Self-organized intelligent monitoring of a vehicle fleet in Sweden

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Newspaper stories

February 2011: Nine out of nine inspected buses failed inspection. During the autumn and winter period a total of 68 out of 77 inspected buses were taken out of traffic.
http://www.gp.se/nyheter/goteborg/1.541701-nio-av-nio-bussar-underkanda

March 2012: 8 buses burned down in Gothenburg to an estimated cost of 15 MSEK
The police: Most likely a technical error, either overheated brakes or oil leakage
http://www.gp.se/nyheter/goteborg/1.892884-bussbranden-kostar-tiotals-miljoner

Trafikbloggen 2012 – On average one bus burns down **every 3 days** in Sweden
http://blogg.gp.se/trafikbloggen/2012/03/20/brinnande-bussar-stor-fara/

August 2012: All 21 buses that were randomly inspected was taken out of traffic right away due to technical (fuel or oil leakage, etc) or other errors
http://www.gp.se/nyheter/goteborg/1.1036613-alla-bussar-underkandes

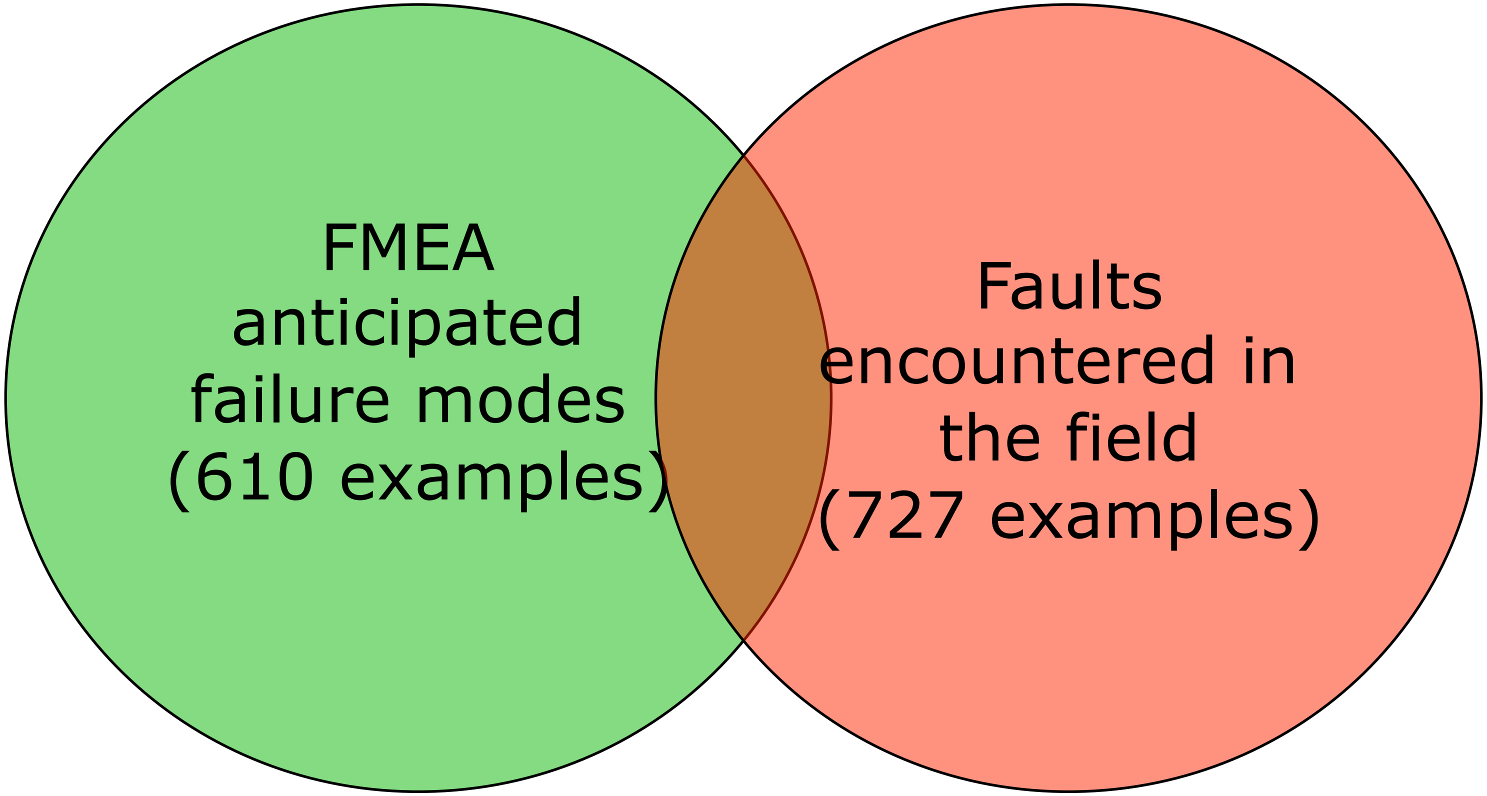
January 2013: Almost all buses that were inspected had serious errors
http://www.gp.se/nyheter/goteborg/1.1248358-nya-busskontroller-gamla-fel

The problem

- Systems are becoming more and more complex
  - We need better (or different) diagnostic and fault detection systems
- Building specific diagnostic systems is expensive
  - It is unrealistic to expect that for each individual fault
- Without usage data it is not known exactly what to look for
  - Or sometimes what is “known” turns out to be wrong
- In automotive industry, diagnostics is an afterthought
  - Components are rarely designed with fault detection in mind
  - It is not common to install additional, specialised sensors

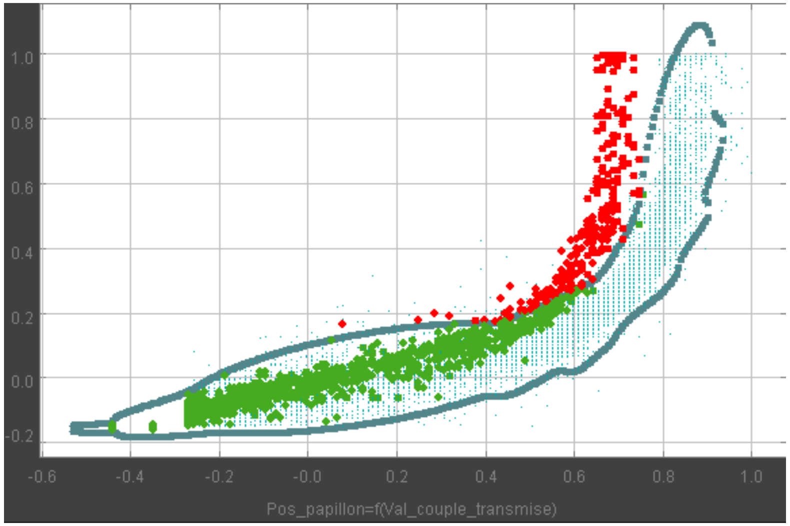
Targeted Diagnostics

Data based on Alen Atamer (2004) *Comparison of FMEA and Field-Experience for a Turbofan Engine with Application to Case-Based Reasoning*, IEEE Aerospace Conference.

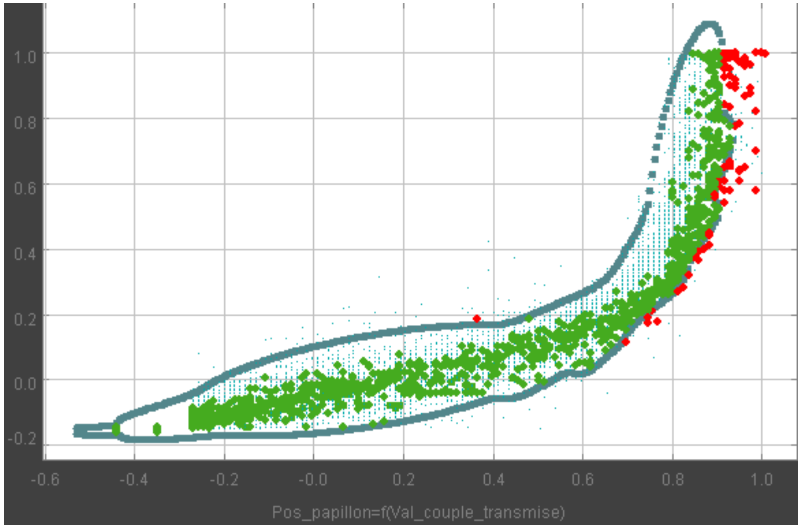


23% overlap (142 examples)

Classical Approach



Air admission blocked



Injector blocked

- Expert defines which signals to look at + what is normal and what is not
  - and lists/identifies possible faults (before they happen)
- This approach works well and is reliable
  - But does not scale well

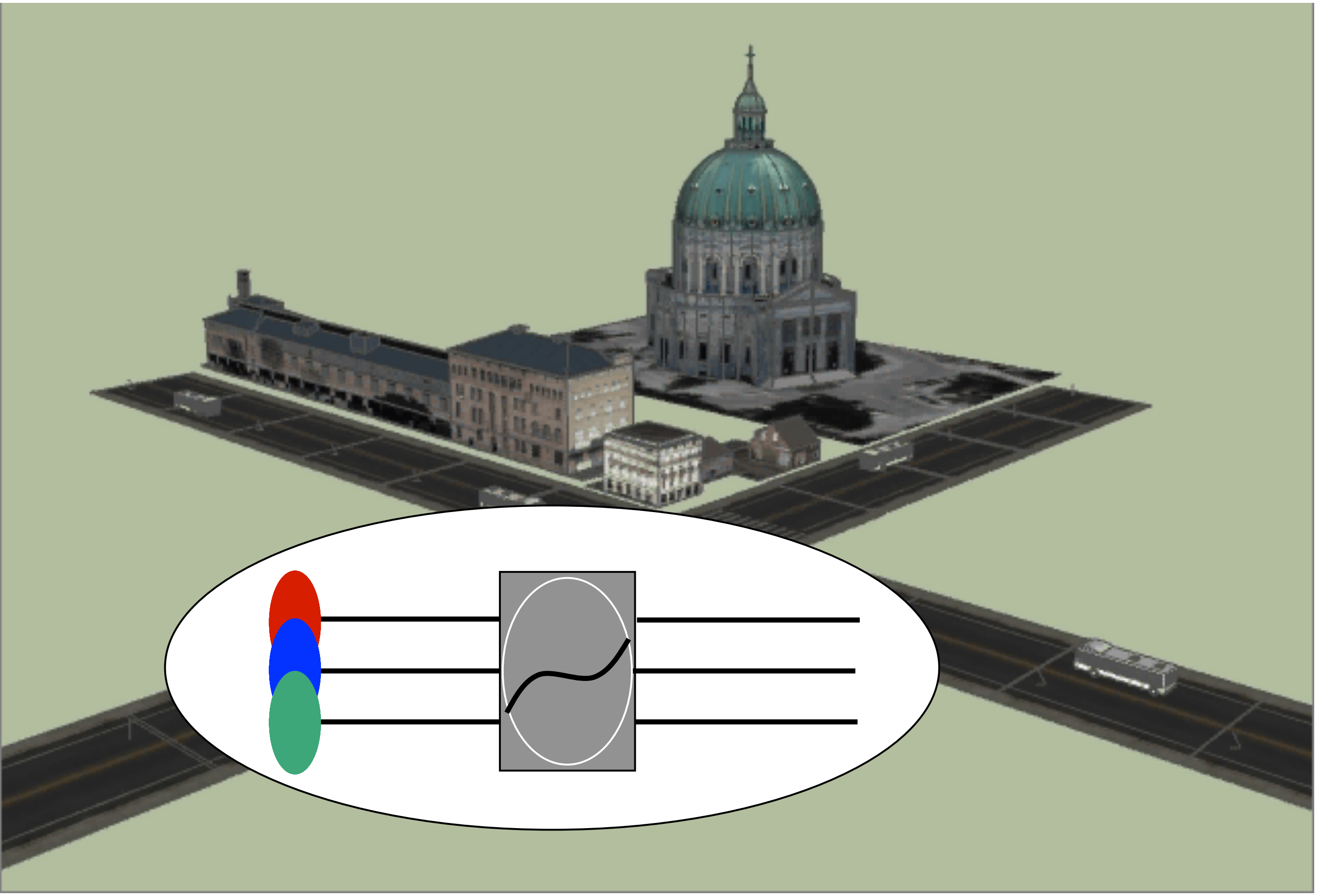
Our idea

Consider a fleet of city buses...

Driving around, over fixed routes, day in and day out...

...under similar weather and load conditions, etc...

Our idea

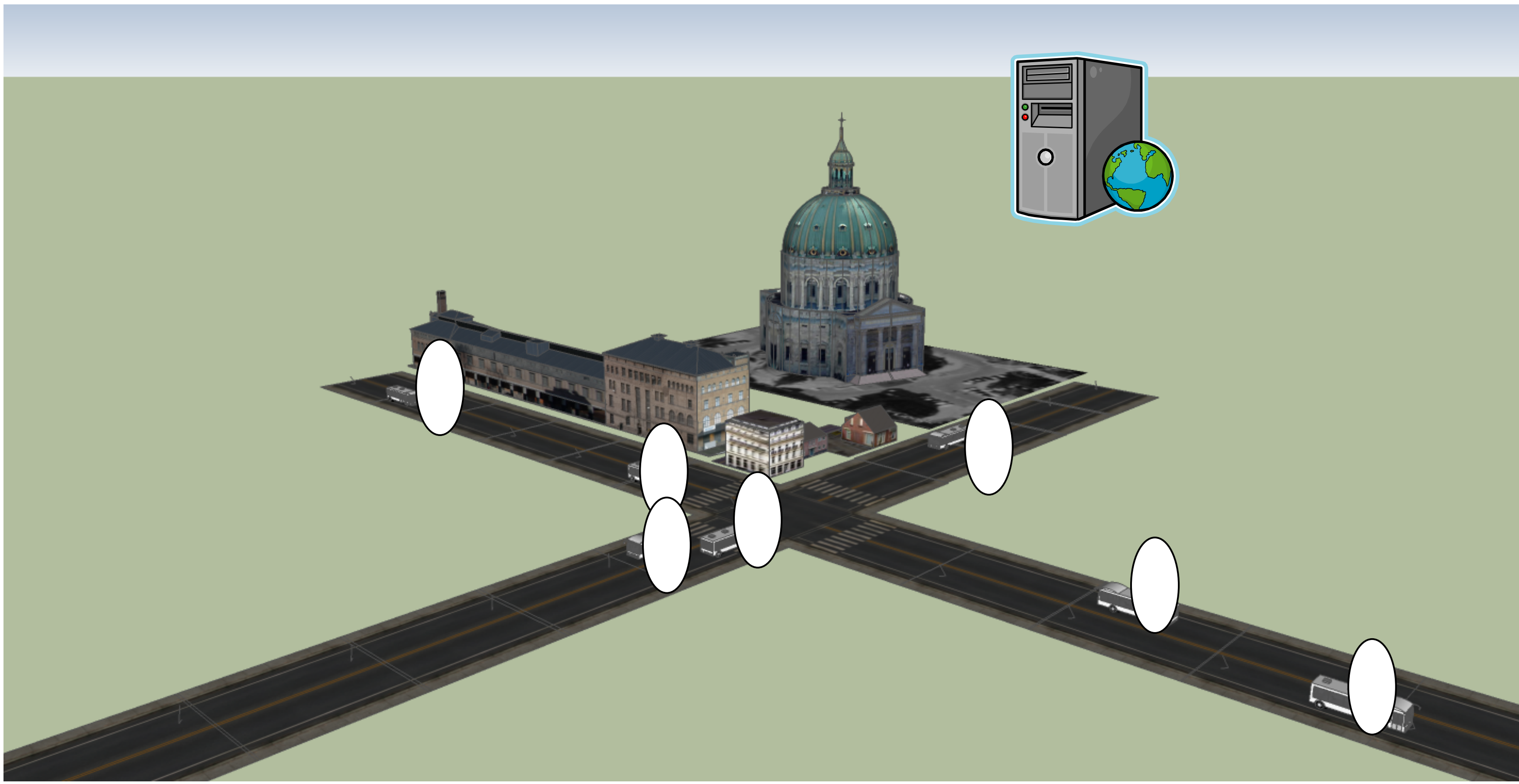


Each listening to sensor and control signals on internal data network…

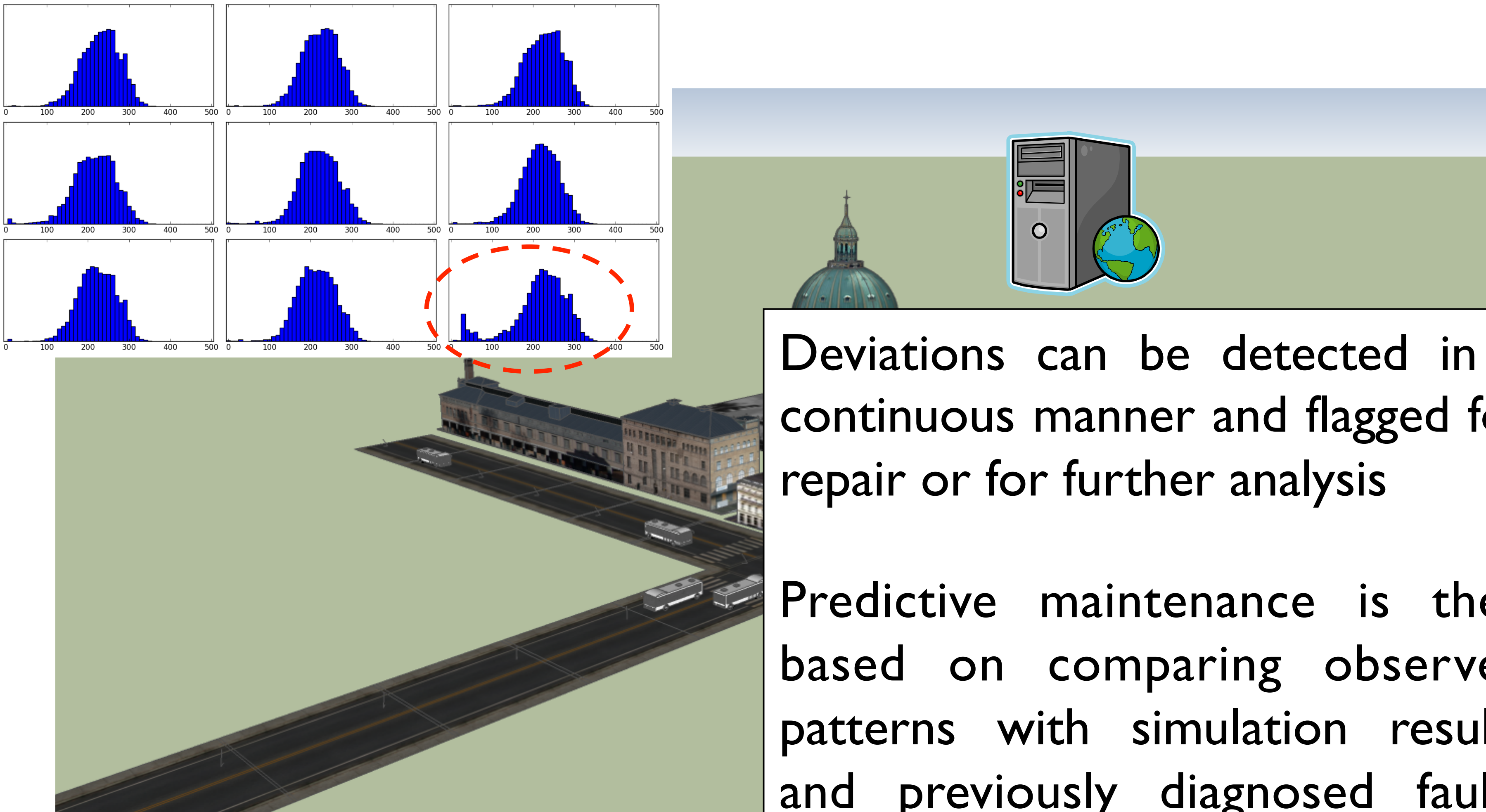
Discovering and saving interesting relationships…

Looking for own characteristics of each individual vehicle…

Every now and then, all the buses report selected relationships to a central server via a telematics gateway.



This allows for discovery of deviations without the need to *a priori* define how the normal behaviour looks like.



Deviations can be detected in a continuous manner and flagged for repair or for further analysis

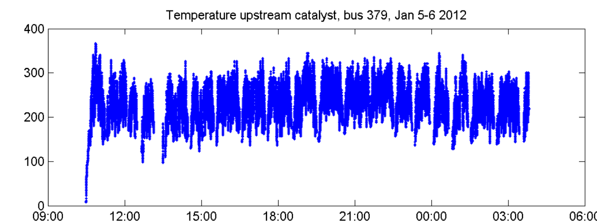
Predictive maintenance is then based on comparing observed patterns with simulation results and previously diagnosed faults from a database of repair histories

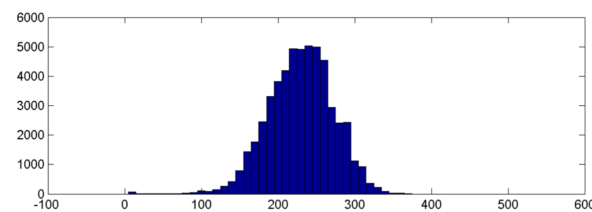
Challenges

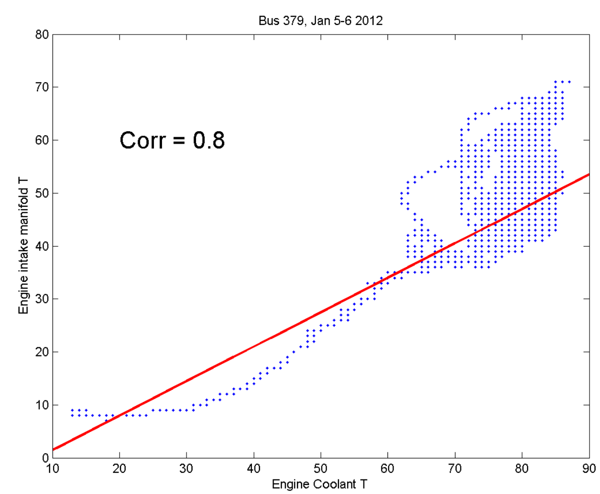
- Define vehicle characteristics that are simple yet informative
  - Possible to compute efficiently in the hardware available onboard
  - Represent a huge compression of the raw data for transmission
  - Can be analysed off-board for future reference & comparisons
  - Useful for human experts in verifying results & in diagnostics
- Efficient methods to search through the space of (endless) vehicle characteristics and evaluate their usefulness
  - Ways to tell if a characteristic is (potentially) interesting
  - Comparisons of different characteristics (metrics and statistics)
- Link characteristics with data about repairs, specifications, etc.
  - Fuse information of different modalities (also unstructured)

Vehicle Characteristics

- Compressions of signal data
- Unary relation(s):
  - Histograms
  - Hellinger distance
  - Rank interestingness by entropy and variation
- Binary relation(s):
  - Linear correlation/model
  - Mahalanobis distance
  - Rank interestingness by out-of-sample mean square error





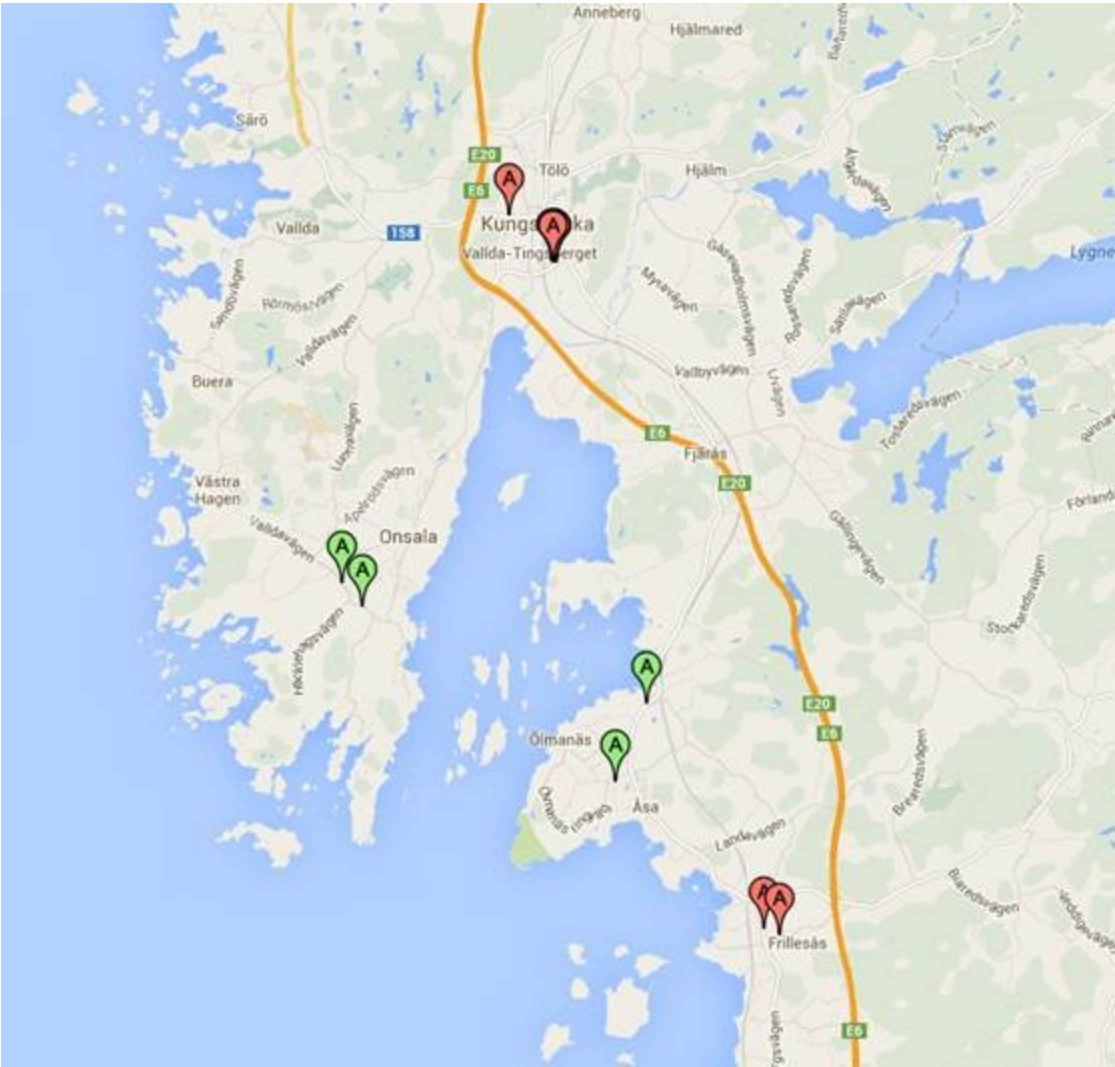


Long-term pilot study

- 2 years (fall 2011 – fall 2013)
- 19 Volvo buses (8500 model)
  - 14 from 2007
  - 1 from 2008 and 4 from 2009
  - driven about 100,000 km/year each
- In service around Kungsbacka
  - 30 km south of Göteborg
  - rotating routes and drivers
- Logging approximately 100 signals
  - at 1 Hz frequency
  - around 500MB/week/bus
- Access to maintenance records, operator notes, and driver comments

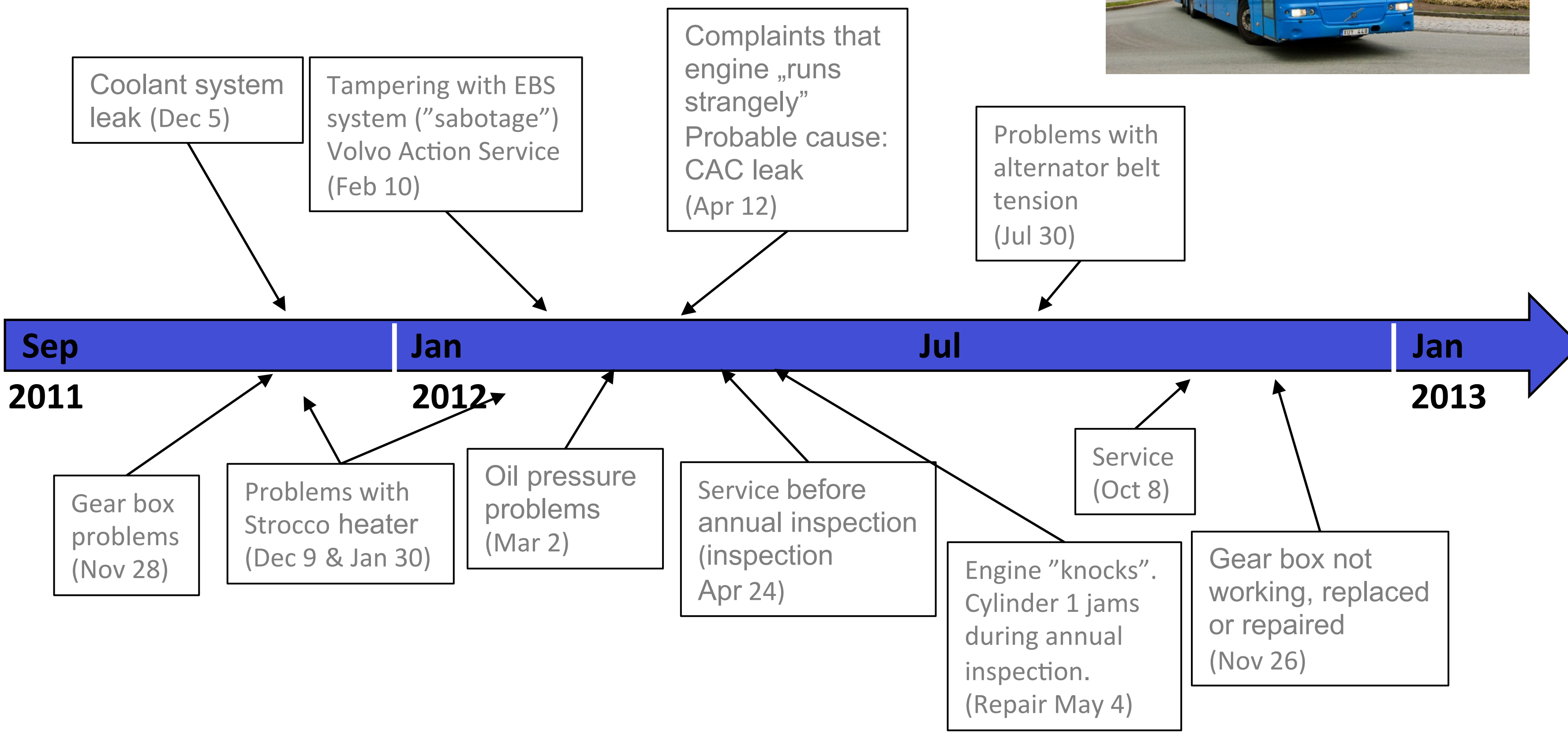
The VACT system
(*Volvo Analysis and Communication Tool)*

- DynaFleet hardware
  - software developed in the ReDi2Service project
- Communication
  - GPS, GPRS modem
  - 3 CAN interfaces
  - USB memory
- Configurable logging and on-board, on-line analysis capabilities

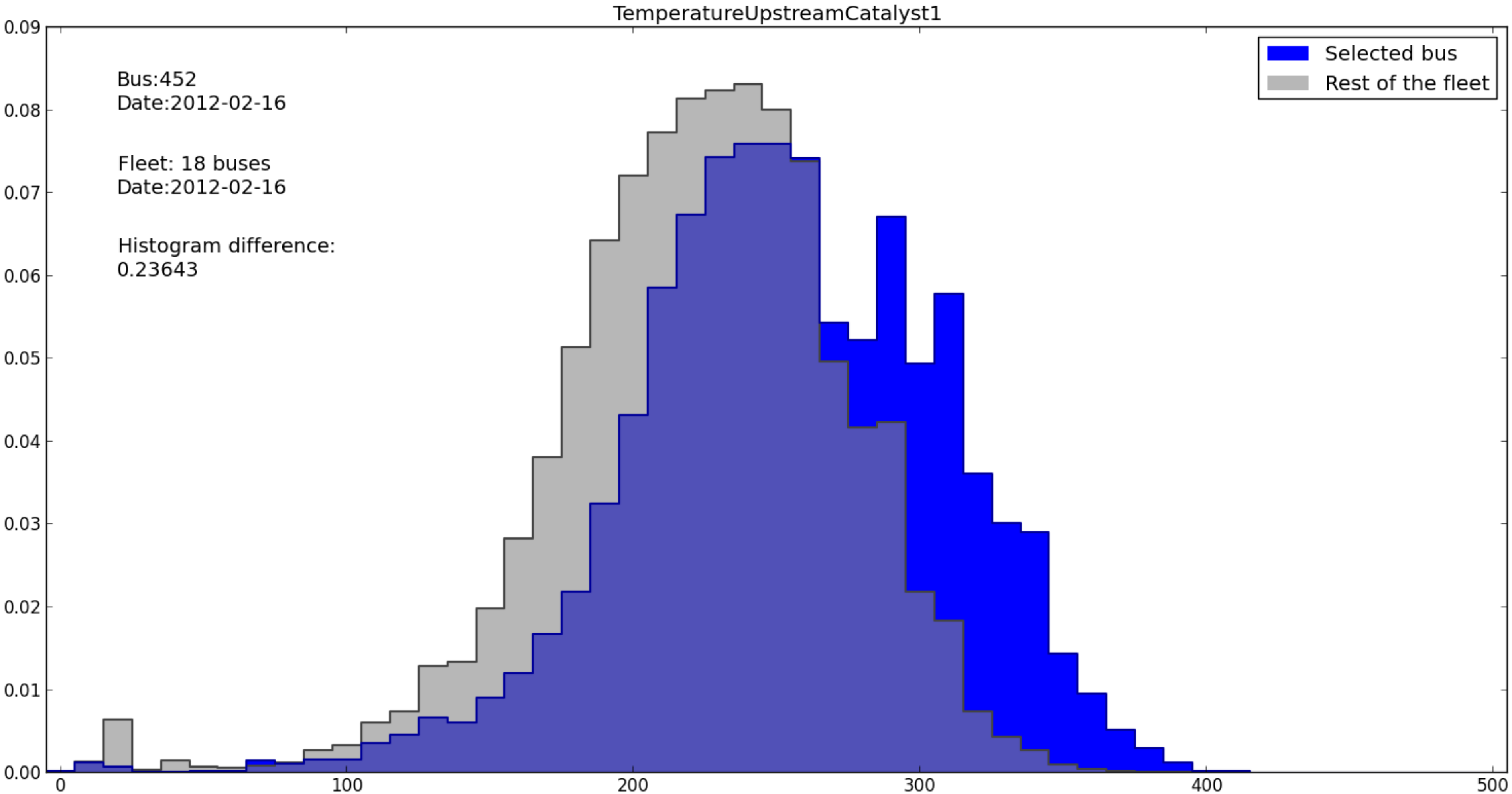


Bus 452

- 2009 model

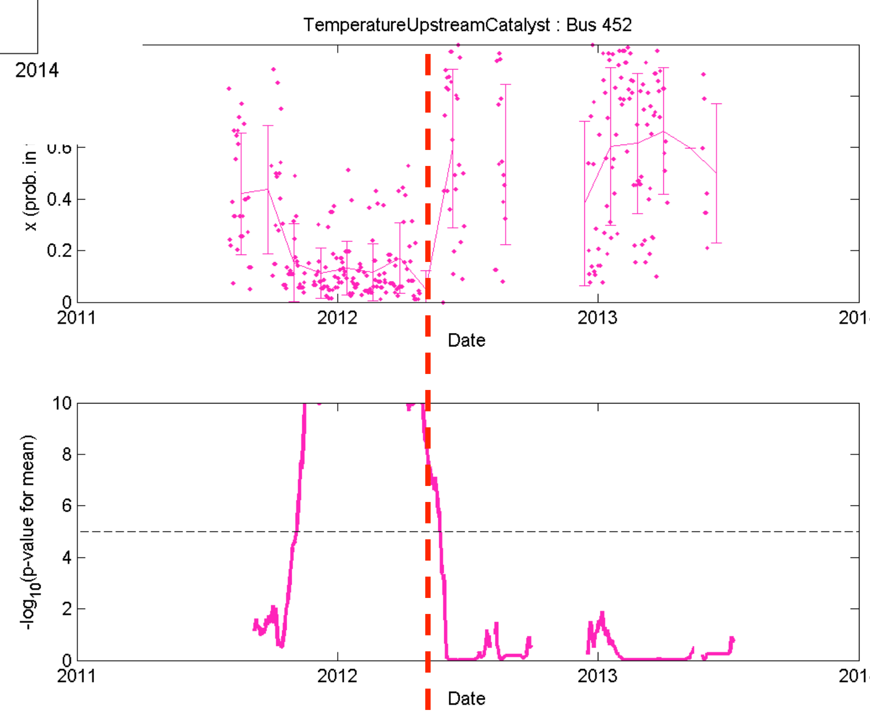


Bus 70452 – The Data

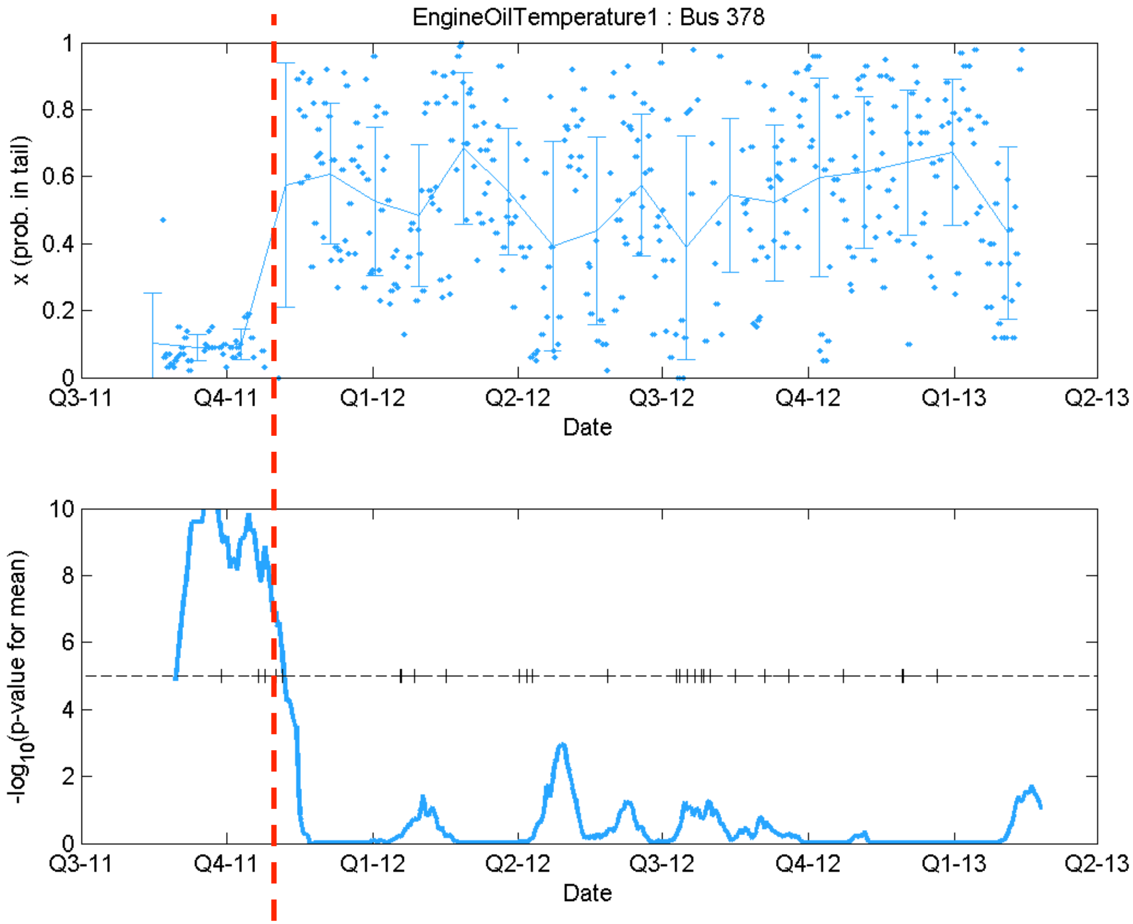


Those two temperatures both show significantly abnormal characteristics since November 2011

Both those deviations disappear in May 2012



Bus 70378 – The Data



The ECU was replaced on October 24

Oil leaked into the contact so that the circuit was shorted

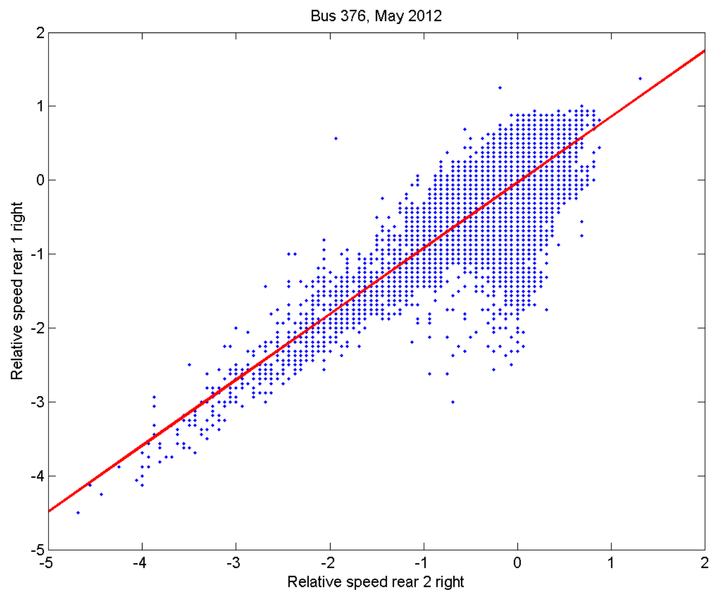
This caused cooling fan to be running at full speed all the time

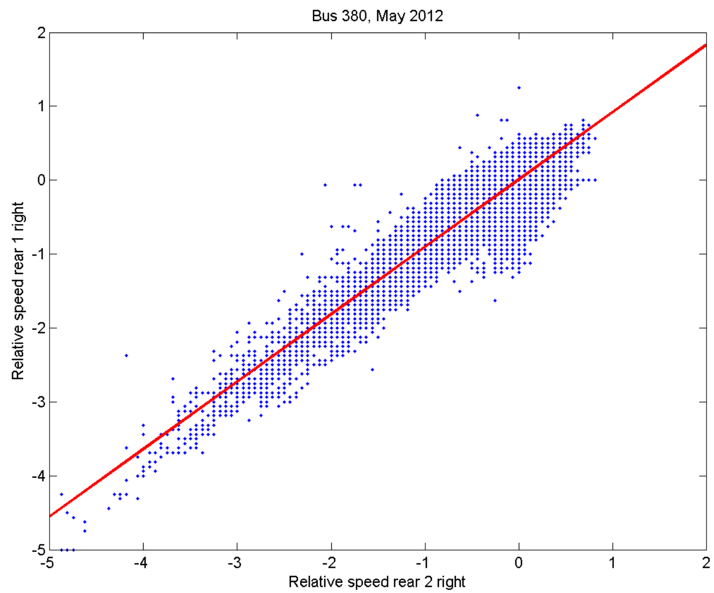
Is the cooling fan speed an important problem?

A cooling fan that runs at full speed all the time does not cause lethal accidents but it leads to:

- Higher energy consumption
  - The fan's power consumption grows like $(\text{speed})^3$
  - At maximum speed it consumes a significant amount of power (about 15 kW = 20 hp), which is 5-7% of the total engine power.
  - A normally operating bus should use maximum speed for the cooling fan less than 10% of the time.
- Discomfort for the driver (colder bus and more noise)

Linking Deviations to Repairs

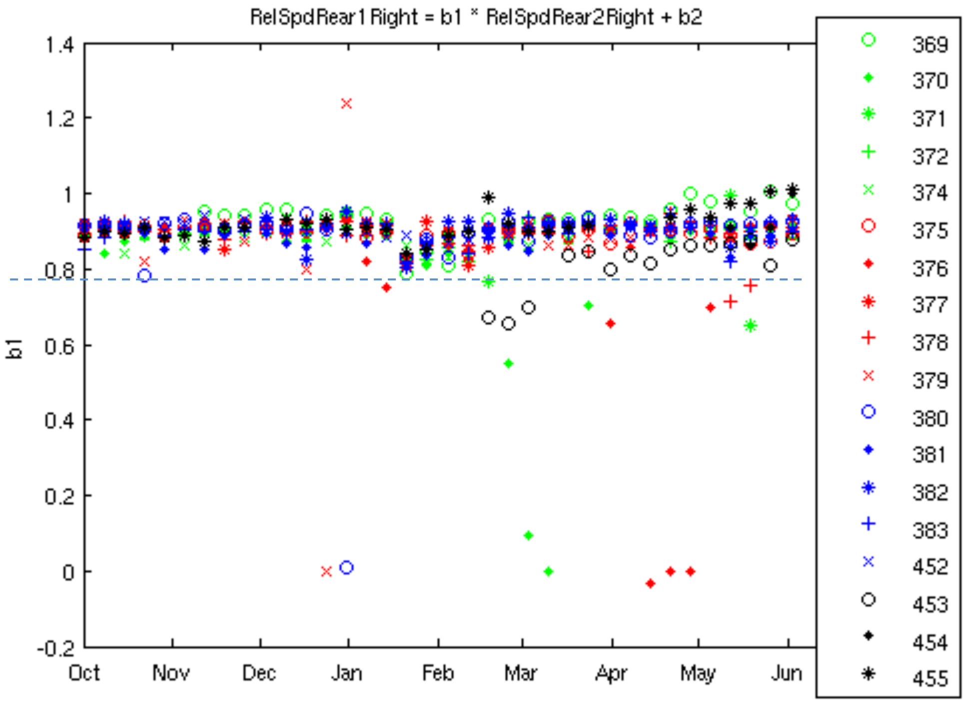




Linear relations between wheel speed sensor signals can show strong deviations

Either the sensors or the EBS modulators can be broken

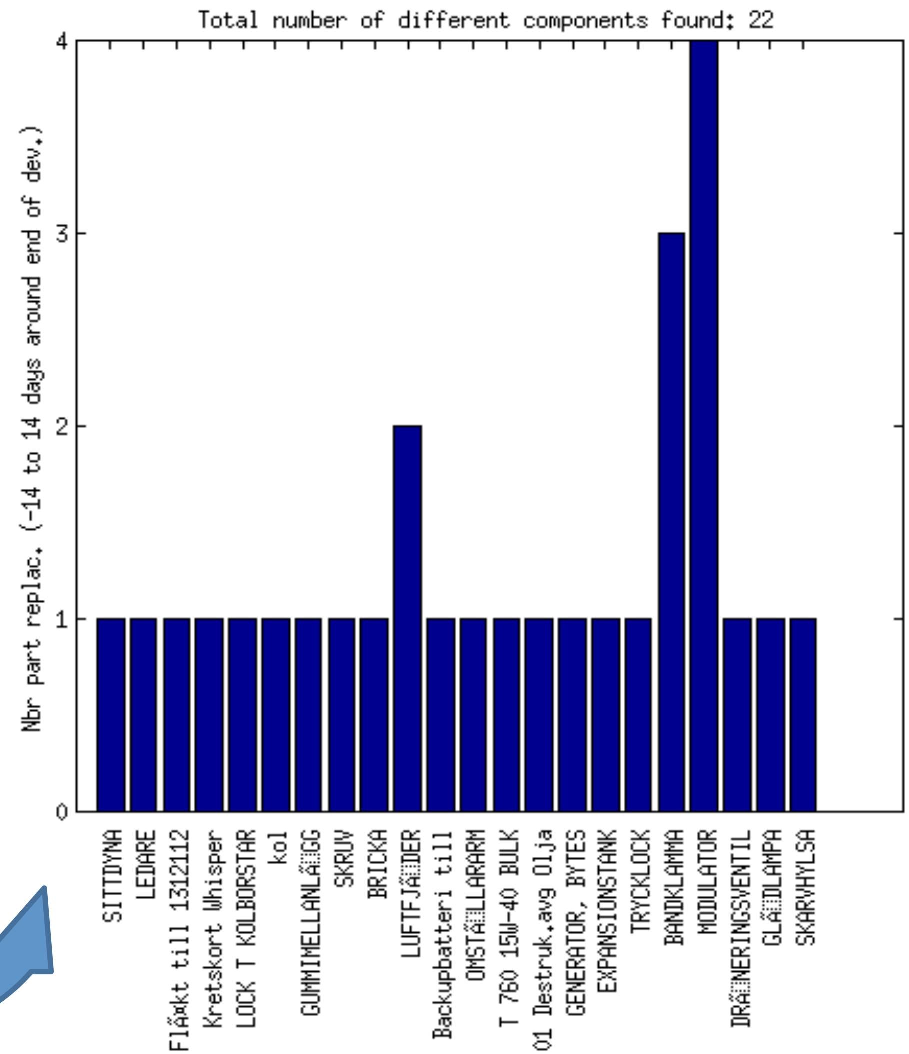
How to find out what is the actual cause?



Unsupervised explanation discovery

How to (automatically) generate an explanation to these deviations?

1. Deviations from the fleet were automatically discovered using leave-one-out p-value test
2. The point in time at which each deviation ended was estimated
3. The replaced parts in VSR (stored in a SQL database) at these points in time were counted



Summary

- Self-monitoring of commercial vehicles by mining on-board data streams is possible
  - without expert knowledge as to how the system is designed
  - can be cost efficient for “rare” faults
- Our experiences from Kungsbacka buses show that
  - several problems could be reliably detected early to save unplanned stops
  - some examples of found issues are jammed cylinder in the engine, ECU problem affecting cooling fan, NOx sensor wear, compressors, wheel speed sensors and modulators, ...
- Discovered data patterns can be further analysed
  - By learning associations between deviations and repairs
  - and/or taking advantage of knowledge from component experts

Learn more about us

Video

See our concept demo video on youtube (you can find it by searching for ”ReDi2Service”):

http://www.youtube.com/watch?v=KJ5hMkWPEGY

Publications

Mail me for a list of related publications:

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Website:

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