Diagnosis in vehicles and other applications

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Today

- Basic principles
- OBD - EVAP and misfire
- What next — prognostics and a heavy-duty truck use-case

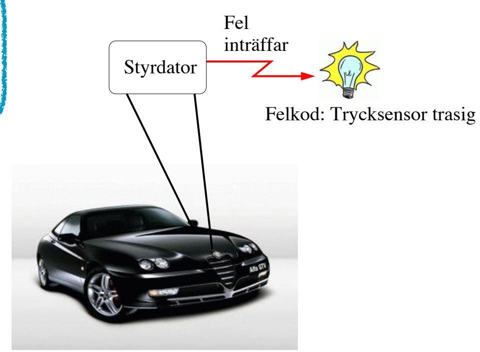
What is diagnosis?

Automatically, preferably under normal operation,

- Detect faults
- Isolate faults
- Sometimes: change control to adapt to new fault situation

Guide workshop technician

- Information about which fault
- Search strategies to quickly determine fault location(s)



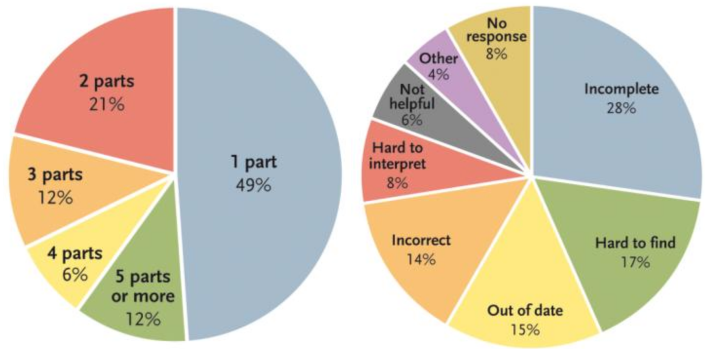
Why diagnosis in vehicles?

- Legislation imposes tougher and tougher requirements. Originally from California OBD/OBD-II, but now also in the rest of USA/Europe/World
- Also for trucks (2005 basic Euro 4, 2006 Euro 4, 2008 Euro 5, ...)
- Availability, repairability, mechanic support
- Large part of emissions come from a small set of vehicles with fault emission systems

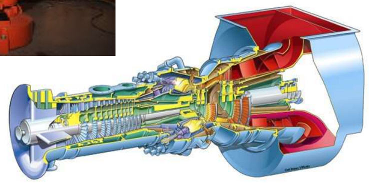
What is required?

- All components that can affect emissions must be supervised
- For example, a hole with diameter 0.5 mm in the fuel evaporative system must be detected

Why diagnosis in vehicles?



Why diagnosis in other applications?



CM & D Financial Impact

Process Equipment Maintenance costs

- **From a report by DuPont[1]…**
  In many plants, maintenance budget is about 2/3 of annual net profit
  Maintenance is today the largest single controllable expenditure in a plant
- **From study by Dow Chemicals[2]**
  Cost of unnecessary maintenance about the same size as plant profit
- **From a study by ARC (November 2003)**
  Asset management activities (checking, troubleshooting, calibration, repairs) are one of the leading time consuming activities. 80% of the survey see it as important /extremely important to reduce it

Maintenance costs represent a huge savings opportunity!

1 3rd. largest Chemical Company worldwide with 27 Billion USD in sales, 81,000 Employees and 12.5% Sales growth in 1 year

2 2nd largest Chemical Company worldwide with 32 Billion USD in sales, 46,000 Employees, and 18% Sales growth in 1 year

Source: Hoovers.com October 21, 2004

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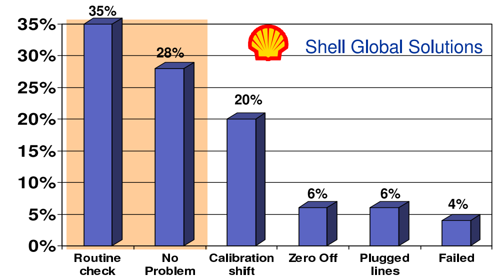
CM & D Financial Impact

Instruments Preventive Maintenance

Potential for Predictive Maintenance with pressure transmitters



63% of instrument maintenance labor results in no action taken = waste of resources

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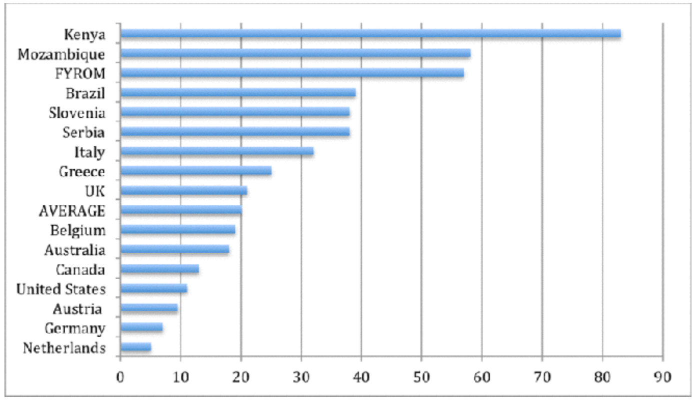
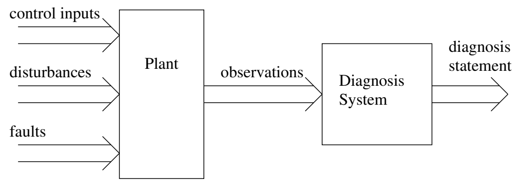
Vattenläckage



A difficult problem

- A substantial part of the ECU code in cars is directly related to diagnosis and supervision (often more than 50%)
- Something that is often done late in the development process; much to gain if supervision was developed in parallell with other designs
  - Sensor placement and selection
- Methodology needed, just for other functions in control systems

What is diagnosis more formally?



Diagnosis

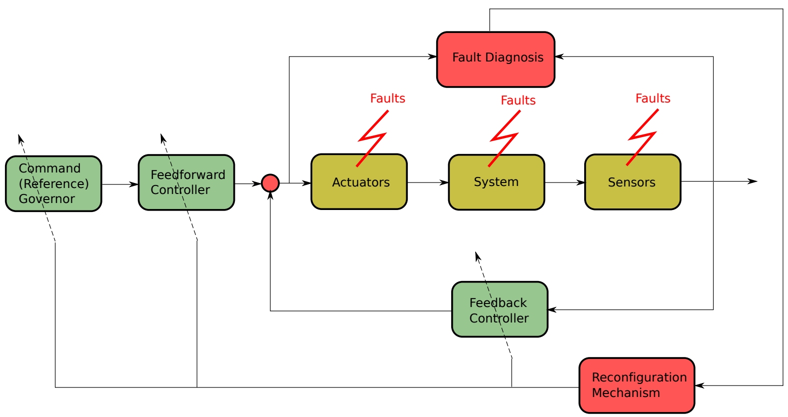
Given observations, a diagnosis is a statement of component state that is consistent with observations

Diagnosis system

Given observations, find all diagnoses

$$\text{all diagnoses} = f(\text{observations})$$

Fault Tolerant Control



Principles

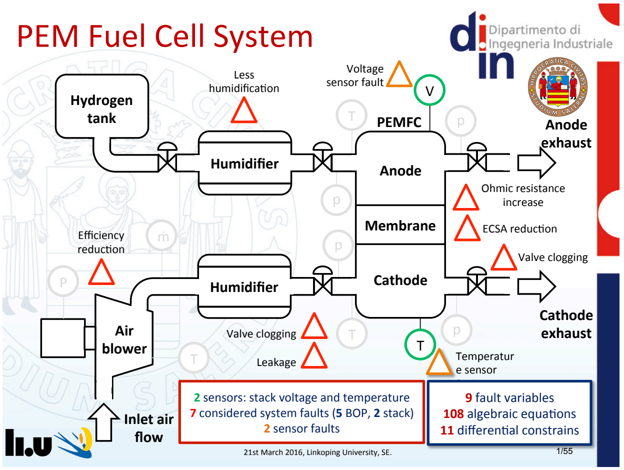
Traditional and model based diagnosis

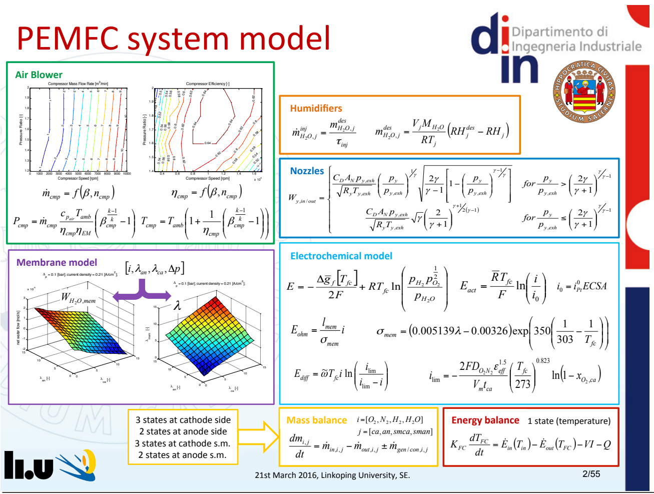
- Hardware redundancy
- Thresholding of measurements (limit-checking)
- Change rate limitations of physical properties
- Often different limits in different parts of the operating range

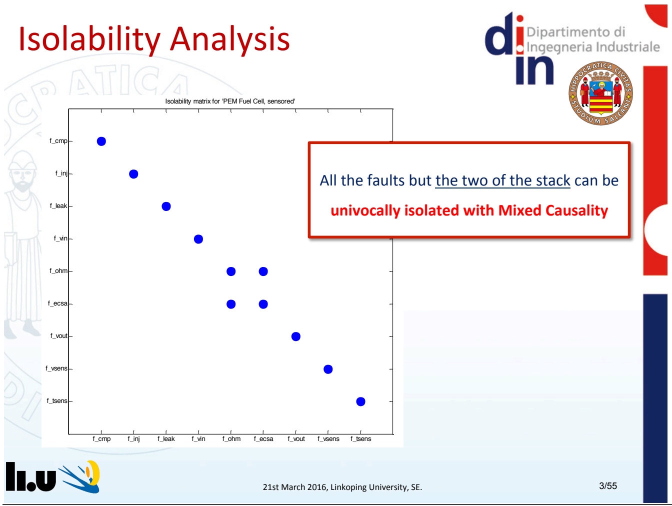
Traditional diagnosis is model based, only with very simple models

With more advanced models; there is a possibility to increase diagnosis performance, more exact fault isolation, fewer false-alarms. Comes at the price of developing better models.

Also a possibility to reduce the number of sensors needed.

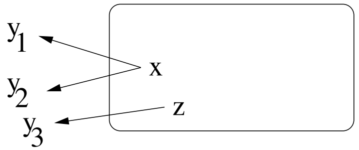






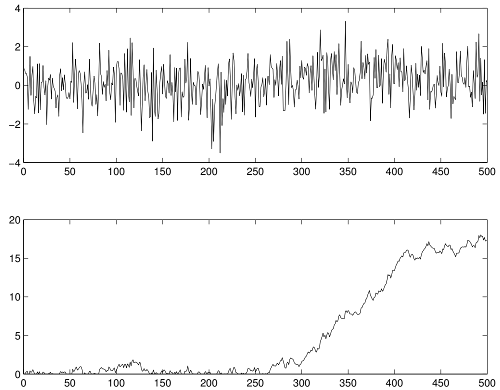
Redundancy, models, and model based diagnosis

- A requirement for all diagnosis is *redundancy* which can be given by:
  - Extra hardware, for example extra sensors measuring the same quantity
  - Models

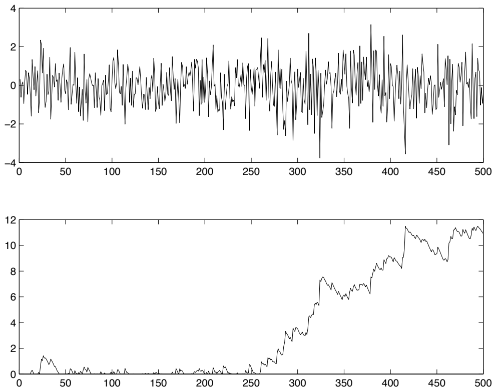


$$r_1 = y_1 - y_2$$
$$r_2 = y_1 - f(y_3)$$
$$r_3 = y_2 - f(y_3)$$

Where is the change in mean?



Where is the change in intensity?



Fault isolation

- Assume y_1, y_2, and u known. Then three residuals can be formed as

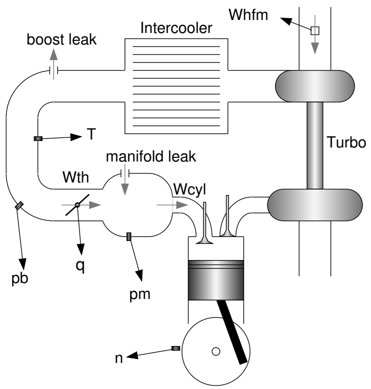
$$y_1 = 2u$$
$$y_2 = 4u + 1$$

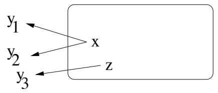
$$r_1 = y_1 - 2u, \quad r_2 = y_2 - 4u - 1, \quad r_3 = 2y_1 - y_2 + 1$$

- All is 0 when the equations are satisfied, i.e., the system operates in nominal mode
- The three residuals react differently to faults in sensors and actuators $\Rightarrow$ Fault isolation possibilities

	f_1	f_2	f_u
r_1	X		X
r_2		X	X
r_3	X	X	

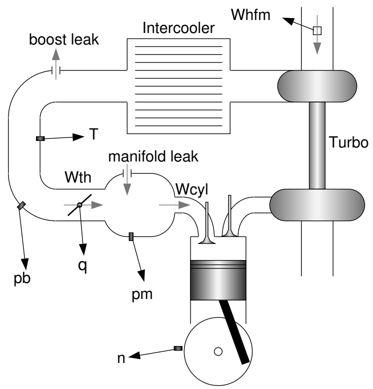
Fault isolation in a production engine





- Same approach applicable as in the simple case, only more advanced models
- Dynamic systems
- Signal processing
- State-observer techniques

Example on analytical redundancy in the engine model



$$W_{cyl} = f_1(n, p_m)$$
$$W_{th} = f_2(\alpha, p_m, p_b)$$

- In stationary operation, all flows are equal

$$r_1 = W_{hfm} - W_{th} = W_{hfm} - f_2(\alpha, p_m, p_b)$$
$$r_2 = W_{hfm} - W_{cyl} = W_{hfm} - f_1(n, p_m)$$
$$r_3 = W_{cyl} - W_{th} = f_1(n, p_m) - f_2(\alpha, p_m, p_b)$$

- Sensitive to different faults, i.e., possibilities for fault isolation

Modelling

- Same kind of mean value engine models you have already seen in the course are useful also for diagnosis.
- For example, the flow past the throttle is models by the equations

$$W_{th} = \frac{K_{th} p_{boost}}{\sqrt{T}} \Psi(\frac{p_{man}}{p_{boost}})$$

with

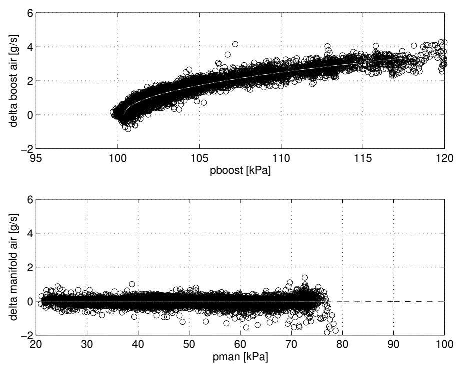
$$\Psi(\frac{p_{man}}{p_{boost}}) = \begin{cases} \sqrt{\frac{2\kappa}{\kappa-1}\left\{\left(\frac{p_{man}}{p_{boost}}\right)^{\frac{2}{\kappa}} - \left(\frac{p_{man}}{p_{boost}}\right)^{\frac{\kappa+1}{\kappa}}\right\}} \\ \qquad \text{if } \left(\frac{p_{man}}{p_{boost}}\right) \geq \left(\frac{2}{\kappa+1}\right)^{\frac{\kappa}{\kappa-1}} \\ \sqrt{\kappa\left(\frac{2}{\kappa+1}\right)^{\frac{\kappa+1}{\kappa-1}}} \qquad \text{otherwise} \end{cases}$$

Modelling faulty behaviour

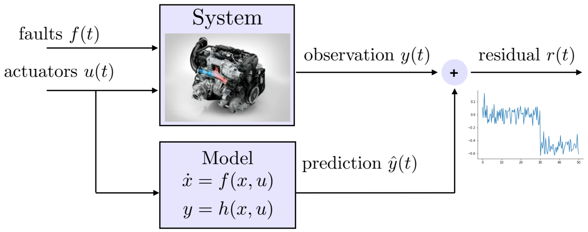
- Not only the nominal behaviour needs models
- Sometimes, but not always, models for faulty components are needed

$$W_{boostLeak} = k_b \frac{p_b}{\sqrt{T}} \Psi(\frac{p_{amb}}{p_b})$$
$$W_{HFM} = W_{th} + W_{boostLeak}$$

where kb represents efficient leakage area.



Problem illustration (1/2)



- If model is perfect, all residuals are "equally good"

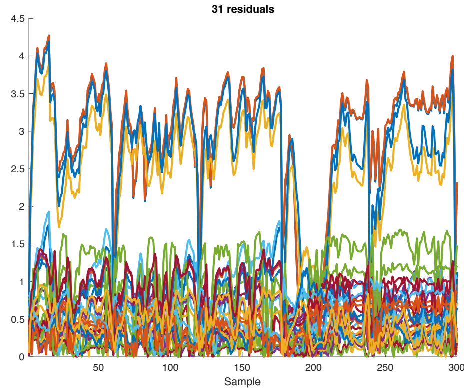
$$r = \begin{cases} 0 & f = 0 \\ \neq 0 & f \neq 0 \end{cases}$$

- #res.gen. exponential in model redundancy
- For single fault isolation #res ~ #faults
- Our engine application: 208 residuals and 7 faults
- 42 residuals used as input data here

Problem illustration (2/2)

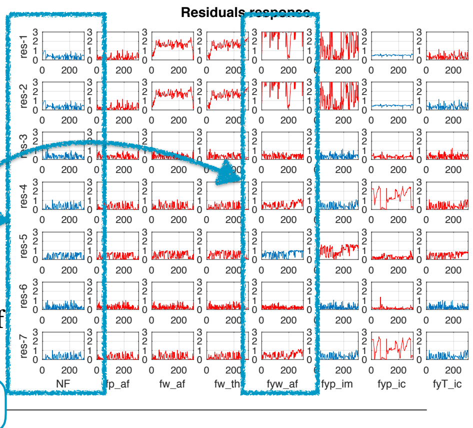
- Set of residuals sensitive to fault
- Clearly all are not equally good
- Select for detection, easy
  - Fault-to-noise ratio
- Select a set to achieve isolability performance, not as easy
- Complexity issue: number of sets to choose from

$$2^{\text{no residuals}}$$



Residual data from our engine test-cell

- Code for residuals generated using Fault Diagnosis Toolbox https://faultdiagnosistoolbox.github.io
- Transient operation of engine
  - Normal driving
- 7 different fault modes
- 42 residuals designed
- Each residual generator ≈ 10 states
  - complex, good to reduce number of residual g

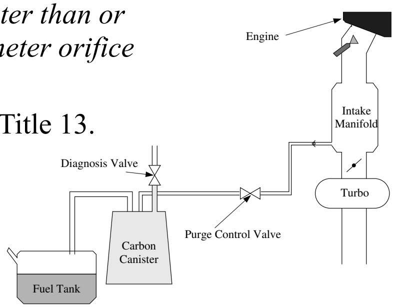


EVAP diagnosis and misfire detection

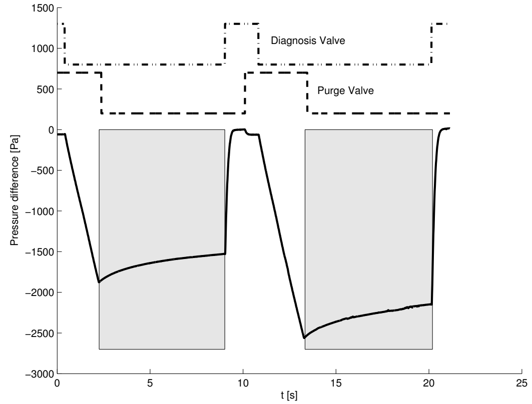
Evaporative systems monitoring

The OBDII system shall detect an evaporative system malfunction when the complete evaporative contains a leak or leaks that cumulatively are greater than or equal to a leak caused by a 0.040" diameter orifice

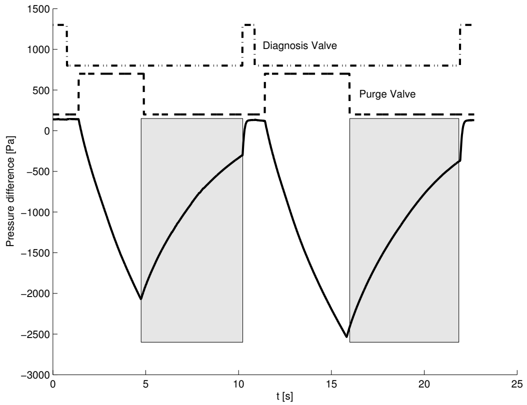
- California Air Resource Board, OBDII regulations, section 1968.2, Title 13.



Pressure trace for tank with no leakage



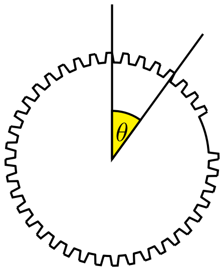
Pressure trace for tank with 1 mm leakage

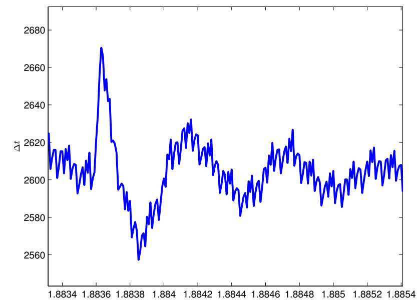


Misfire

Misfire: No combustion in cylinders has to be detected, otherwise

- Increased emissions, uneven torque, catalyst damage (fast)

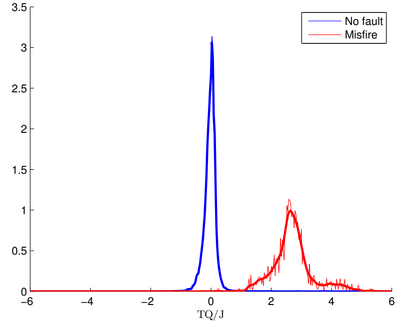




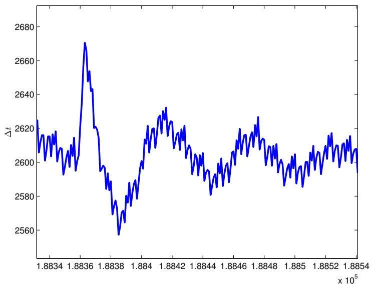
(Severe) Effects of misfire

Misfire

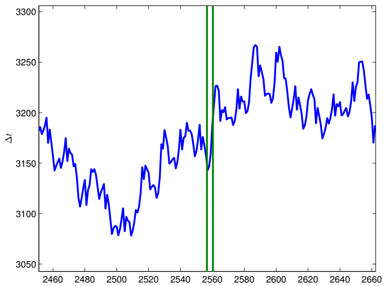
Create alarm signal, for each cylinder, that with high probability detects misfire but do not raise false alarms



Misfire



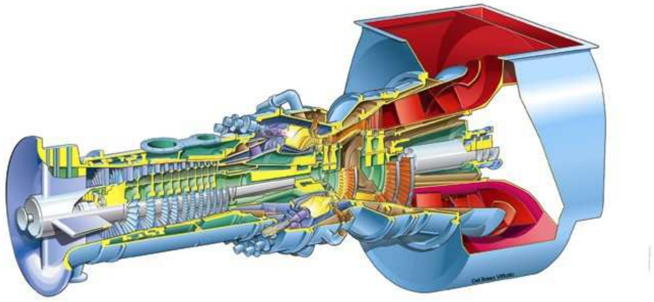
Easy operation point:
- In the middle of the operating range
- Medium load



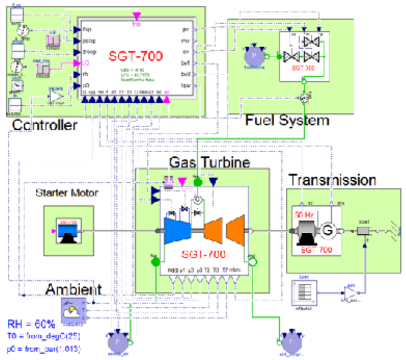
Difficult operation point:
- Cold start, slow combustion
- Low load, uneven torque

Other applications and future directions

Supervision of industrial gas turbine from Siemens

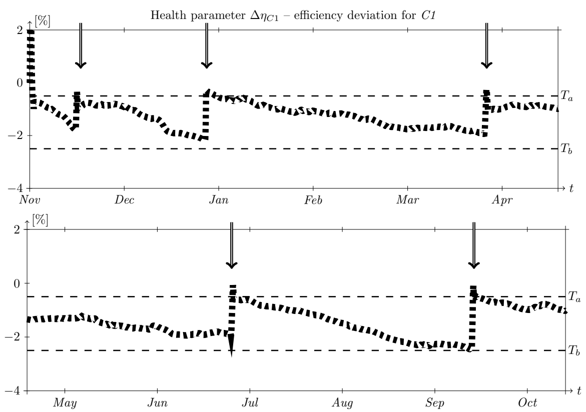


Supervision of industrial gas turbine from Siemens

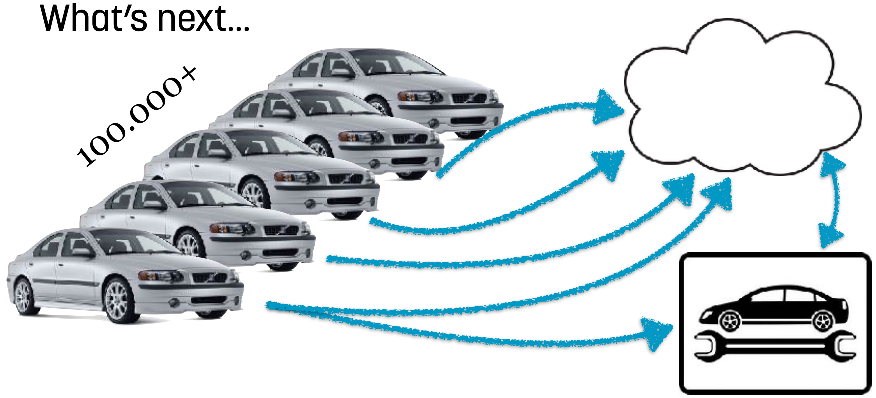


- Model in Modelica
- Consists of approximately 1,000 equations
- Supervise efficiency in compressors, turbines, sensors, …

Supervision of industrial gas turbine from Siemens



What’s next…



Prognostics

Maintenance philosophies

Reactive/corrective

Fix it when it breaks

Preventive/scheduled

Maintain it at regular intervals so it do not break

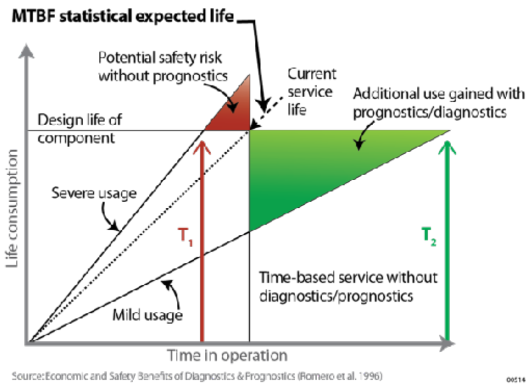
Predictive/
Condition-based maintenance

Predict when it breaks and maintain it accordingly

Preventive vs condition-based maintenance

In preventive maintenance the maintenance interval is important.

- Selecting maintenance intervals is a compromise between
  - achieving low failure probability
  - utilize component life
- If usage and degradation rate is different, an individualised condition-based maintenance is beneficial.



Use-case: Lead-acid battery prognostics in heavy vehicles

Lead-acid starter batteries

- Batteries cause Vehicle Off Road
- Wear/aging of battery highly dependent on
  - usage profile
  - individual variances
  - surrounding components
  - vehicle configuration
  - …

Battery prognostics

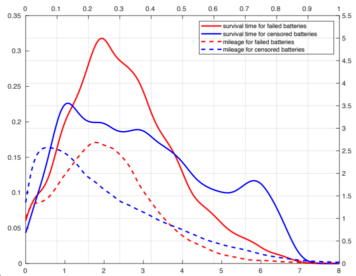
- Two main principles:
  - Physical modeling of aging and wear
  - Analyze, large amounts of, data
- Batteries are difficult to model
- Here, a data-driven approach is explored

Fleet data

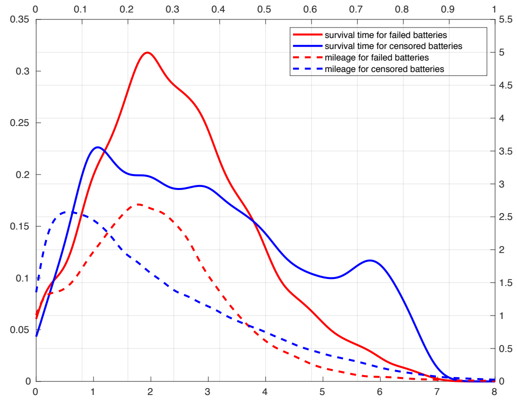
- Scania records data from all vehicles; remote diagnostics
- Transmits data either by mobile-link or when in a Scania workshop
- Coarse data
  - “static”, no time-series
  - selected variables
- Multi/no purpose data

Our test-case - Scania fleet data

- Here; ~50,000 vehicles in 5 European markets (Sweden, Germany, Belgium, Netherlands, and France)
- ~120,000 readouts
- In each data readout; 417 variables used
  - Configuration variables
  - Histograms of temp., load., speed, …
- No variable directly related to battery health
  - No current measurement
  - Voltage only measured before ignition
  - No battery relaxation compensation

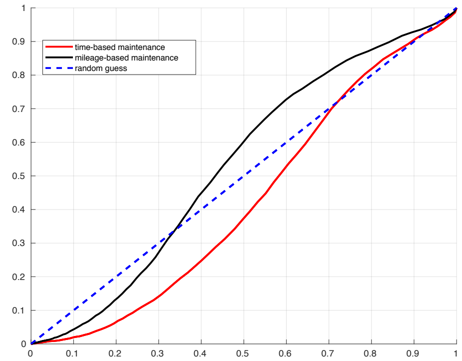


Time and mileage distributions



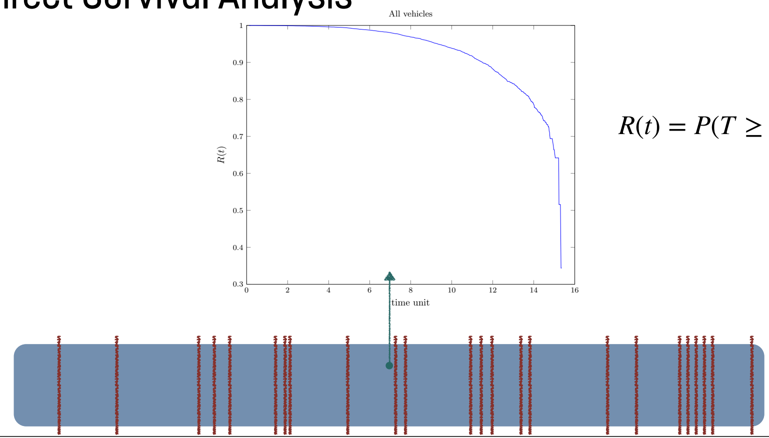
Performance of time/mileage maintenance policies

- Maintenance policies based on time or mileage
- Not much better than random guesses
- Large potential for condition based maintenance
- Indicates strong influence from usage



Direct statistical analysis on data

Direct Survival Analysis



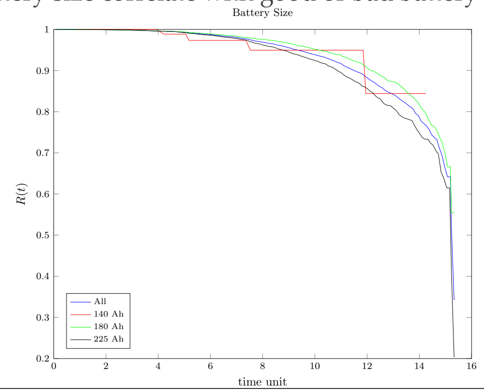
$$R(t) = P(T \geq t)$$

All vehicles are not equal

- Number of truck configurations very large
- The usage profiles of two vehicles typically differ significantly
  - Haulage missions on freeways
  - Distribution vehicles in cities
  - Battery usage; for example heat during nights when sleeping in the cabin
- Do configuration and usage pattern matter?

Vehicle usage and configuration matters

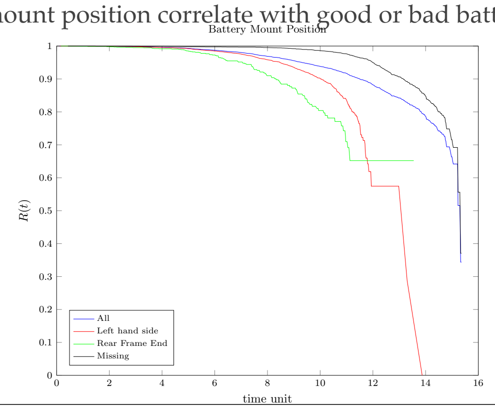
Do battery size correlate with good or bad battery life-time?



$$R(t) = P(T \geq t)$$

Vehicle usage and configuration matters

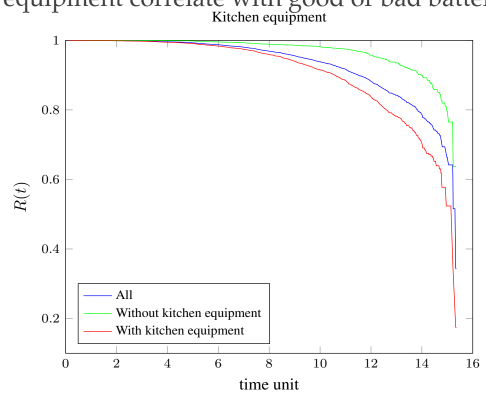
Do battery mount position correlate with good or bad battery life-time?



$$R(t) = P(T \geq t)$$

Vehicle usage and configuration matters

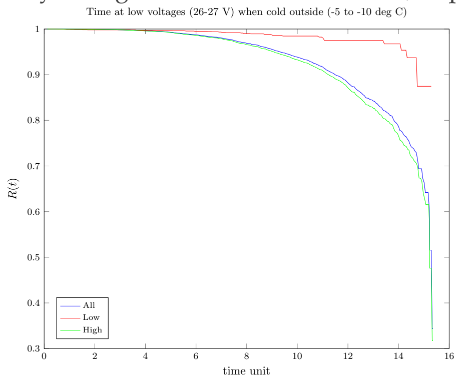
Do kitchen equipment correlate with good or bad battery life-time?



$$R(t) = P(T \geq t)$$

Vehicle usage and configuration matters

Low battery voltages when it is cold outside, important?

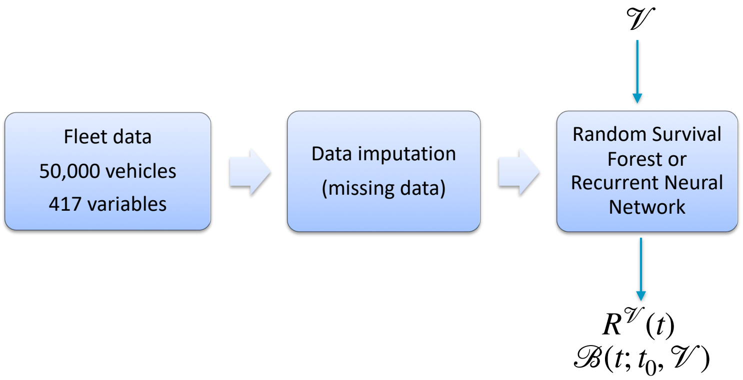


$$R(t) = P(T \geq t)$$

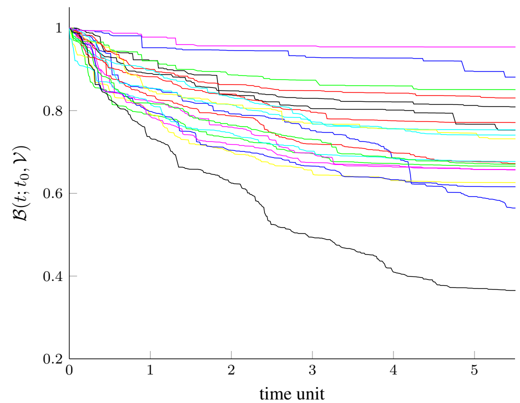
Conclusions so far …

- Component lifetime varies significantly within the fleet
- Usage patters matter
- Very difficult to understand exactly how to weigh different risk factors
  - Temperature
  - Speed
  - Load
  - …
- We would like some automated procedure that figure this out for us! Machine learning models is one way to do this.

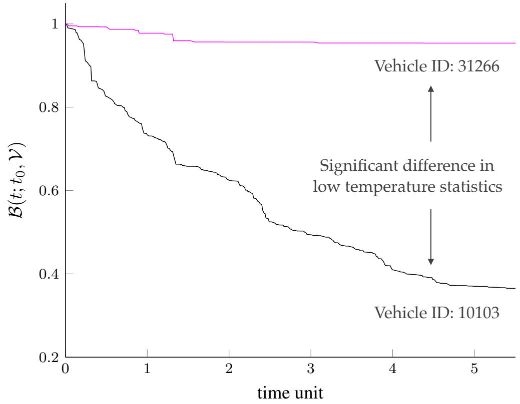
Basic procedure to building predictive models



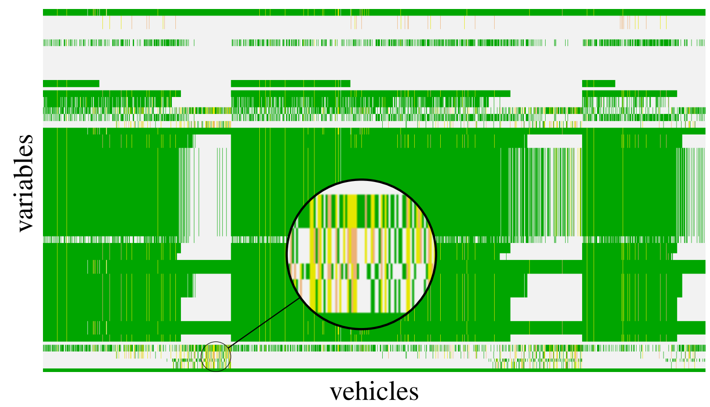
20 vehicles of same age and mileage



When to schedule next maintenance?

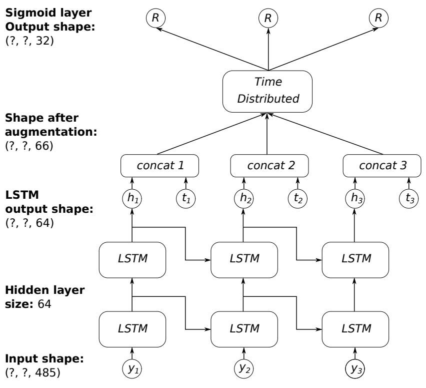


Imputation of missing data



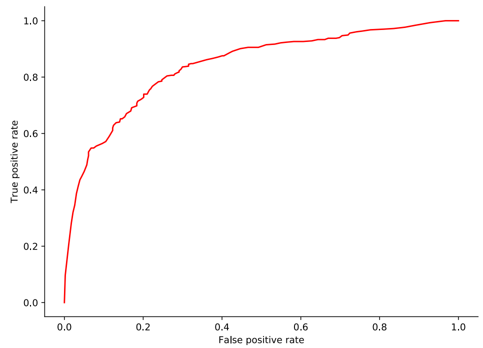
Recurrent Neural Network models

- Multiple readouts per vehicle gives sequence of data instead of static
- Sparse and irregular readouts
- A recurrent neural network is designed
- Neural networks is sensitive to imbalanced data — special measures included
- Outperforms RSF models



Best performing model

- Ensemble of 5 LSTM networks
- ~ 800,000 trainable parameters
- Trained using standard stochastic gradient descent with mini-batches
- ~ 100 epochs
- Trained in about 2 hours on a computational resource at the department (nothing really special)



TSFS06 - Diagnosis and supervision

If this sounds interesting and you would like to know more

TSFS06, Diagnosis and supervision is a unique course in Sweden, no other university gives such an in-depth course focused on diagnosis

- 6hp. Starts in March
- Theoretic and method oriented (although many examples will come from automotive applications)
- Cross disciplinary. Leverages on knowledge from many areas: automatic control, signal processing, statistics and probability, logic, artificial intelligence
- Course within a research intensive area, content close to research frontiers
- Possibilities for master thesis work (exjobb)

Diagnosis in vehicles and other applications

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