Sensor-based Particulate Measurement
(Some Tall Tales from the Trenches)

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I & M Testing

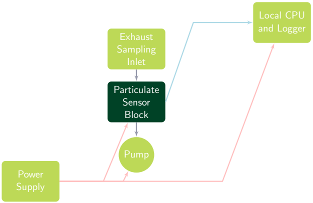
Current generation routine stop-and-check and in-garage testing methods are approaching obsolescence because they are based on opacity which is

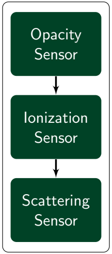
- Relatively insensitive to the finer PM produced by modern vehicles
- Cross-sensitive to by-products of some modern emission control systems, e.g. NO_2 from SCRs

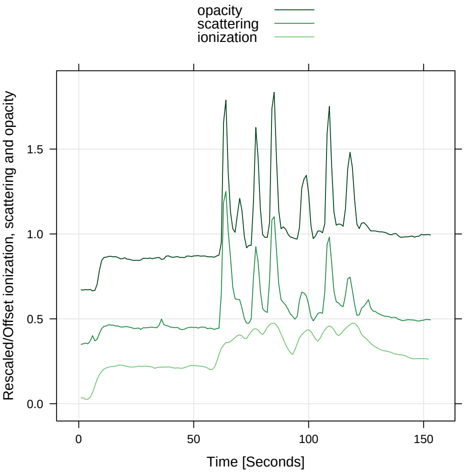
Various strategies have been employed to attempt to address the limitations of opacity but

- Most focus on replacing one single metric with one set of 'blind-spots' with another single metric with others
- Few address the practical issue of unit cost

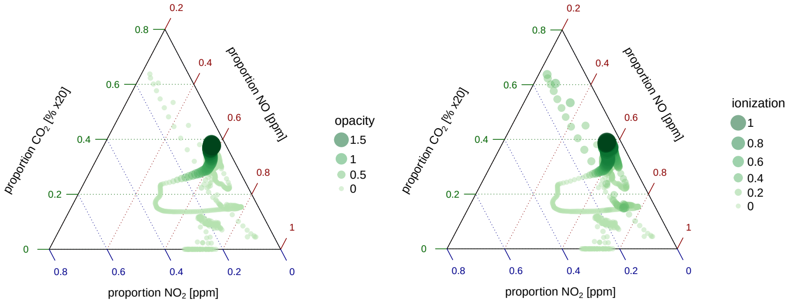
parSYNC® Sensor Module





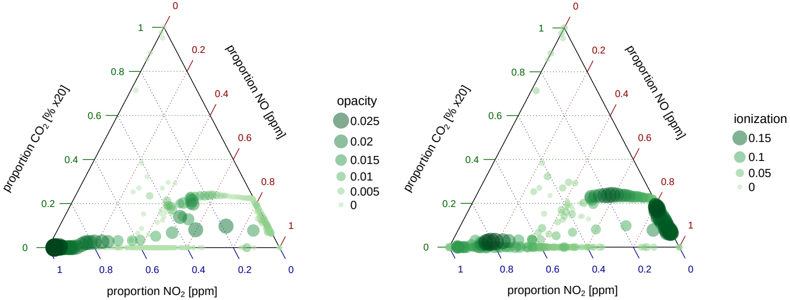


An Older Dirtier Vehicle



PM emissions of this vehicle are relatively coarse/large
(Note, opacity measure of PM stronger than ionization measure, 1.5x comparing scales, but trends for both are highly similar)

A Newer 'Cleaner' Vehicle



PM emissions of this vehicle are relatively fine/low

(Note, ionization lower but 6x opacity and trends are different)

But here SCR is also over-dosing/producing excess NO_2 which the opacity sensor is cross-sensitive to

(Note, the larger relative NO_2 contribution and the more pronounced opacity increase with increasing NO_2)

Response Mapping

The current multiplex function (parSYNC*) attempts to

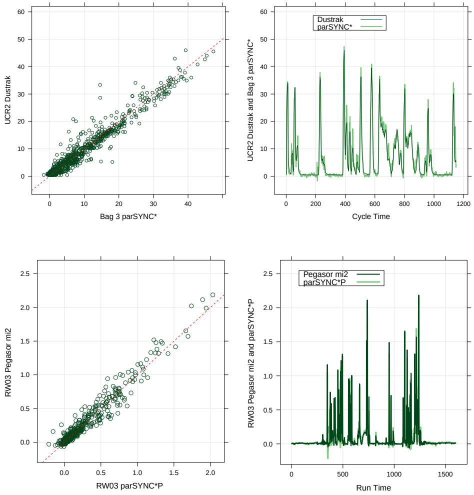
- Map the cross/non-cross correlation behavior of individual sensors onto a reference method *robustly*
- Correct for the different time resolutions of the sensors and reference method

Three Sensor Fit

$$\begin{aligned}\text{parSYNC*} = [\text{REFERENCE}] = \; & \text{f}(\text{parSYNC1}_{t=-1,0,1}) + \\ & \text{f}(\text{parSYNC2}_{t=-1,0,1}) + \\ & \text{f}(\text{parSYNC3}_{t=-1,0,1})\end{aligned}$$

Validation of Mapping

- DUSTRAK and Pegasor sensor maps, parSYNC* and parSYNC*P
- Blind testing on replicate runs
- Both three sensor maps
- Both R $>$ 0.95



A Serious Caveat

At this stage, this all looks very promising

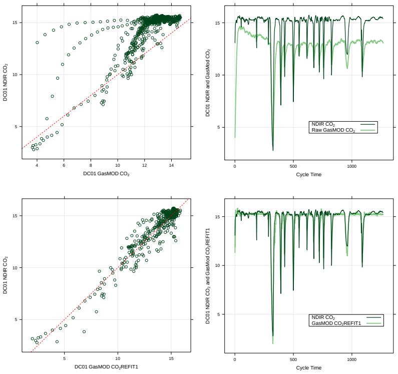
1. Buy yourself a sensor (or bundle of sensors)
2. Run it (or them) alongside a reference method to make a calibration dataset
3. Model the dataset and, if you get a good calibration, you are good to go, right?

Unfortunately, it is not that simple...

A ‘Bad’ Map

One Sensor Fit

$$\text{GasMOD } CO_2\text{REFIT1} = [\text{NDIR}] = \text{f}(\text{GasMOD } CO_{2,t=-1,0,1})$$



Raw sensor comparison

- Here both sensor response time and changing exhaust water content are affecting agreement

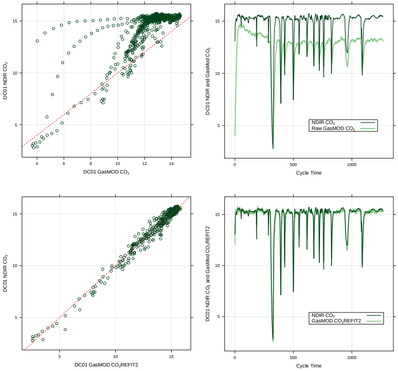
REFIT1 comparison

- Here fit looks good and blind testing with same vehicle will seem to confirm that
- But can you spot what REFIT1 is actually doing?

A Better Map

Multi Sensor (Multi-Parameter) Fit

$$\text{GasMOD } CO_2\text{REFIT2} = [\text{NDIR}] = \text{f}(\text{GasMOD } CO_{2,t=-1,0,1}) + \text{f}(H_2O, \textit{temperature}_{t=-1,0,1})$$



Raw sensor comparison

- Same start point as REFIT1

REFIT2 comparison

- The fit statistics are not that much better than REFIT1
- BUT this tracks changing water content and temperature
- So it tracks rather than suppresses features above 15%

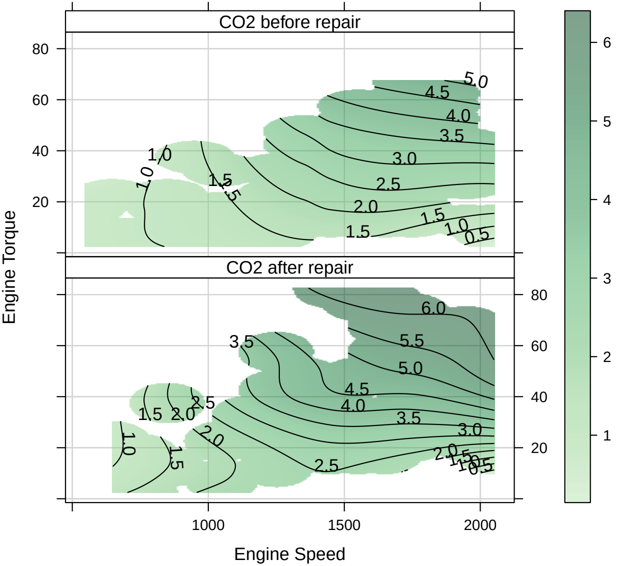
Before/After Repair Comparison

Another option is to compare vehicle emissions before and after a repair

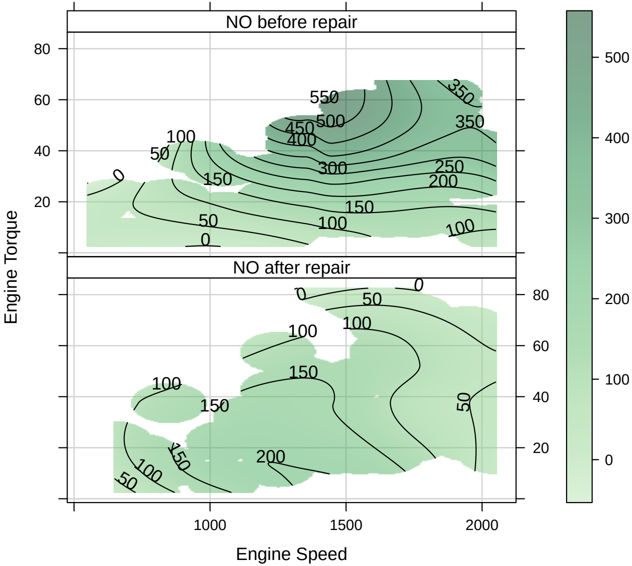
- This is perhaps the most informative option
    - Vehicles independently identified as faulty - *so this is real-world*
    - Garage inspection of failure - *so problem is confirmed and characterized*
    - Vehicles then repaired - *so emission monitoring at start and end of this process means both failures and repairs can be investigated*
- But logistically it is the most challenging and, typically, it is also the most time-consuming

The following examples show dynamometer drive cycle and SNAP test emissions from one vehicle, identified as faulty by OBD codes, before and after the associated repair

CO_2 Before/After Repair



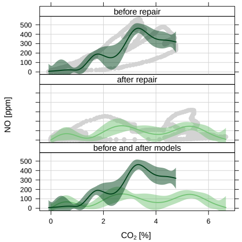
NO Before/After Repair

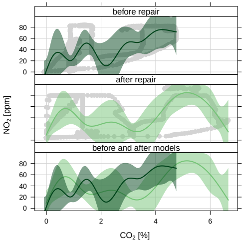


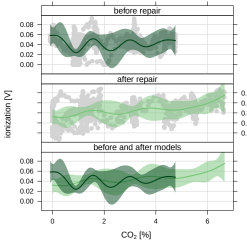
More On-board Metrics

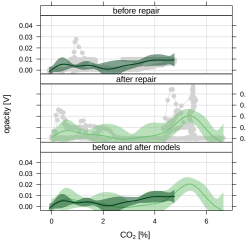
We are looking to develop a range of ‘on-board’ metrics and diagnostics because a tester will need standalone information from a test unit

(By the way, good repair or bad?)



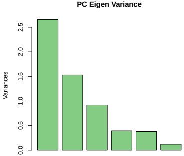


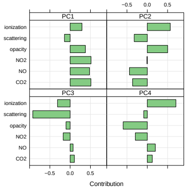


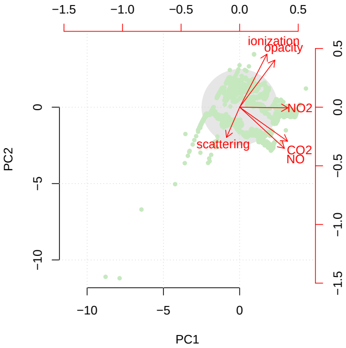


More Data Analysis

We have only just begun looking at the data we have



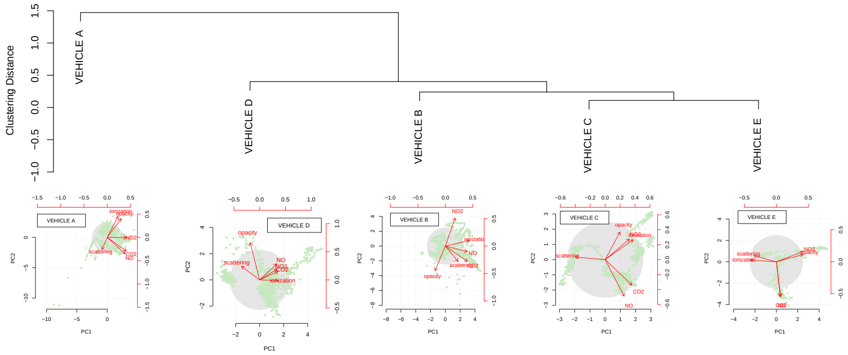




Above, a preliminary PCA of one vehicle, showing, amongst other things, extreme outliers amongst the scattering measurements

(Hopefully) More Sampling

We are seeing interesting trends in the data we have...



...but we really need more if we want to make the work robust

Thank You

We gratefully acknowledge the contributes of many others who anonymously contributed vehicles, equipment, labor and parallel data

Without your input this work would not have been possible

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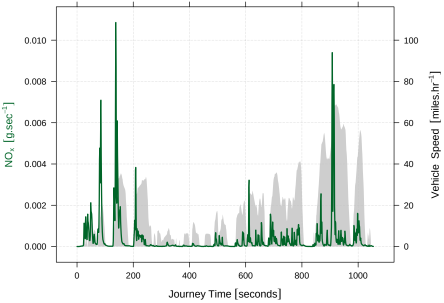
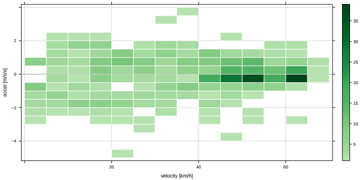
Dave Miller - davidmiller@3datx.com

Acknowledgments

Data analysis carried out in R and pems.utils





pems.utils R package
(https://sites.google.com/site/karlropkins/rpackages/pems)