Analysis of Diesel Engine Sensor Signals for Fault Detection

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Trucks and Engines

Outline

- Diesel Engines and Mechanical Engineering
- Models for Physical Systems
- Analysis of Processes in Time
- Singular Spectrum Analysis

Mechanical Engineering and Diagnostics

Interested in making mechanical systems (engines) better

- More efficient
- More powerful
- More eco-friendly
- Less prone to breakdown/problems

Heavy-duty Diesel Engines

- Complex physical systems
- Very efficient but eco-unfriendly
- Expensive to fix

Emissions

- New environmental regulations in 2007 and 2010
- Random enforcement
- Need constant on-board checking
- *Problem:* Good sensors can be very expensive.

Types of Pollutants

- Smog: Particulate matter and CO
- Hydrocarbons
- NO_x

Tradeoff with Pollutants

- Reducing NO_x can be accomplished by reducing system temperature.
- However, a reduced temperatures mean less burning and more smog.

Solutions

- Different fuels
- Aftertreatments
- Checking for emissions-producing mechanical problems

Maintenance

- Troubleshooting: $50 per hour
- Maintenance: $500 to $2000 per hour
- Cost of lost productivity
- Can lead to increased emissions
- Problems tend to develop over time.

There is an extreme incentive in using cheaply acquired information to detect problems in performance and environmental impact.

Sensors

- Cannot use simple principles or physical laws to understand or predict engine behavior.
- Instead, an array of sensor information must be processed.
  - Mostly temperature and pressure
  - Different parts of engine
  - Reliable measurements of emissions expensive to obtain.
  - Some observations (e.g., speed, load) controlled by user

Faults

- Thresholds specified by manufacturers/users
- Triggering leads to end-shift or immediate maintenance
- *Example*

$$\text{High-Intake Manifold Temperature} = \begin{cases} > 190^\circ\text{F for 90 seconds} \\ or \\ > 200^\circ\text{F for 10 seconds} \end{cases}$$

Results in immediate shutdown

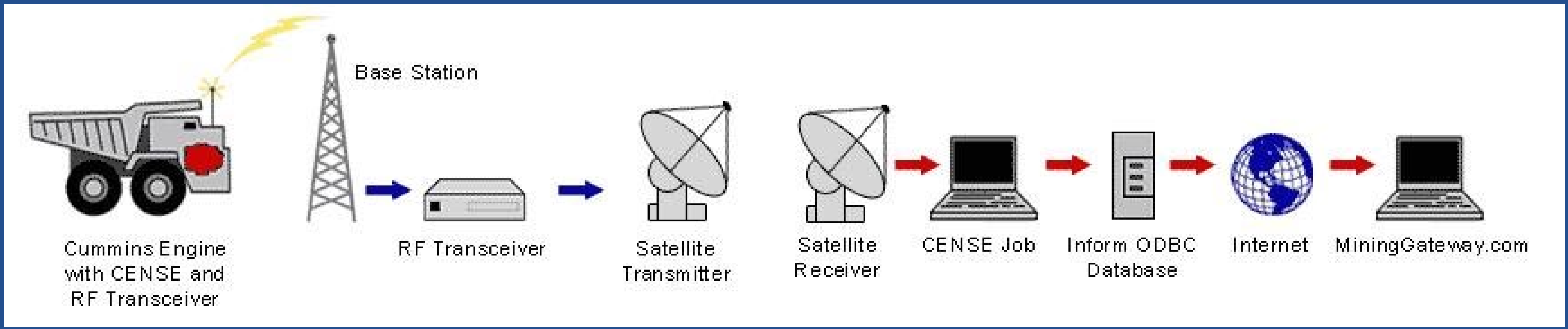
Faults as Symptoms

- Threshold faults do not point to particular physical problem in engine system.
- **Example**
  - *Symptom:* Low oil pressure
  - *Fault:* Bad oil pump
- One fault can indicate several mechanical problems.
- One mechanical problem can have several different fault indicators.
- Symptom trees (based on manuals) typically used for relating faults to actual mechanical failure.

- Unfortunately, specific maintenance records (relating fault to maintenance action taken and cost) are difficult to obtain.

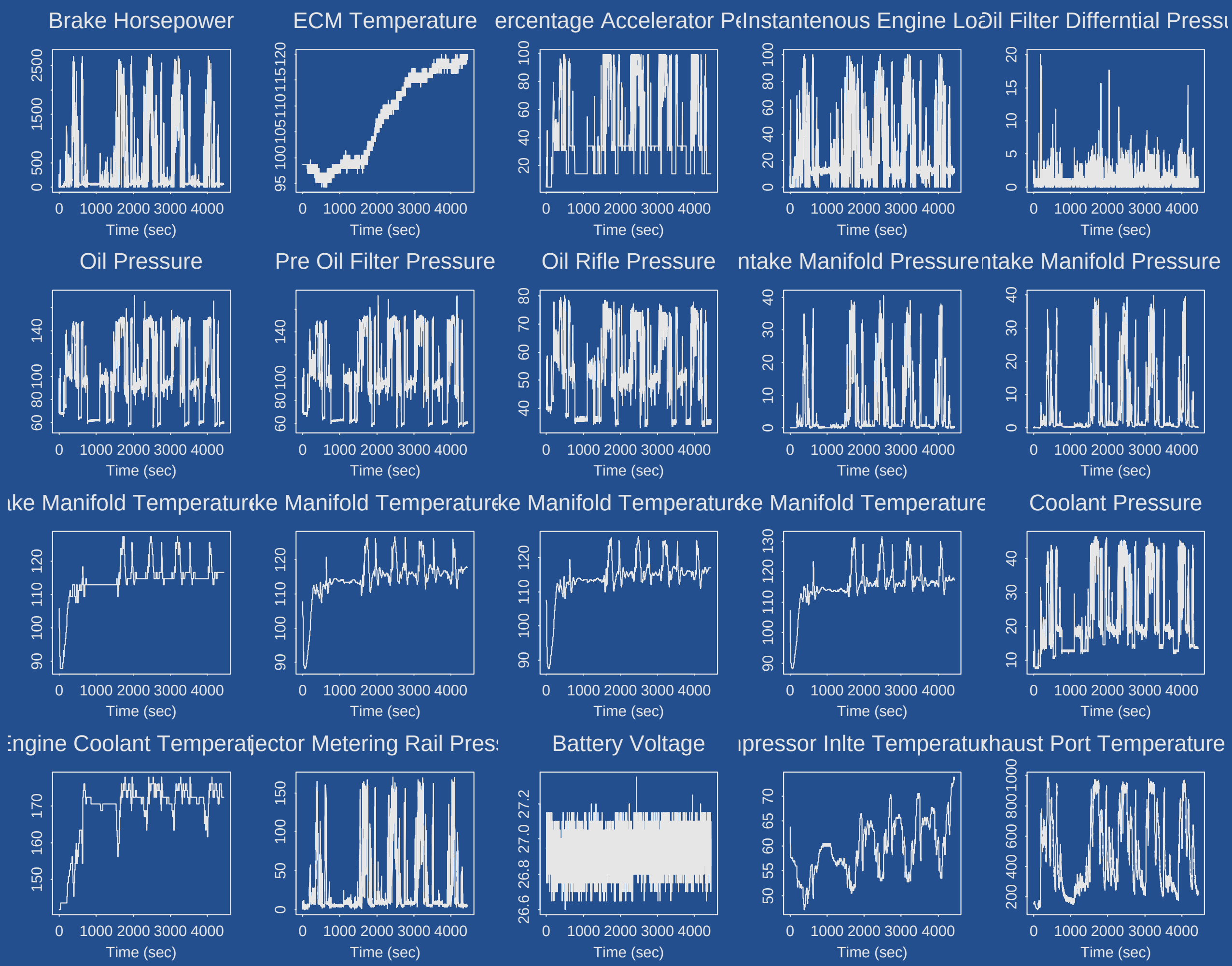
Data

Transmitted



- Approximately 43 sensors
- *Healthy operation:* One-hour windows – collected at 1 Hz – across several engines (∼20 000 observations)

- *Fault conditions:* 150-second windows – 30 seconds before; 120 seconds after (∼21 000 observations)



Laboratory

- Healthy readings and experimental results from “simulation” of specific mechanical problems
- Not all problems can be simulated.

Goals

- *Fault prognosis* – detecting trends to faults in sensor readings
- *Fault detection* – (indirectly) detecting faults that lead to increased emissions
- *Fault classification* – matching likely mechanical problem(s) to sensor readings

Tradeoffs

- Computational efficiency vs. accuracy
- Costs of false positive, false negative, bad prognosis, incorrect classification

- Training to specific engines
- Gradual vs. sudden fault onset
- Drift to fault vs. drift of aging
- Environmental impact vs. maintenance

Models for Physical Systems

Main Conceit

"Health" is a monotonic function over time that eventually crosses a threshold into fault state.

- Frames the nonlinear difficulty of the problem.
- "Health" is hard to define.
- More accurate reflection of components rather than systems
- Monotonicity is interrupted by maintenance, accelerated by heavy use.

Takens Model

- Nonlinear signals exist as a smaller dimensional subset ("manifold") of a larger dimensional space.
- Sensing "folds" the higher dimensional signal into smaller dimensional space.
- *Example*

  "True" signal exists as ~ 30 dimensional signal in > 100 dimensional space, seen via ~ 43 sensors.
- Extra dimensionality expressed as lagged signal history.
- **Stipulation:** Signal – conditional on nonrandom factors such as speed and load – is "stationary" or "ergodic", except for wear/aging and trends to fault.

- **Deignan Modification:** Dimensionality changes locally because of events in time.
  - *Examples:* strokes $\uparrow$, faults $\uparrow$, shifting gears $\downarrow$
- Not clear how noise is accounted for

Information on Sensed Processes

- *Stable, natural measures of attractors* – marginal distribution that does not account for time but is conditional on other, controlled factors
- *Lyaponov exponent* – rate at which small (hypothetical) deviations become big deviations
  - Measures chaotic attractor
- *False nearest neighbors* – method for using similar points in history for prediction and parameter estimation
- *Correlation dimension* – dimension of manifold “attractor”
- *Delay coordinates* – multidimensional representation of signal and its history, sufficient to represent fuller dimensional process

- *Mutual information* – nonlinear measure of dependence between signals and within signal history that is locally related to dimension
- *Shadowing/pseudo-orbit* – deterministic system “close to” sensed signal

Methods for Analysis

- *Real-space methods* – characterizing marginal distribution
  - **Early result:** Fault signals and healthy signals are well-separated.
  - **Faults:** Changes in location, spread, shape, etc.
- *Harmonic analysis*
  - What is periodic structure?
  - Are there any localized events?
  - Can stationary/periodic processes be separated from long-term trends?
  - **Faults:** Change in energy at frequency/set of frequencies

- *Dynamic Modeling*
  - Autoregressive models
  - Moving average models
  - Markov chain models
  - State space models
  - **Faults:** Change in defining parameters

Singular Spectrum Analysis

- General tool for analyzing time series using tools of multivariate analysis on trajectories (process and its history)
- **Typical tasks**
  - Prediction
  - Harmonic parameter estimation (alternative to Fourier analysis)
  - Trend identification
  - Signal separation
  - Noise filtering
  - Change-point identification

- **Nonstandard tasks**
  - Classification of signals
  - Clustering
  - Multisignal smoothing
  - Signal decomposition via other signals
  - Linear modeling via other signals
  - Independent Component Projection
  - Fault detection via goodness-of-fit testing
- Requires few assumptions
- Often use smoothing constraints/penalties
- Can be computationally expensive

Mechanics

- Replace single process $\{\ldots, X(-2), X(-1), X(0), X(1), X(2), \ldots\}$ with its L-dimensional trajectory representation

$$Y(t) = \begin{bmatrix} X(-L\delta + t) \\ X(-(L-1)\delta + t) \\ \vdots \\ X((L-1)\delta + t) \\ X(L\delta + t) \end{bmatrix}.$$

- Important technical side issues:
  - Window length L

- Lag between times in trajectory δ
- Tradeoff between statistical precision and computational tractability

- $Y(t)$'s are now multivariable representations of dependent processes
  - Dynamic process information captured in marginal distribution
- Thus, interested in estimating and characterizing joint distribution of $Y(t)$.
- Often interested in distribution of $Y(t)$ conditional on $Z(t)$, where $Z(t)$ represents exogenous factors such as speed, load, weather, age (accumulated workload)

Tasks

- *Fault Detection via Goodness-of-Fit*
  - Data from long run of healthy operation used to give empirical representation of $[Y_0(t), Z_0(t)]$.
  - Collect new window of data $[Y_1(t), Z_1(t)]$
  - Goodness-of-fit Null Hypothesis: $\mathcal{L}\{Y_0(t)|Z_s(t)\} = \mathcal{L}\{Y_1(t)|Z_s(t)\}$ any load condition $Z_s(t)$.
- *Independent Component Projection*
  - Find $r \times Lp$ transformation Ψ ($p =$ number of signals) such that components of $\Psi Y(t)$ are (more or less) independent with no lagged information.

- *Signal Decomposition via Other Signals*
  - Decompose $Y(t)$ such that

    $$Y(t) = \Phi A(t) + \Delta\epsilon(t)$$

    for some sensed signal $A(t)$ and linear transformations Φ and Δ (and noise process $\epsilon(t)$).
  - Good for measuring information gained by using different signal set.
- *Classification*
  - Use signals to establish empirical estimate of joint distribution of signal window.
  - Classification of new signal window is based on likelihood of health, different faults.

- *Smoothing/Filtering/Separation*
  - **Main Component:** Toeplitz matrix Σ

$$\Sigma_{i,j,k,\ell} = cov(X_k(t), X_\ell(t - (i - j)\delta)),$$

    where X_k and X_ℓ are the kth and ℓth signal components.
  - Highly symmetric matrix
  - Eigenvalues $\lambda_1, \ldots, \lambda_M$ of $\hat{\Sigma}$ approximate loading on harmonic frequencies.
  - Smoothing involves shrinkage/zeroing/constraining eigenvalues

– *Example*

Lasso constraint: smooth signal $\tilde{\theta}$ minimizes

$$\|Y - \theta\|^2 \text{ such that } \sum |\lambda_k^{(\theta)}| < t$$

for some value t.

– Finding optimal smoothing (i.e., value of t) requires bootstrap or likelihood modeling.

– Often interested in decomposition into polynomial/exponential components

$$Y(t) = \sum_{\ell} A_\ell e^{\alpha_\ell t} \cos(2\pi\omega_\ell t + \phi_\ell) t^\ell + \epsilon(t)$$

Future Work

- Currently analyzing signals for characterization of engine operation.
  - Age trends
  - Engine-to-engine variability
  - Discrimination between healthy and faulty

    What trends are expected?
- Experiments on engines in lab are beginning.
  - How are lab processes different?
  - *Goal:* Match mechanical issues to feature in sensor signals.