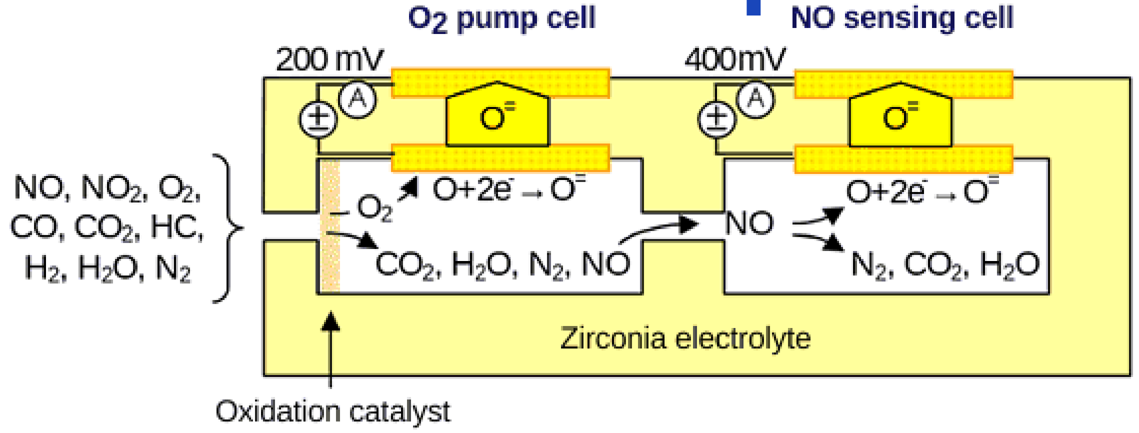
14th Annual International OSAR Conference

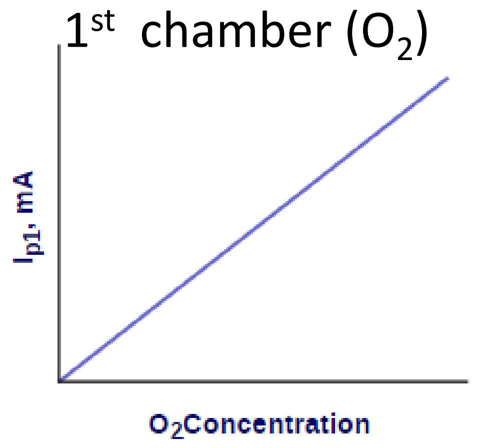
Background and Objective Under CARB Contract 22RD019

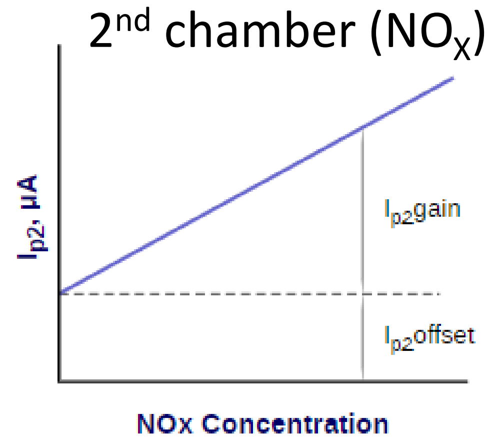
- Growing demand for understanding real-world in-use emissions
- Increasing move towards in-use compliance monitoring using on-board sensors (OBM, On Board Monitoring)
  - China VI, Euro VI ISC, Euro VII OBM
- NO_X sensors are essential to these approaches
  - These can show significant errors compared to Reference methods for a variety of reasons
- Focus on Tailpipe sensors at Low NO_X levels
- Program objectives
  - Can we understand what is actually driving NO_X sensor measurement errors ?
  - Can we find a way to correct for these errors ?

“Amperiometric” NO_X Sensor Architecture and Operation









Nernst Equation: $U_s = (RT/4F)\ ln(p_{ref} / p_{exh})$

U_s - sensor signal, V
T - temperature, K
p - partial pressure of oxygen
R - gas constant = 8.314 J/mol
F - Faraday constant = 96,485 sA/mol

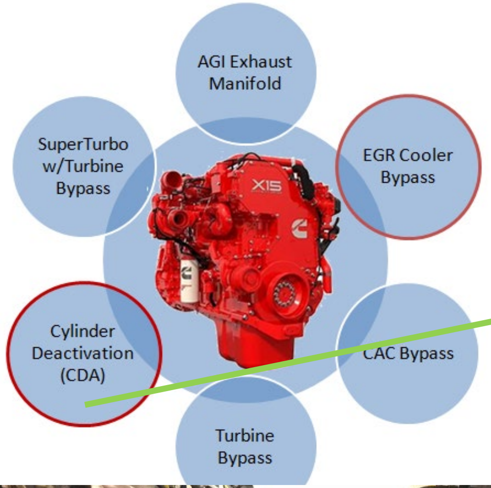
- Voltage is applied across each cell which results in pumping of oxygen ions
- First chamber (O_2) is usually pumped not to zero but to fixed lambda
  - Pumping current is controlled via a PID loop to reach target Nernst voltage
  - **Current (i_{P1}) is proportional to amount of O_2 pumped (O_2 measurement)**
- Second chamber (NO_X)
  - PID loop on voltage
  - **Measured current gain (i_{P2} gain) is proportional to O_2 liberated from NO_X**
- Note that these measurement signals are based in **actively controlled parameters**

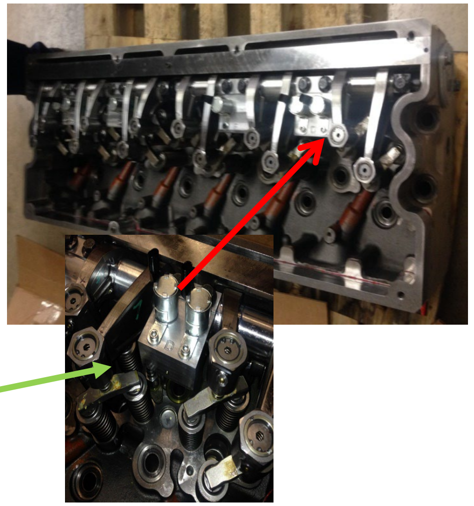
Test Article - Stage 3RW Low NO_X Demonstration Engine

2017 Cummins X15 Engine

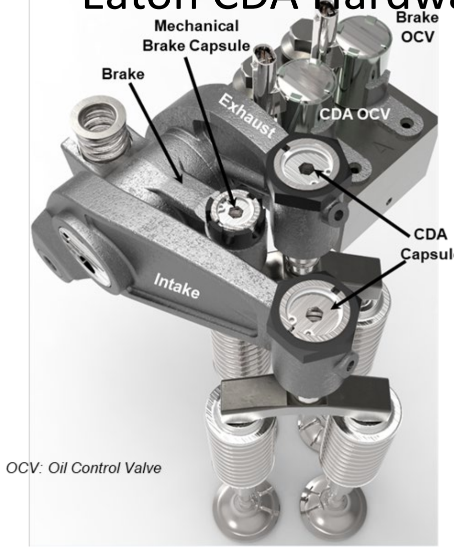
Full System Details
SAE Papers
2023-01-0357
2021-01-0589

Additional Engine Hardware (Cylinder Deactivation)

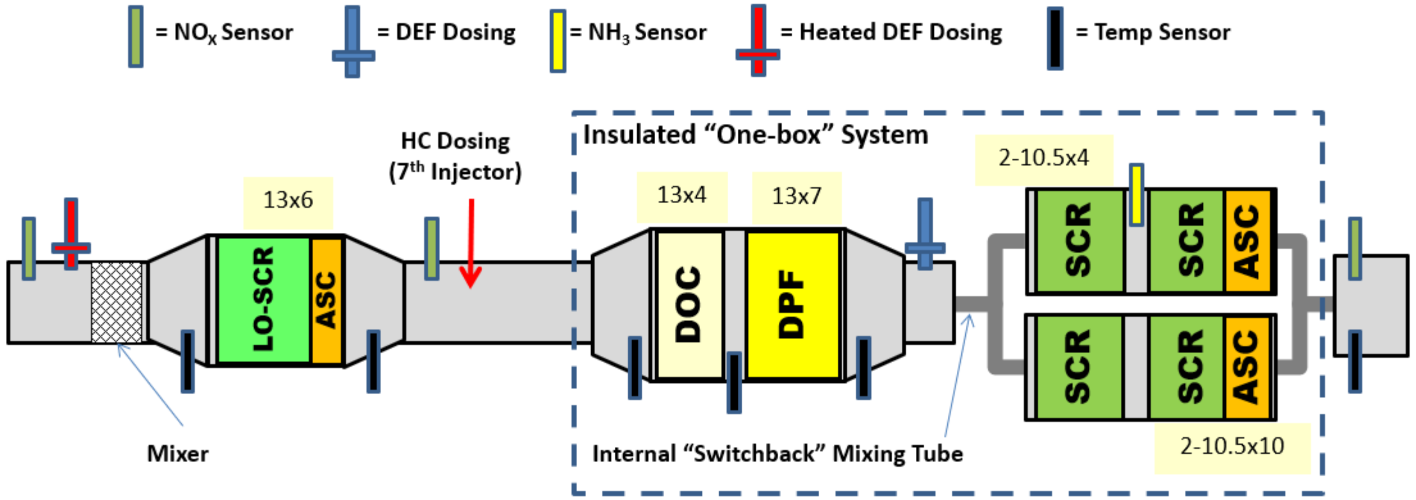




Eaton CDA Hardware



Advanced Low NO_X Aftertreatment (Dual SCR-Dual Dosing)



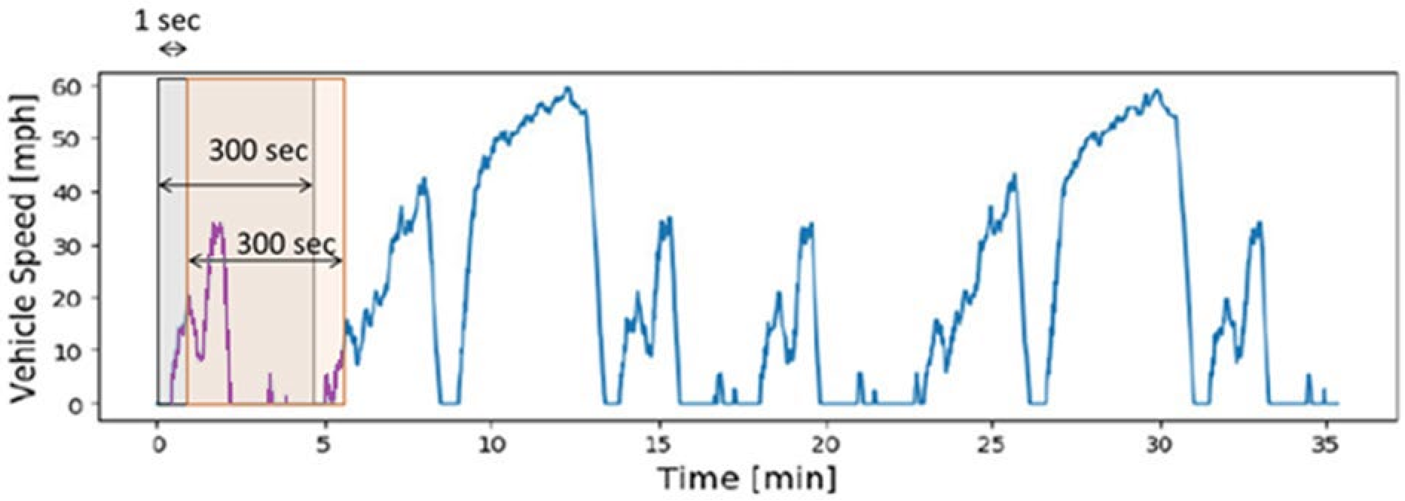
- FTP NO_X ~ 0.02 g/hp-hr
- LLC NOX ~ 0.05 g/hp-hr
- **Real World B-MAW Bin 2 ~ 0.02 to 0.03 g/hp-hr**

Program NO_X Sensors

- 3 Bosch 4th Generation (newest)
- 3 Vitesco 4th Generation (newest)
- 3 Vitesco 3rd Generation (current, from previous program)
- 1 NH_3 Sensor for real time NH_3 tracking to help assess data
  - Parallel FTIR measurement
- Mounted in same pipe and setup used previously for NO_X sensor testing in EMTC program
- Tested before and after aging

U.S. In-Use Compliance - 2B-MAW Basics

- Utilized in test runs of nearly any length
  - There are some minimums for number of windows in each bin
  - Still require at least 3 hours of non-idle operation for a valid test day
- The entire data set is utilized including cold-start

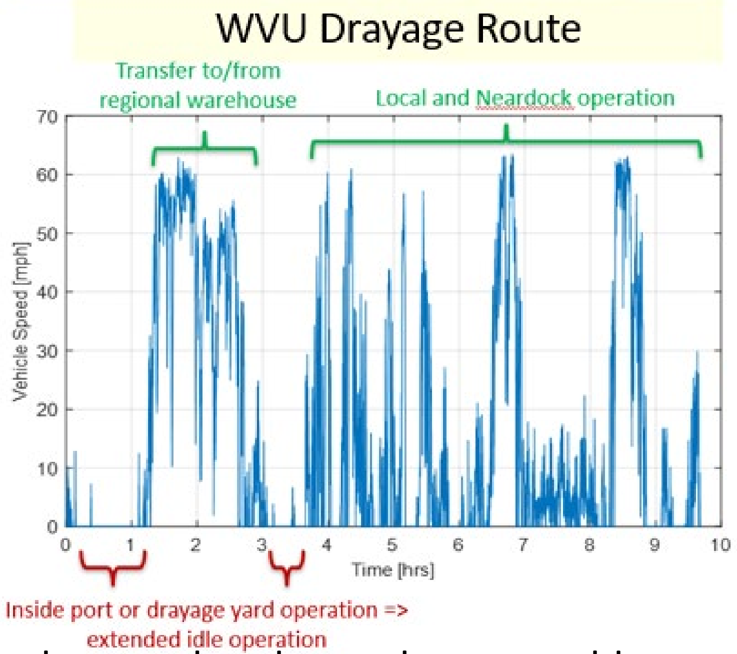


- The 2B-MAW method uses a <u>fixed-length</u> 300-second average window
- Average window is stepped through the data file in 1-second increments
- Each window is sorted into one of 2 load bins based on "normalized CO_2"
  - NO_X mass (all bins) and CO_2 mass (Bin 2)
- A sum-over-sum calculation is done for each bin to generate final numbers (Bin 1 is just NO_X mass rate in g/hr)

CARB / EPA On-Highway In-Use Standards MY 2027+

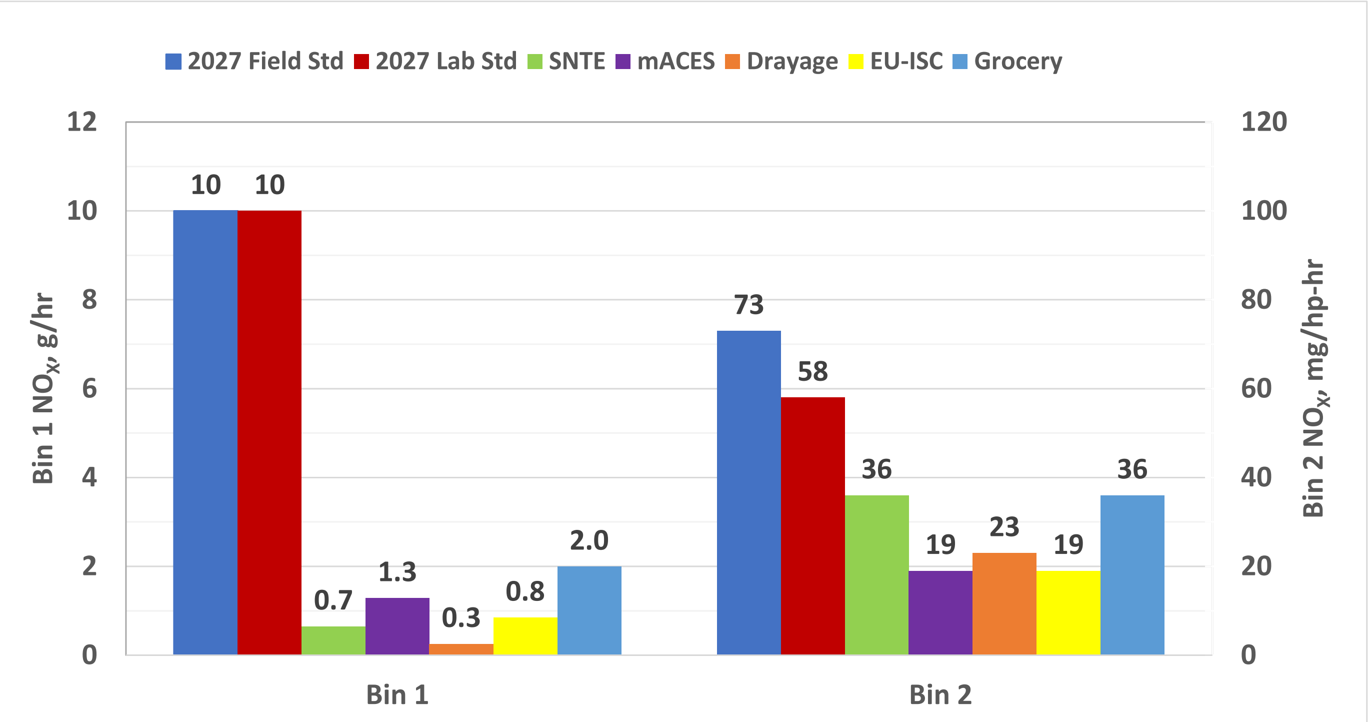
Off-Cycle Bin	NO_X	Temperature adjustment [a]	HC mg/hp·hr	PM mg/hp·hr	CO g/hp·hr
Bin 1	10.0 g/hr	$(25.0 - \bar{T}_{amb}) \cdot 0.25$	—	—	—
Bin 2	58 mg/hp·hr	$(25.0 - \bar{T}_{amb}) \cdot 2.2$	120	7.5	9

Real World Duty Cycles



Real-world routes run by WVU on trucks, translated to cycles we could run on engine-dyno using Stage 3RW system (stock system performed similarly to field data…we are duplicating the field duty cycle accurately)

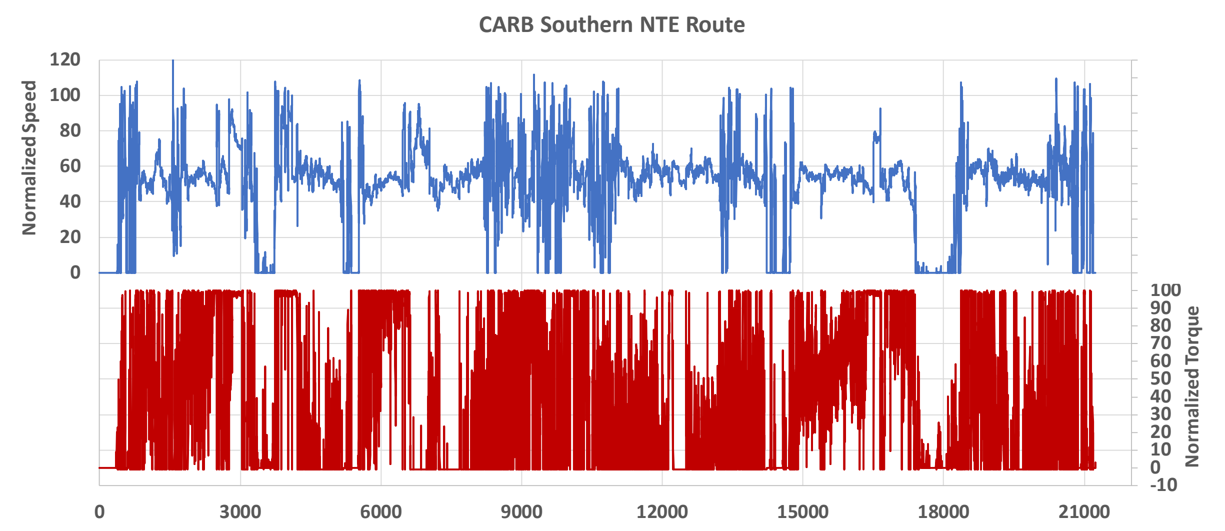
2-bin MAW* In-Use Method Results

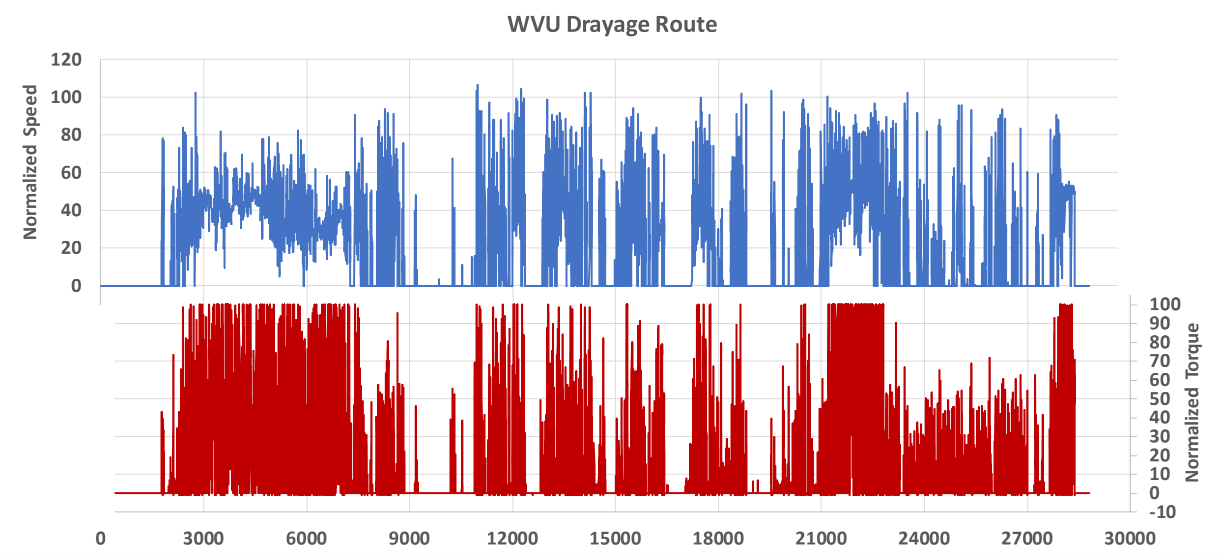


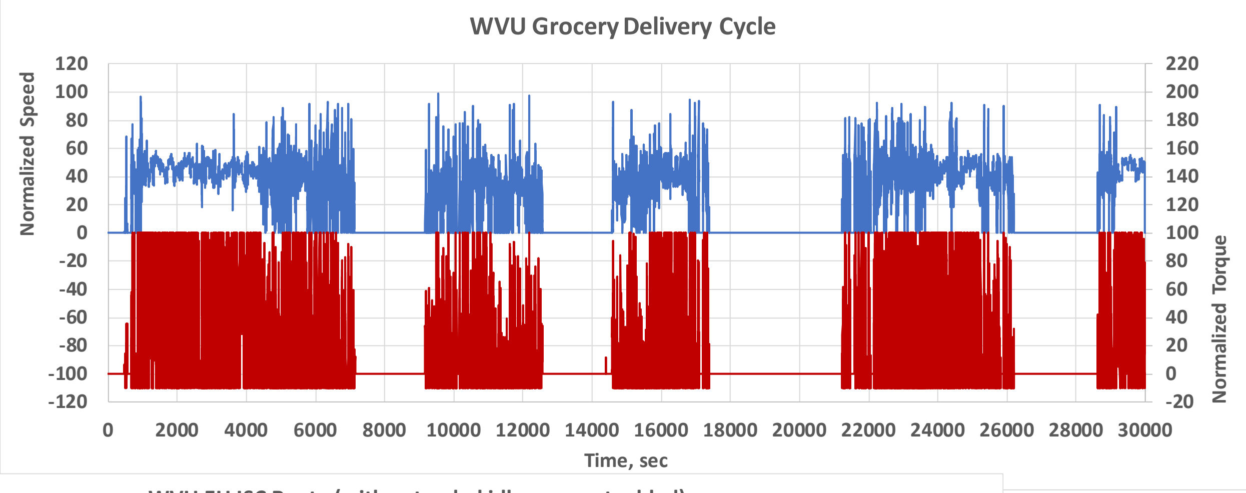
- Regulatory Cycle performance (with LLC) <u>does translate to real-world performance</u> for this system
- Bin 1 – well below 2027 in-use Standards
- Bin 2 – below 2027 in-use standards with some margin

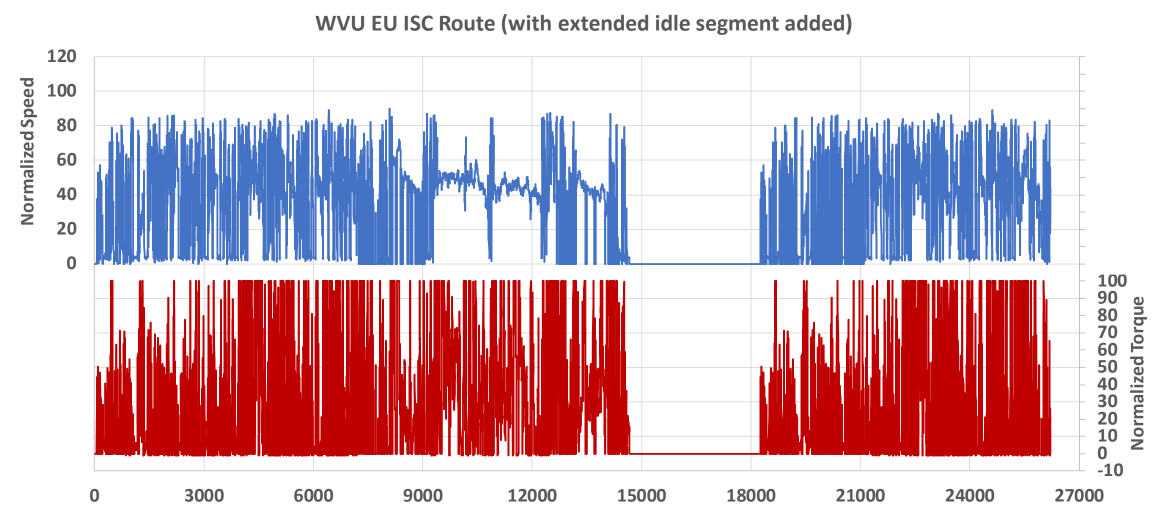
* 2-bin MAW is the new in-use testing protocol (EPA/CARB), considers all operation including cold-start, 5-min averaging window results sorted into two "load" bins

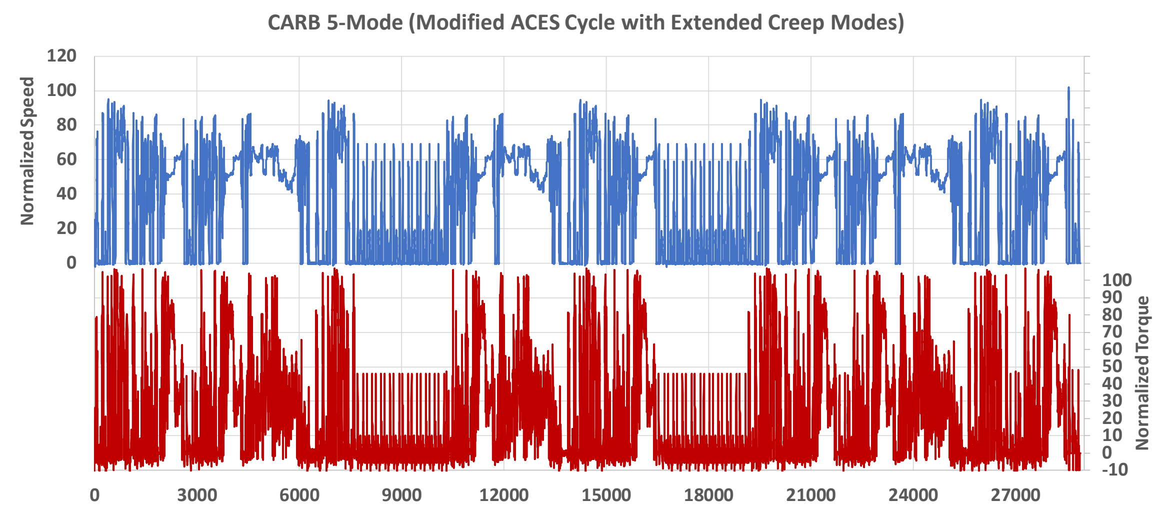
On-Highway Duty Cycle Variations







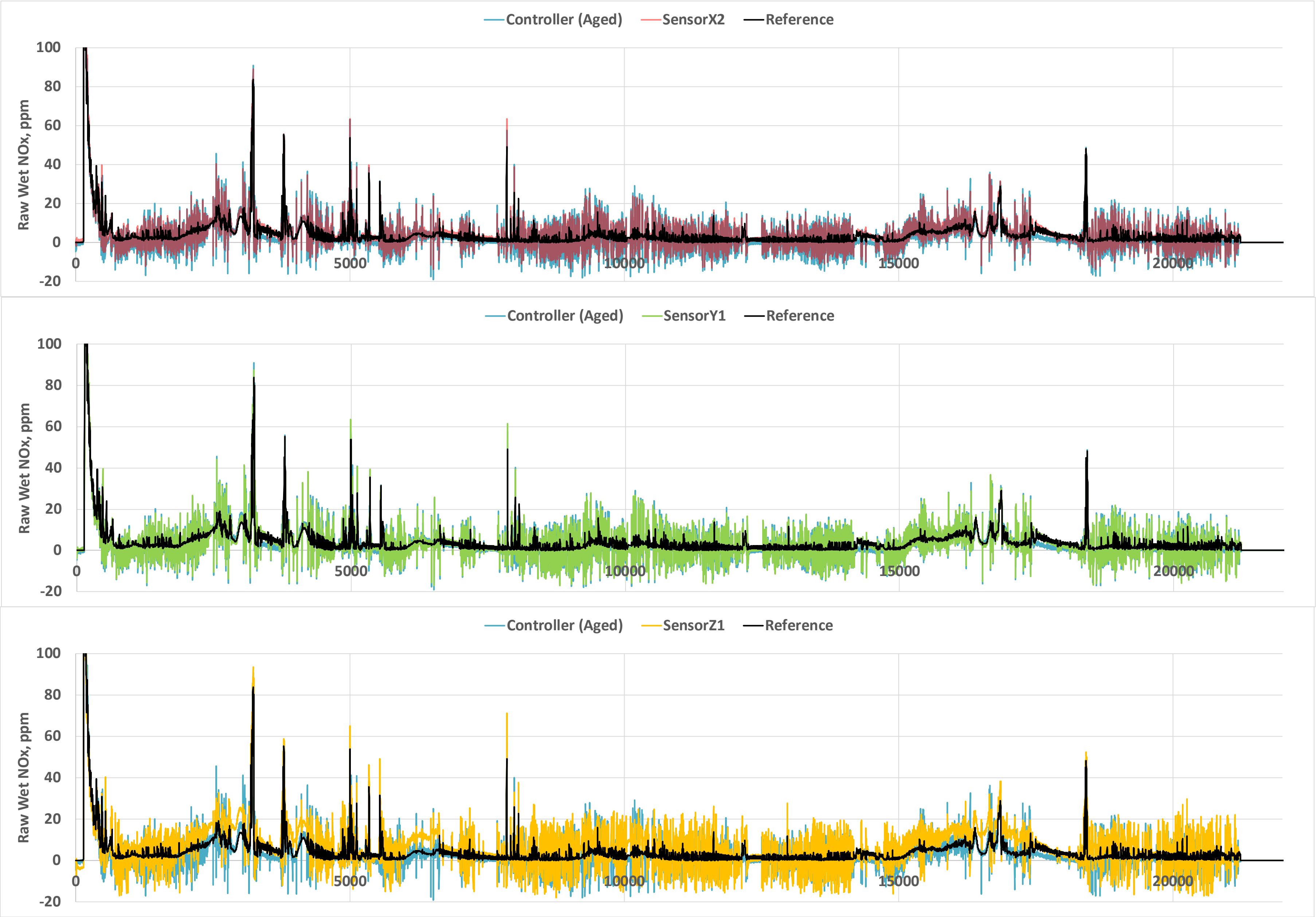




- Wide range of operation profiles and conditions
- Allows for examination of trends on many different driving patterns

Individual NO_X Sensor Comparisons versus Lab Reference

SNTE Full Cycle



- Data is from same SNTE field cycle as PEMS examples
- Controller is tailpipe NO_X sensor from test article (~1200 hours)
- Sensor X/Y/Z examples from different suppliers
  - Not Aged Sensors
- Lab Reference is same as for PEMS comparisons
- At this scale data appears to be very "noisy" compared to Lab
  - Larger features are still captured
- Aged Controller sensor does appear to show a negative offset compared to Lab and other sensors
  - This is just one sample…

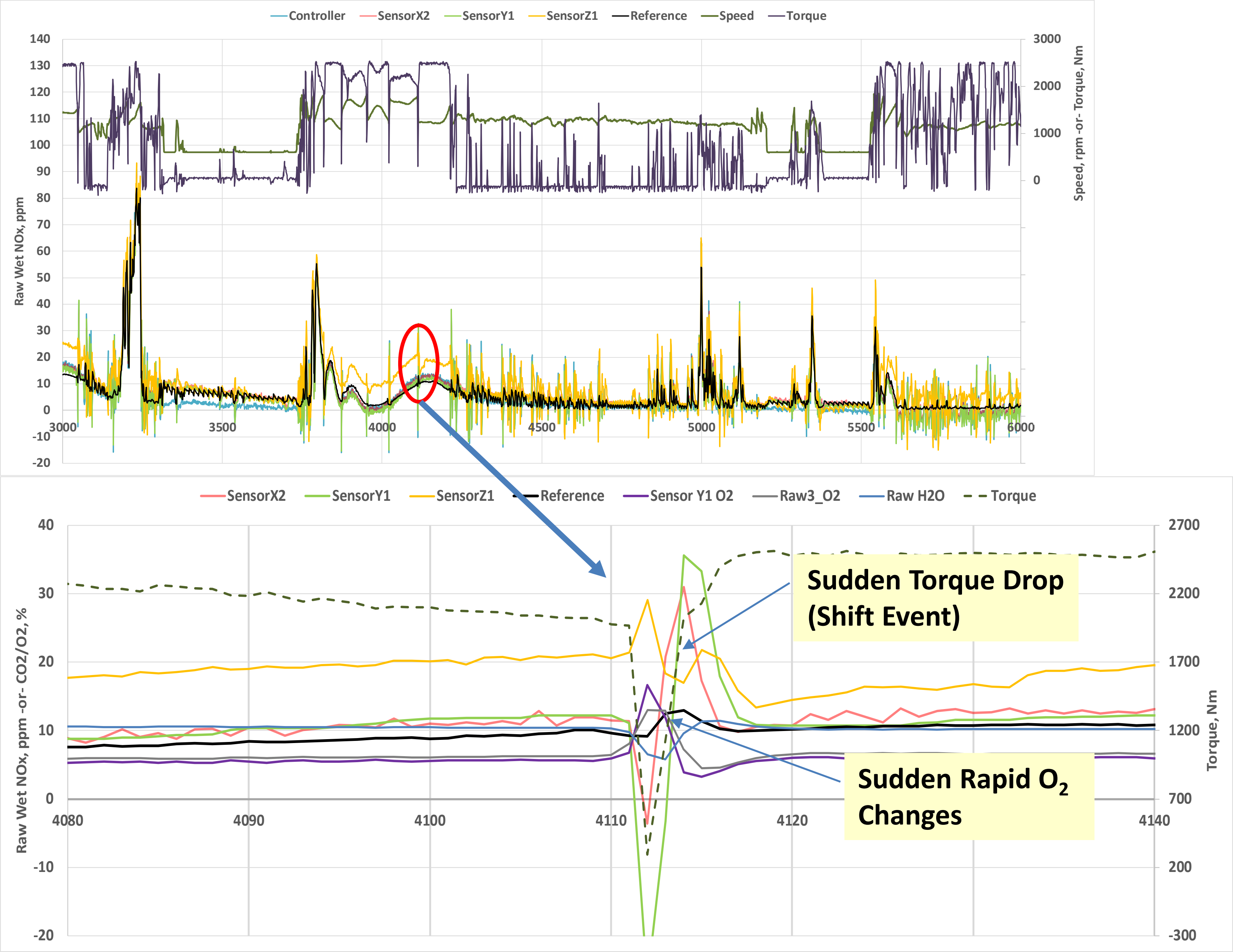
Analysis of Sensors Compared to PEMS – 2B-MAW Bin 2 (Preliminary)

Bias + 95th Percentile Variance, g/hp-hr			
Sensor Y1	0.017	PEMS 1	0.007
Sensor Y2	0.023	PEMS 2	0.002
Sensor Y3	0.024	PEMS 3	0.005
Sensor X1	0.011		
Sensor X2	0.019		
Sensor X3	0.020		
TP Sensor (aged)	0.013		
Sensor Z1	0.047		
Sensor Z2	0.055		

- **NONE OF THESE SENSORS ARE AGED EXCEPT THE TP SENSOR**
- **THIS IS A TINY SAMPLE OF PRODUCTION VARIATION FROM ONE BATCH**

- Using similar methodology to what was developed for PEMS values used by EPA
- Note that Sensor exhaust flow and fuel flow (CO_2) were fairly close to Reference (and PEMS)
- Even excluding Sensor Z these values are still 2X to 5X PEMS allowance of 0.005 g/hp-hr
  - With Sensor Z as much as 11X
  - Variation even within sensor manufacturer
- **Filtration of high frequency (1-hz) noise did not change these values and did not address this problem**

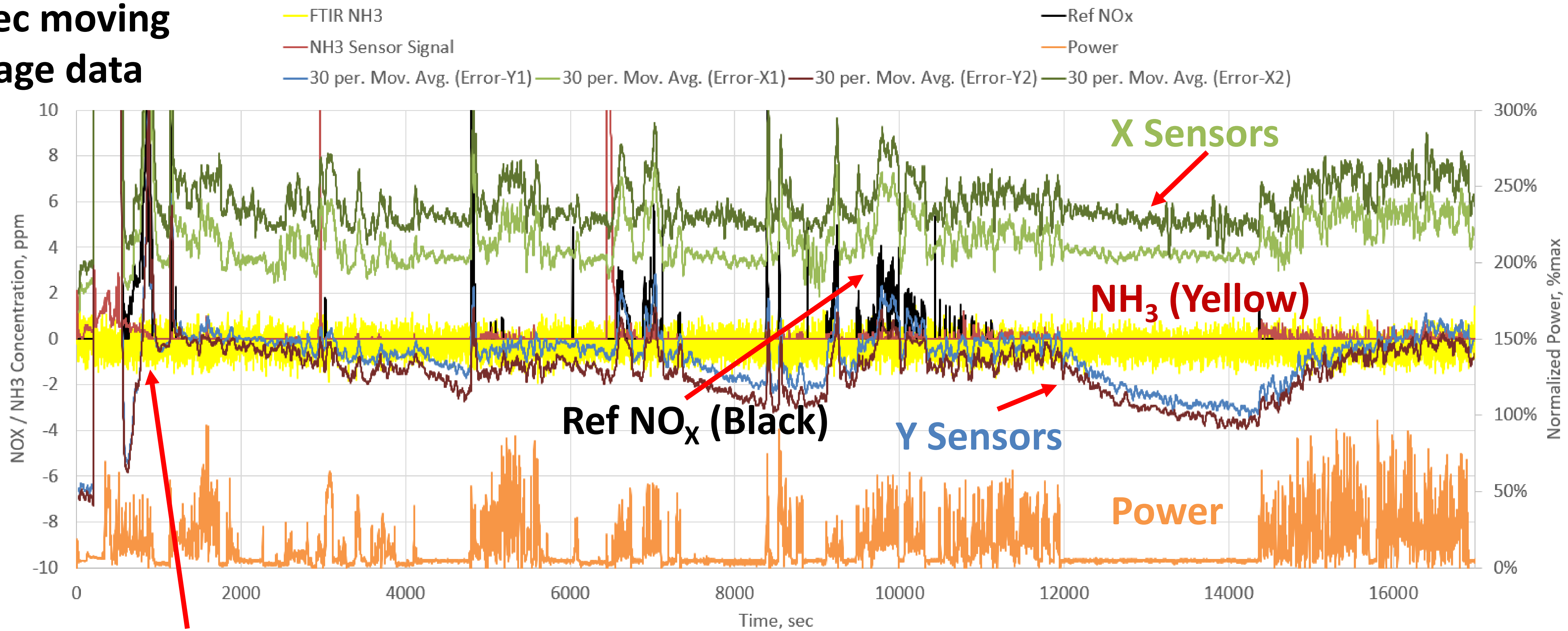
High Frequency Noise - NO_X Sensor Behavior versus Engine Operation



- Rapid changes in speed and/or torque result in significant "noise"
- Sensor behavior impacted by rapid rates of change in load
  - this event show a large but momentary load drop (but not quite a fuel cut event)
- Large swings in O_2 cause disturbance in NO_X sensor reading
  - this can cause positive or negative errors
- This is likely the sensor PID loop for first chamber O_2 having to catch up with rapid transient in O_2 (and then overshooting)
- This "noise " is not a problem for 2B-MAW (300-sec averaging window)

Example of Longer Time Constant NO_X Sensor Errors over Field Cycle

30-sec moving average data



Note: Larger negative errors during cold-start warm-up…but small influence due to high NO_X levels

- All NO_X sensors of a given type act similarly, but there are offsets between them
- Engine load appears to influence NO_X sensor error on longer timescales
  - This is the case whether or not there is NO_X present
  - Ammonia data (sensor and FTIR) indicates this is not ammonia interference

Handling Different Timescales

- <u>We are interested in more than just short-term sensor noise</u>
  - "Real-time" noise is unlikely to be influential in a 5-min b-MAW averaging window
- Analysis has shown that there are both short-term and long-term impacts on the sensor measurements
  - Short-term ~ real-time/1-hz
  - Long-term ~ minutes
  - Note that neither of these include aging which is on a much longer timescale (100s/1000s of hours)
- We need to isolate short-term and long-term errors to see what drives them differently
- Essentially done through auto-regressive smoothing
- We used Exponentially Weighted Moving Average (EWMA) for this purpose

Exponentially Weighted Moving Average (EWMA)

- EWMA is a way to filter data to extract trends from and reduce the impact of noise on time-series data
- Equations:

$$s_t = \alpha x_t + (1-\alpha)s_{t-1}$$

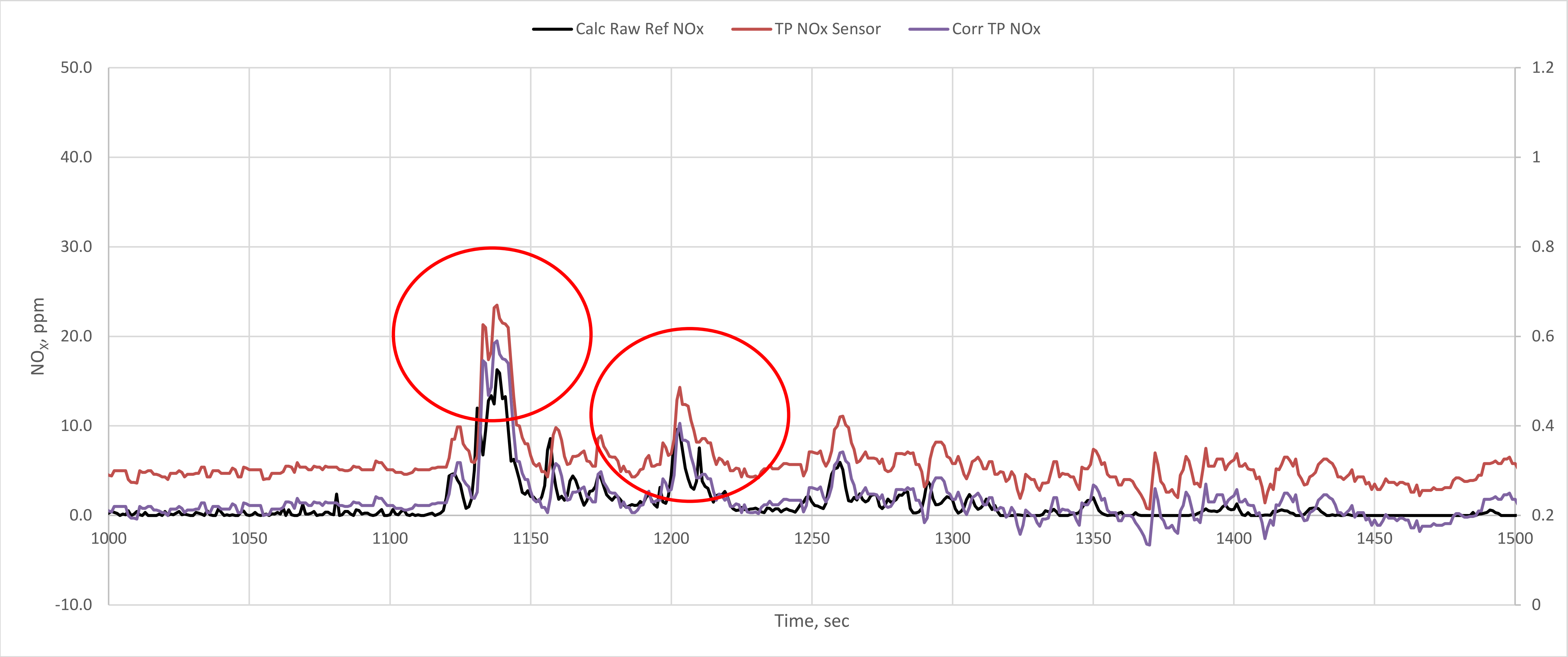
$$\alpha = 1 - e^{-\Delta T/\tau} \Rightarrow \alpha \approx \frac{\Delta T}{\tau}$$

S_t = EWMA result for current time step
X_t = current time series value
S_{t-1} = EWMA result for previous time step
α = Filter weight factor
τ = Filter time constant (sec)

- Why use EWMA ?
  - It can be effective as a filtration method to look at longer time constant impacts
  - It is already used extensively in OBD for noise reduction and trend tracking
    - Can be readily coded into ECMs

30-second EWMA was primarily used, but some functions used a 300-sec EWMA

Can a Zero Offset Be Used Across the Measurement Range ?

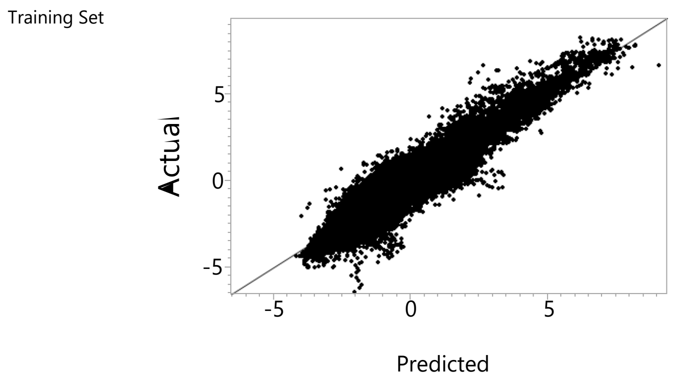


- In this case a sensor with high bias
- Note zero correction applied also brings data in 10-20ppm much closer to Reference..
- Zero offset approach looks to be workable…<u>if we can identify the zero offset</u>

Modeling Approach

- We have a large data set including 100s of hours of field duty cycle operation at Low NO_X levels
  - Multiple sensor types
  - Different field duty cycles
  - Parallel Lab Reference Measurements
  - Tailpipe Exhaust Characterization Data ($NO/NO_2/NH_3$, etc.)
  - Other parallel operating parameter measurements
- Used machine learning techniques to identify potential correlations between NO_X sensor error and other operating parameters

Gradient Boosted Tree Model of NO_X Sensor Error



Y Sensors

Overall Statistics

RSquare	RASE	N
0.887	0.5096209	119821

Column Contributions

Term	Number of Splits	SS	Portion
Sensor Y1 30	616	380616.783	0.5413
Torque 30	553	116036.392	0.1650
Torque 300	848	85464.2914	0.1216
Sensor Y1 300	907	41039.0972	0.0584
10% EWMA Y1 NOx Delta 30	352	34989.2338	0.0498
Y1 NOx Delta 300	244	24363.3694	0.0347
Delta Torque 300	197	11451.0781	0.0163
Y1 NOx Delta 30	145	5652.06422	0.0080
Delta Torque 30	138	3490.69104	0.0050

X Sensors

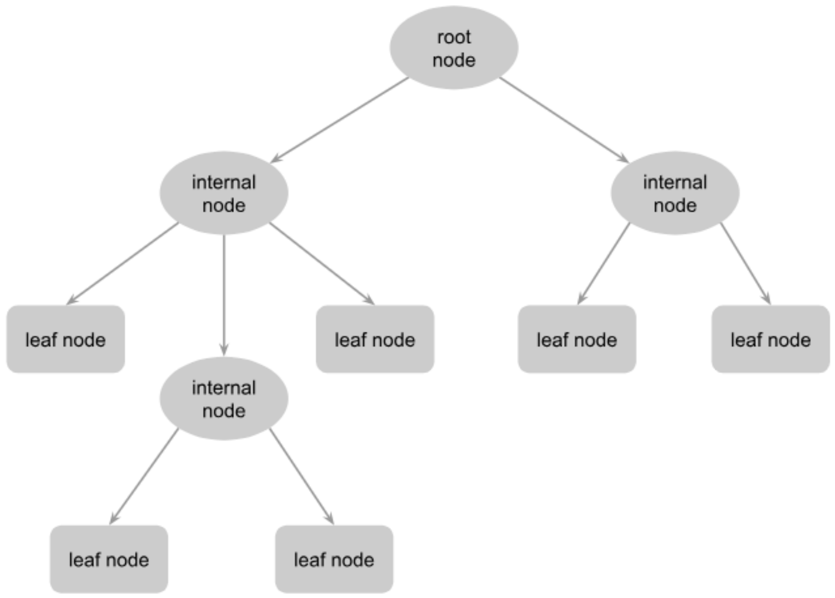
Overall Statistics

RSquare	RASE	N
0.876	0.4607873	141271

Column Contributions

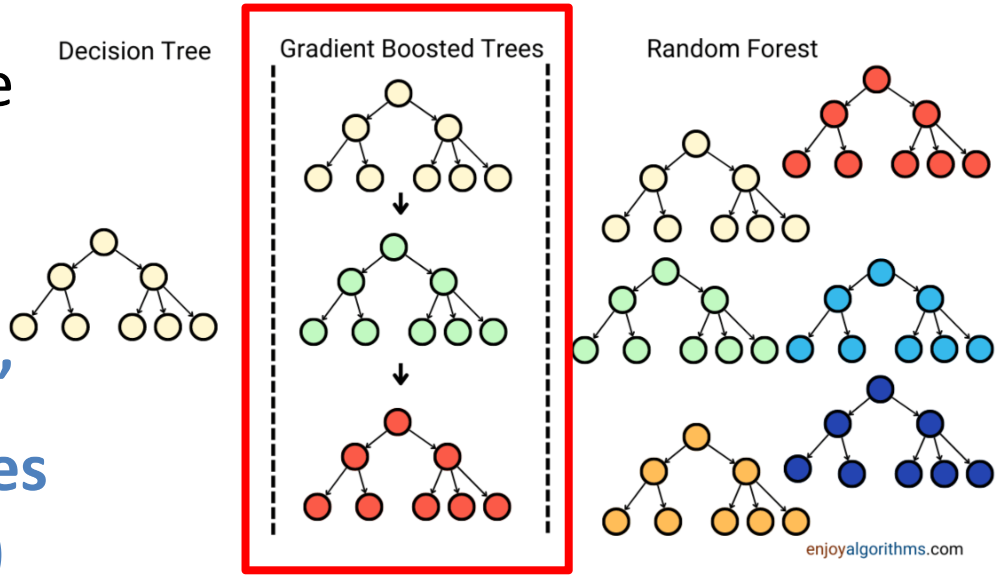
Term	Number of Splits	SS	Portion
Sensor X1 30	905	343633.702	0.5822
Torque 300	1104	137442.739	0.2328
Torque 30	664	55370.6773	0.0938
Sensor X1 300	1127	53826.4277	0.0912

A decision tree can be thought of as a way to split up the data into bins of predictions. For any data point, the decision path is followed until it reaches the end of the tree, and then a prediction is made. Boosted trees and random forests are both collections of decision trees, but they differ in terms of how they make final predictions. Both types of models are prone to overfitting, so validation is important, along with careful understanding of tuning parameters.



<u>Boosted Trees:</u>
Decision trees are sequential, with each new tree attempting to predict the errors (residuals) from the previous one. Final prediction for a new data point is the sum of all of the predictions from the trees.

Model trained on a portion of the data – validated on other duty cycle data from different engine

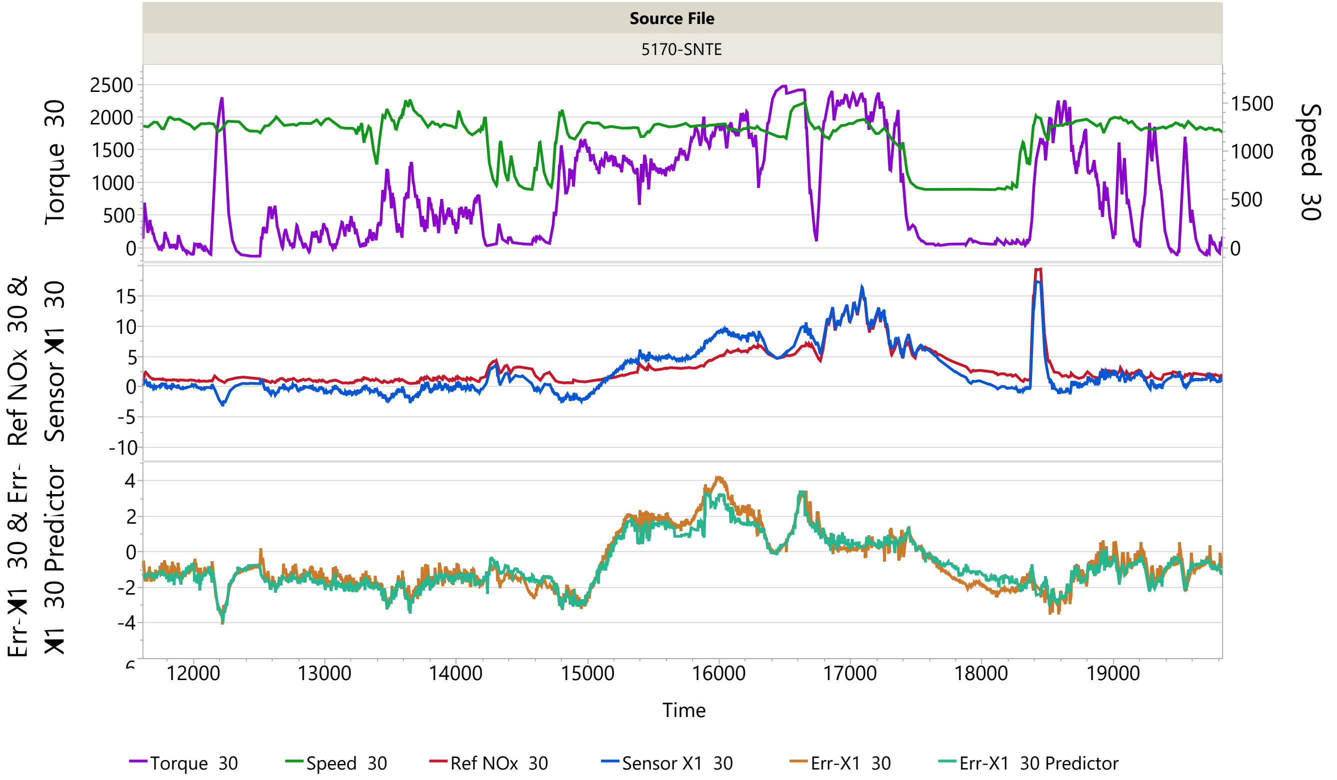


Relationship with engine "load" observed on all NO_X sensor types on a longer timescale (minutes)

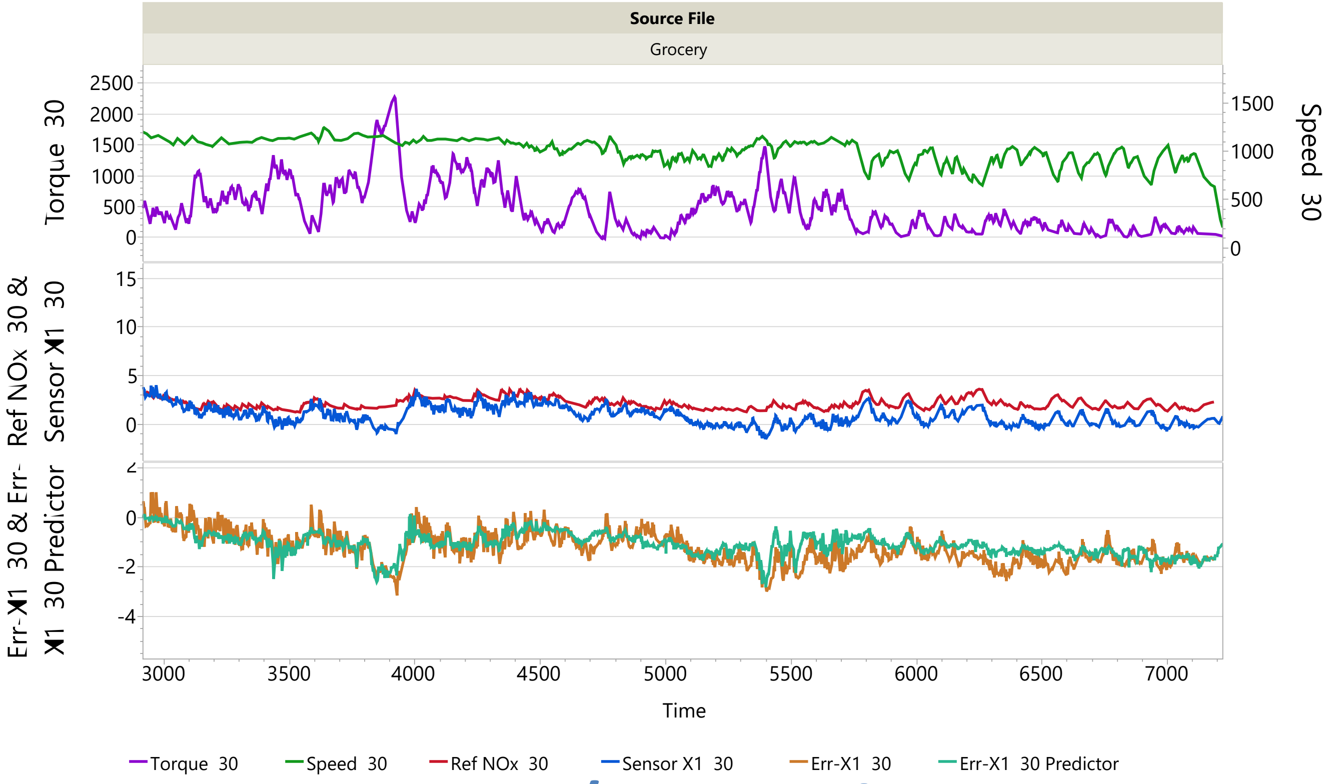
Model Predictions – Sensor Y

Measured error - Brown

Modeled error - Green



Sustained Load Changes = Sensor Error Movement



Intermittent/Low Load = Sensor Error Does not move much

- All NO_X sensors of a given type act similarly, but there are offsets between them
- Model appears to capture load-based changes in NO_X sensor error
- Each sensor type requires different tuning, but all sensors of same type are consistent

Real-time Implementation for ECM

"Transient" Error

- An Auto-Regressive-Moving-Average model with eXogenous inputs (ARMAX) model is a promising candidate for NO_X sensor error prediction and correction toward real-time implementation
- The ARMAX approach is often used in time series analysis and forecasting applications

$$Y_t = \underbrace{\sum_{i=1}^{p} \psi_i Y_{t-i}}_{\text{Autoregressive component}} + \underbrace{\sum_{i=1}^{q} \theta_i \epsilon_{t-i}}_{\text{Moving average component}} + \underbrace{\sum_{i=1}^{b} \eta_i d_{t-i}}_{\text{Exogenous input component}} + \underbrace{\epsilon_t}_{\text{Noise term}}$$

Parameters to be identified

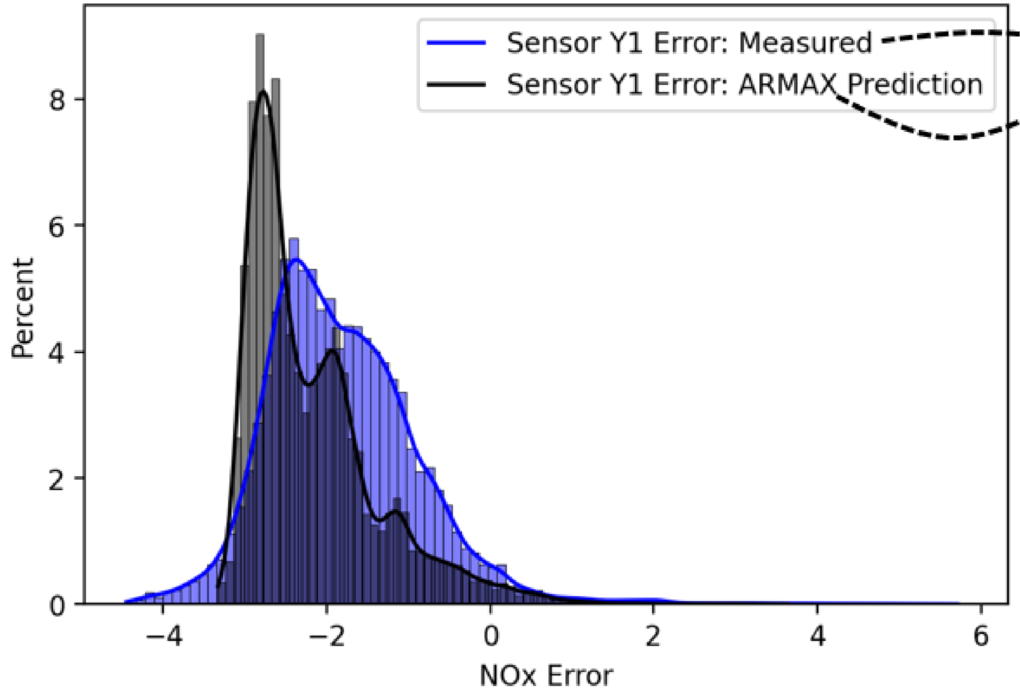
Exogenous inputs are torque-30 and tailpipe temperature-30 and 300

"Steady-State" Bias Correction

- Identify regions of "zero" tailpipe NO_X and use these to characterize individual sensor offset
  - Low Engine-out NO_X, High SCR Temperature, Low Load (High O2), Low Tailpipe NO_X
- Examine sensor within identified windows
- We can use intrusive dosing changes to "check for zero," if necessary, without impacting overall NO_X level
- Sample Enable conditions:
  - Torque 30 < 100 N-m
  - Tailpipe NO_X Sensor-30 < 15 ppm
  - Inlet NO_X-30 < 50 ppm
  - SCR outlet Temp > 300°C

Algorithm must be based on parameters available to an ECM

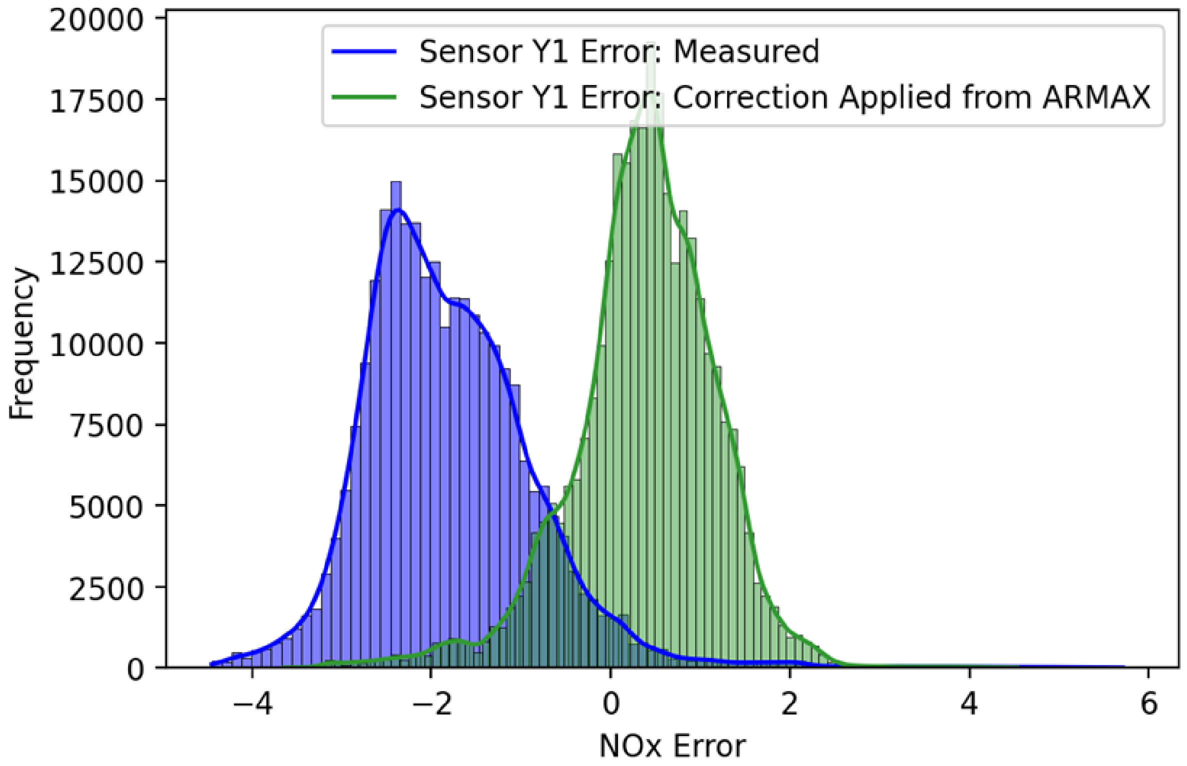
Algorithm Performance - Transient



$e = NO_x^{sensor} - NO_x^{ref}$

$\hat{e}$

$NO_x^{sensor,corr} = NO_x^{sensor} - \hat{e}$



- ARMAX model overlaps measured data relatively well
- Note this is a validation cycle (ACES 5m) that was *not* used for model training
- Correction applied reduces the spread of the error data and shifts the error distribution closer to zero
- There is still a steady-state error which that needs to be fixed (Bias correction function)

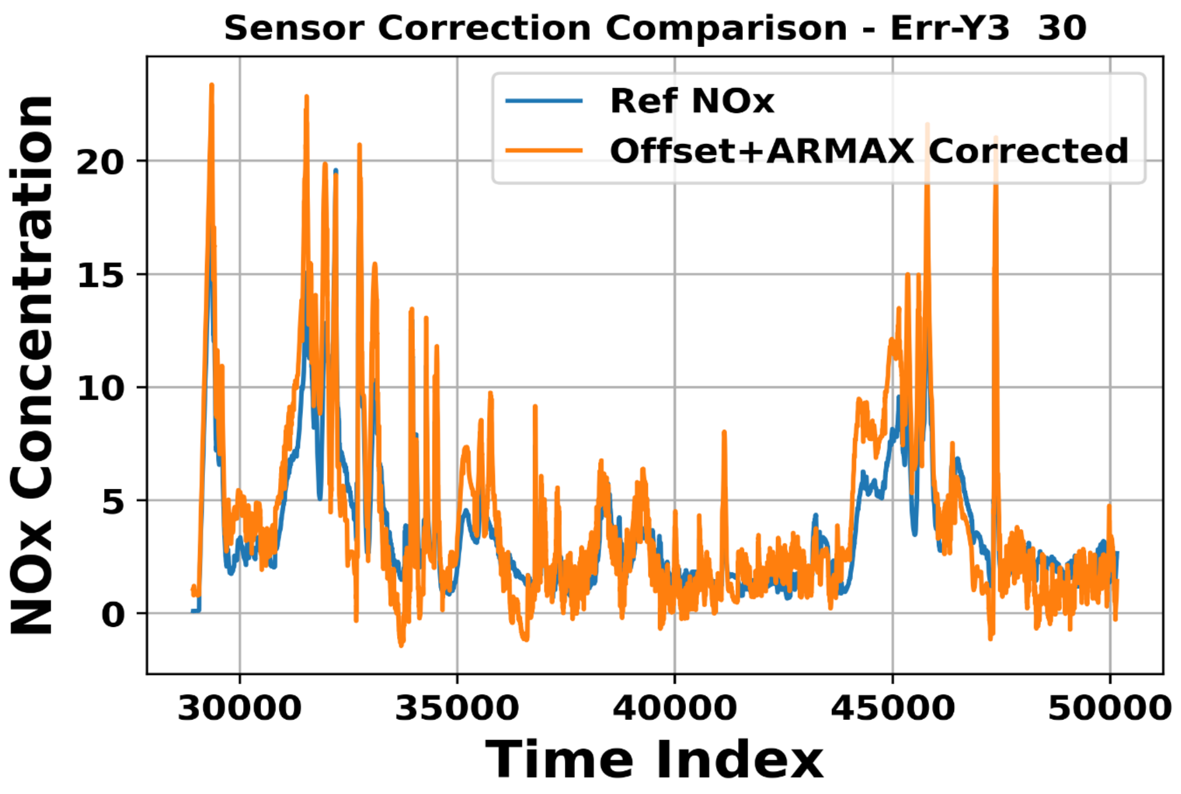
Algorithm Performance – Bias Correction

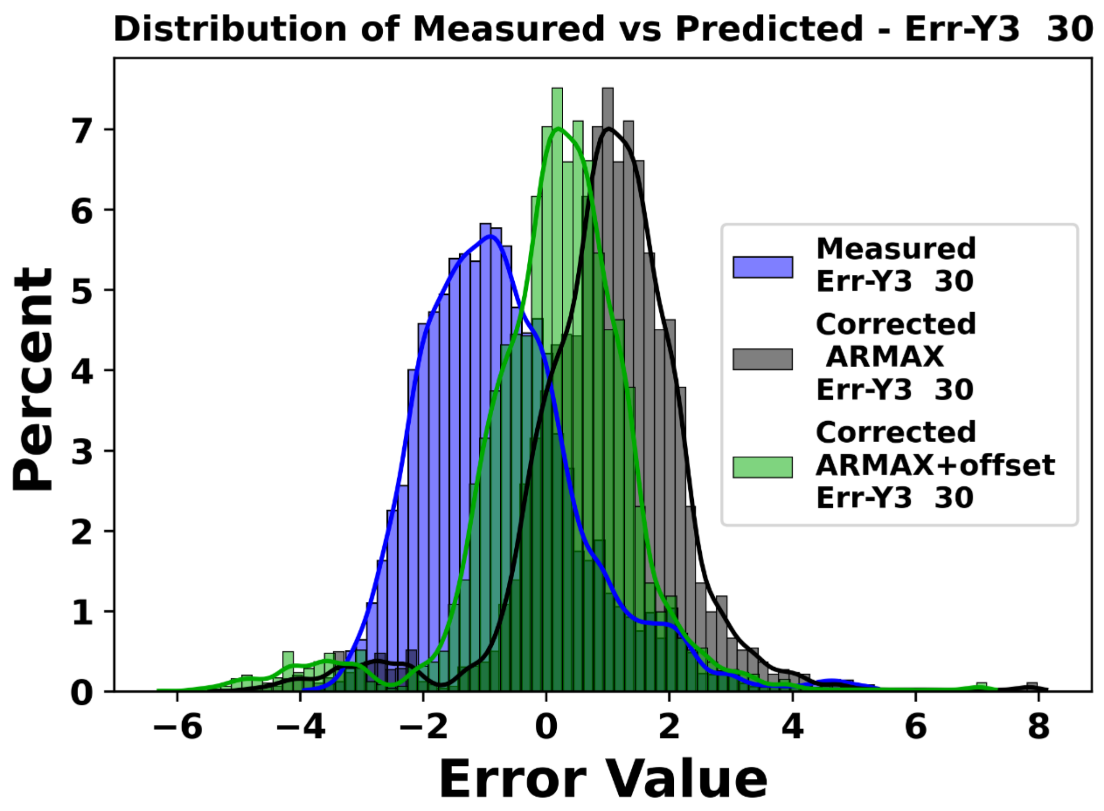
Uncorrected = Blue

Corrected = Red

- "Zero" windows identified in field cycle operation
- Offset applied – negative and/or positive bias is removed
- This example is without ARMAX model, but this can also be applied after the ARMAX model to eliminate residual bias after "transient" error correction
- Algorithm would track sensor over time as aging shifts the offset

Algorithm Performance – Combined Algorithm





- Combination of ARMAX and Bias correction shifted senor close to original reference (in most cases)
- Distribution of sensor errors is narrower and centered around zero for Corrected Sensor signal
- Note this is a validation cycle – data was <u>not</u> used to train the model

Conclusions

- Large database of NO_X sensor data over a variety of duty cycles, different engines at Low NO_X levels, different sensors with parallel laboratory reference signal used to examine sensor error
- Slower moving transient error behaviors driven by engine load identified which appear to be consistent across a given sensor model
  - All sensors seem to do this, but different sensor models respond differently
  - What is the mechanism behind this ? (Water ? Oxygen ? Temperature ?)
- Sensor-to-sensor errors appear to be driven by individual sensor bias offset, which appears to move with aging
- Possible error correction methods identified which could potentially be implemented on ECM
  - Post processing may also be possible…
- Identification of areas affected by NH_3 cross sensitivity still needed…

Thank you!

Christopher Sharp
Institute Engineer
Commercial Vehicle Systems
chris.sharp@swri.org
+1-210-522-2661 (Office)
+1-210-204-8165 (Cell)