NASA Aeronautics Research Institute

Reducing the Environmental Impact of Aviation: A Data Mining Approach to Instantaneous Estimation of Fuel Consumption

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Introduction

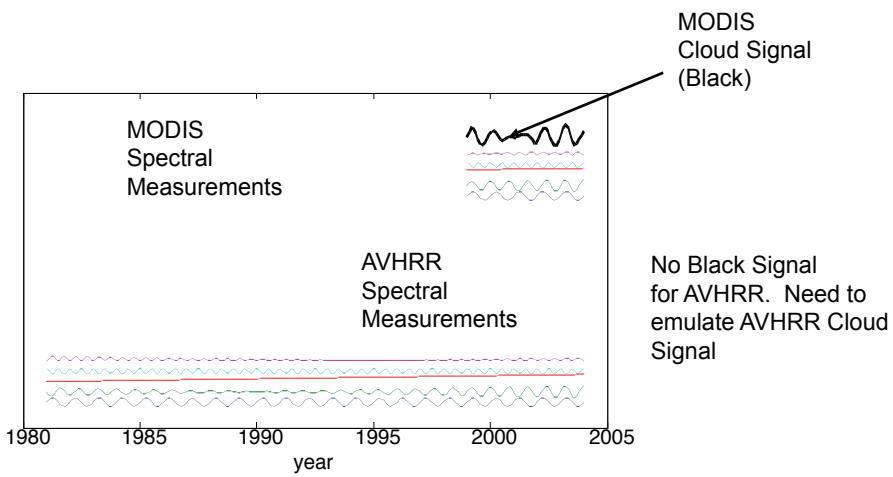
- The environmental impact of aviation is enormous given the fact that in the US alone there are nearly 6 million flights per year of commercial aircraft.
- This situation has driven numerous policy and procedural measures to help develop environmentally friendly technologies which are safe and affordable and reduce the environmental impact of aviation.

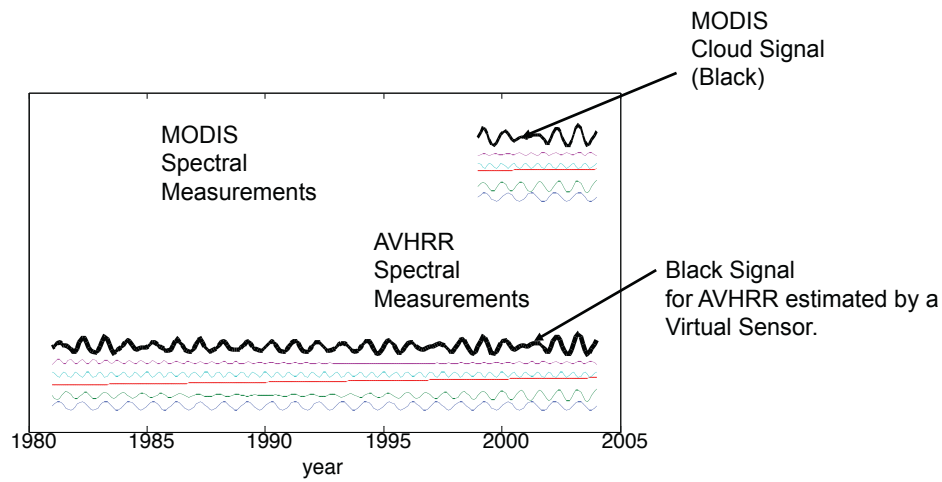
State of the art: Phase 1

- Virtual Sensor–based anomaly identification for fuel consumption
  - Detect fuel consumption anomalies as a function of aircraft state
  - Findings may be used to take timely, corrective maintenance measures on fleet
- What is Virtual Sensors?

Virtual Sensors

- Estimate key measurement from others using regression
- Replace missing measurements
- Compare with true measurements





Innovation

- Improve the algorithm by incorporating new loss function-Huber loss
- Implement a distributed version of the ensemble based virtual sensors technology
- Analysis of FOQA data on a European carrier for fuel over/under consumption

Technical Approach

Parallel Iterated Optimizer for SVR (Parito-SVR) algorithm uses distributed optimization for support vector regression based virtual sensors technology

- Globally optimal distributed optimization technique based on ADMM for solving SVR (ParitoSVR)
- Scales to large datasets via parallel execution on multicores/machines

Distributed Optimization

- ADMM - Alternating Direction Method of Multipliers
  - Technique for solving separable convex problems of the form:

$$\min_{\mathbf{x},\mathbf{y}} \quad G_1(\mathbf{x}) + G_2(\mathbf{y})$$
$$\text{subject to} \quad A\mathbf{x} - \mathbf{y} = 0, \quad \mathbf{x} \in \mathbb{R}^n, \quad \mathbf{y} \in \mathbb{R}^m$$

  - via updates

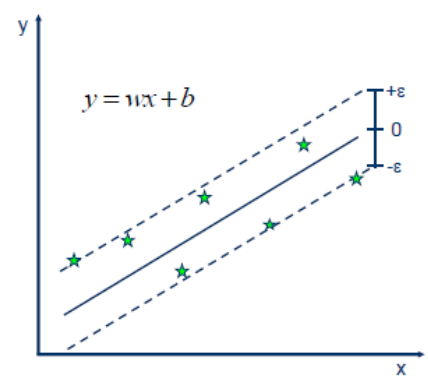
$$\begin{aligned}
\mathbf{x}^{t+1} &= \min_{\mathbf{x}} \left\{ G_1(\mathbf{x}) + (\mathbf{z}^t)^T A\mathbf{x} + \rho/2 \left\| A\mathbf{x} - \mathbf{y}^t \right\|_2^2 \right\} \\
\mathbf{y}^{t+1} &= \min_{\mathbf{y}} \left\{ G_2(\mathbf{y}) - (\mathbf{z}^t)^T \mathbf{y} + \rho/2 \left\| A\mathbf{x}^{t+1} - \mathbf{y} \right\|_2^2 \right\} \\
\mathbf{z}^{t+1} &= \mathbf{z}^t + \rho \left(A\mathbf{x}^{t+1} - \mathbf{y}^{t+1} \right)
\end{aligned}$$

Loss Function

- Given training dataset $\mathcal{D} = (\mathbf{x}_i, y_i)_{i=1}^m$, where $\mathbf{x}_i \in \mathbb{R}^n$ and $y_i \in \mathbb{R}$
- Linear SVR solves $$\min_{\mathbf{w},b} \left[\lambda ||\mathbf{w}||^2 + \sum_{i=1}^{m} \ell_\varepsilon(\mathbf{w} \cdot \mathbf{x}_i + b - y_i) \right]$$

where ℓ_ε is ε-insensitive loss function

$$\ell_\varepsilon(r) = \max(|r| - \varepsilon, 0)$$



SVR using ADMM

- Solve

$$\min_{\mathbf{w}} \left[\sum_{i=1}^{m} \ell_\varepsilon(\mathbf{w} \cdot \mathbf{x}_i - y_i) + \lambda ||\mathbf{w}||^2 \right]$$

$$\Leftrightarrow \min_{\mathbf{w}} \left[\sum_{j=1}^{N} \boxed{\sum_{i=1}^{m_j} \ell_\varepsilon \left(\mathbf{w} \cdot \mathbf{x}_i^{(j)} - y_i^{(j)} \right)} + \lambda \, \|\mathbf{w}\|^2 \right]$$

Computation in a node

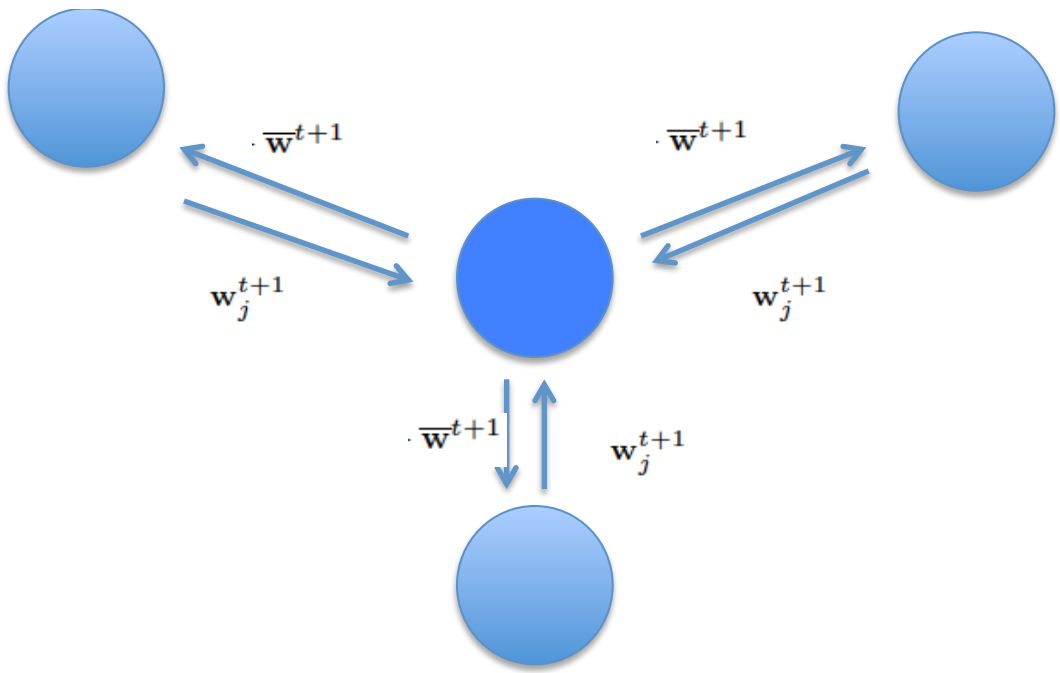
this can be decoupled across the nodes as:

$$\min_{\mathbf{w}_1, \ldots, \mathbf{w}_N, \mathbf{z}} \left[\sum_{j=1}^{N} \sum_{i=1}^{m_j} \ell_\varepsilon \left(\mathbf{w}_j \cdot \mathbf{x}_i^{(j)} - y_i^{(j)} \right) + \lambda \, \|\mathbf{z}\|^2 \right]$$

$$\text{subject to} \quad \mathbf{w}_j = \mathbf{z}$$

ADMM Iterations

$$\left.\begin{aligned} \mathbf{z}^{t+1} &= \min_{\mathbf{z}} \left\{ \lambda \left\| \mathbf{z} \right\|_2^2 + \frac{N\rho}{2} \left\| \mathbf{z} - \overline{\mathbf{w}}^{t+1} - \overline{\mathbf{u}}^{t} \right\|_2^2 \right\} \\ \mathbf{u}_j^{t+1} &= \mathbf{u}_j^{t} + \mathbf{w}_j^{t+1} - \mathbf{z}^{t+1} \end{aligned}\right\} \qquad \begin{aligned} \mathbf{z}^{t+1} &= \min_{\mathbf{z}} \left\{ \lambda \left\| \mathbf{z} \right\|_2^2 + \frac{N\rho}{2} \left\| \mathbf{z} - \overline{\mathbf{w}}^{t+1} - \overline{\mathbf{u}}^{t} \right\|_2^2 \right\} \\ \mathbf{u}_j^{t+1} &= \mathbf{u}_j^{t} + \mathbf{w}_j^{t+1} - \mathbf{z}^{t+1} \end{aligned}$$



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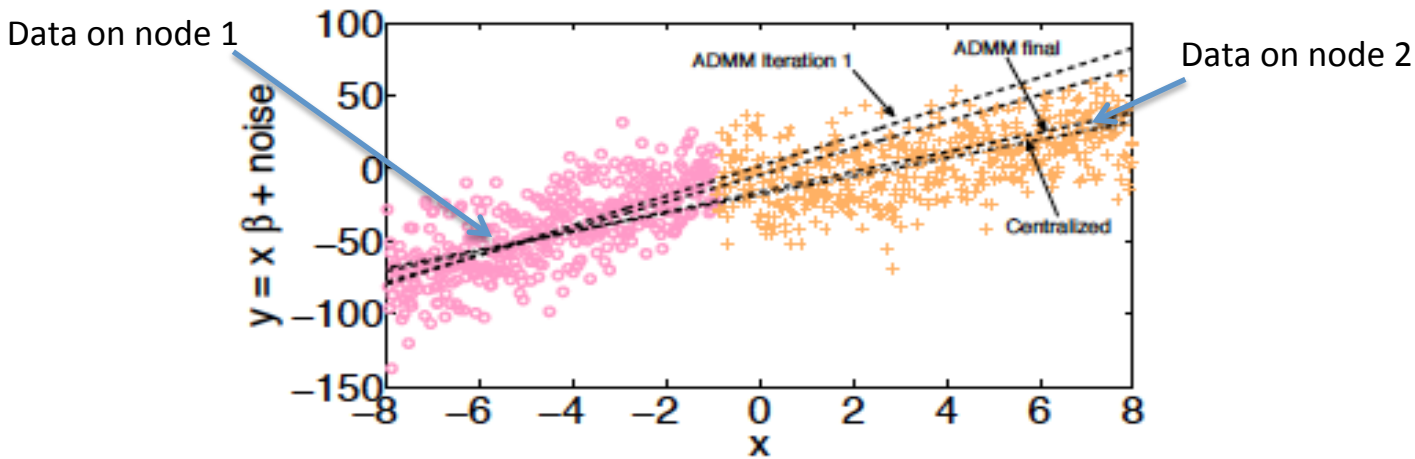
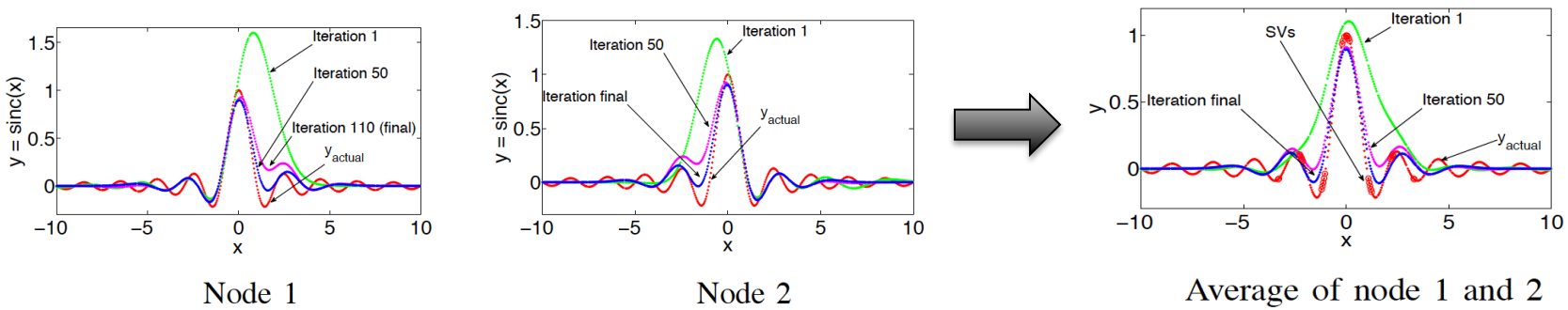
Convergence



Linear model fitting

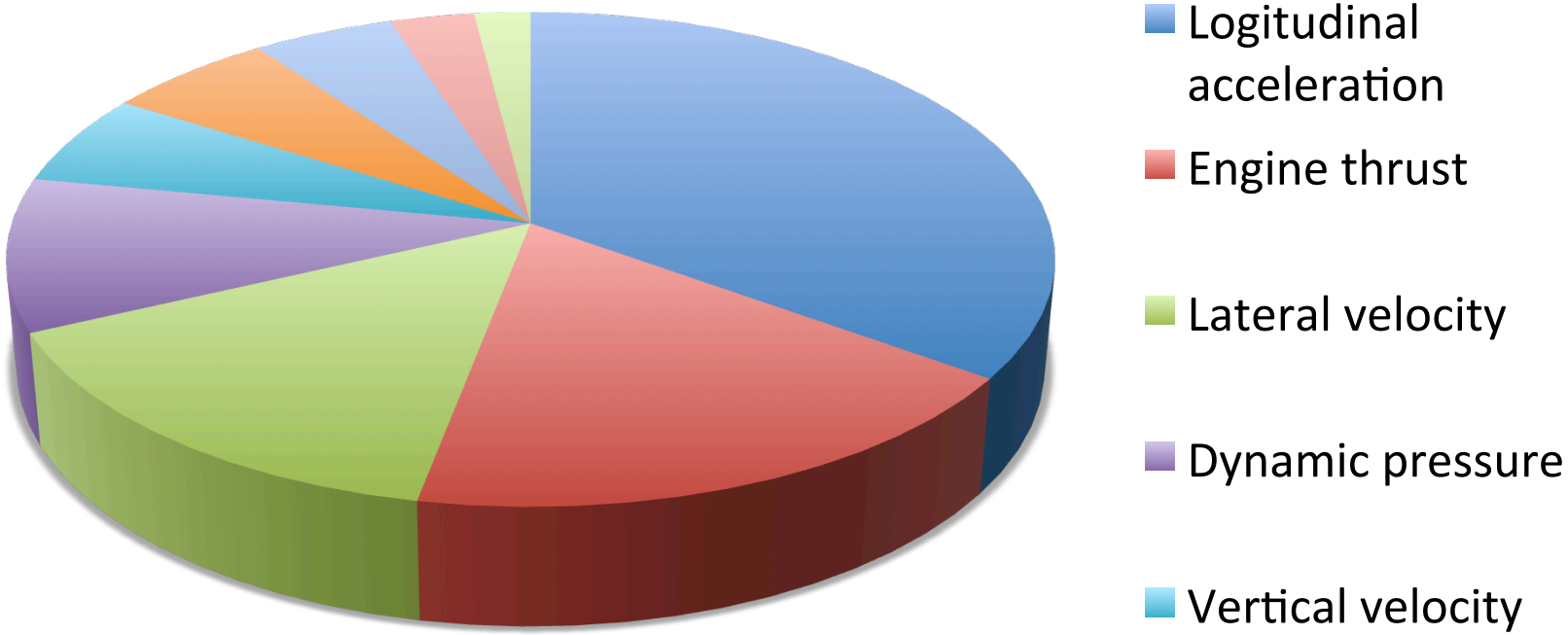


Non-linear model fitting

Application to Fleet of Aircrafts

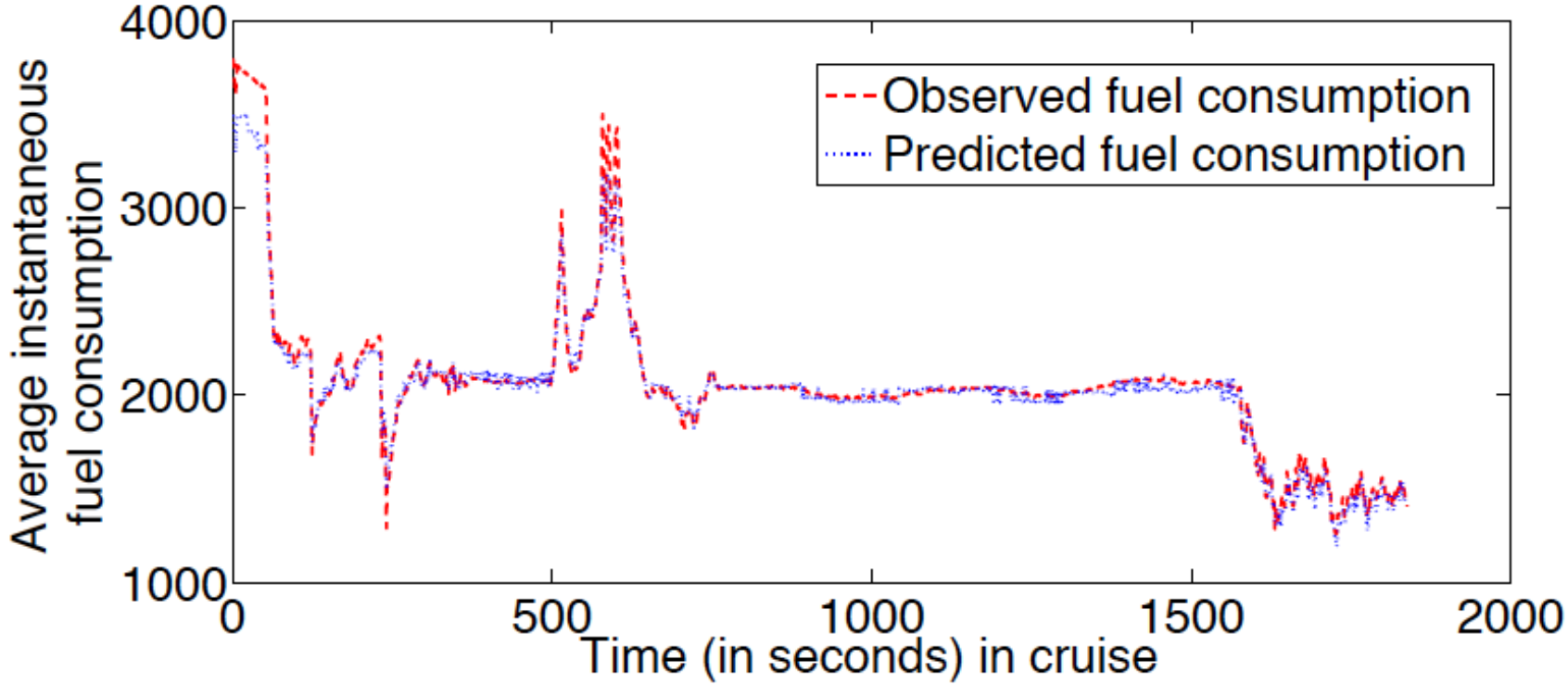
- Model built on all flights for a single tail number taken over 1 calendar year
- Model tested on the same tail number for the next calendar year
  - Total number of training flights: 1505
  - Total number of flights tested: 1947
- Anomalous flights consume fuel outside the statistically acceptable boundary of the mean predicted fuel consumption

Parameters influencing fuel flow



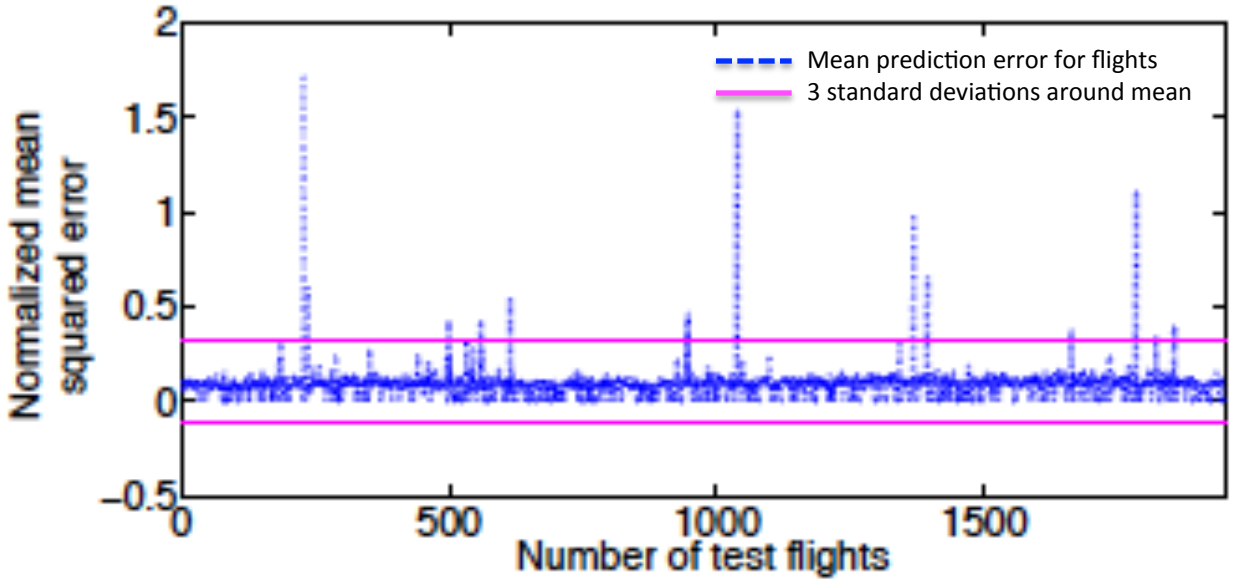
* Parameter weights are decided by the algorithm for the best fit to the training data

Output of method



Instantaneous prediction of fuel flow during cruise phase of the test flights. Figure shows a normal test flight with prediction closely matching the actual fuel flow

Distribution of prediction error



14 flights cross the 3-σ boundary for the mean error for all instances during cruise

Anomalous fuel consumption example

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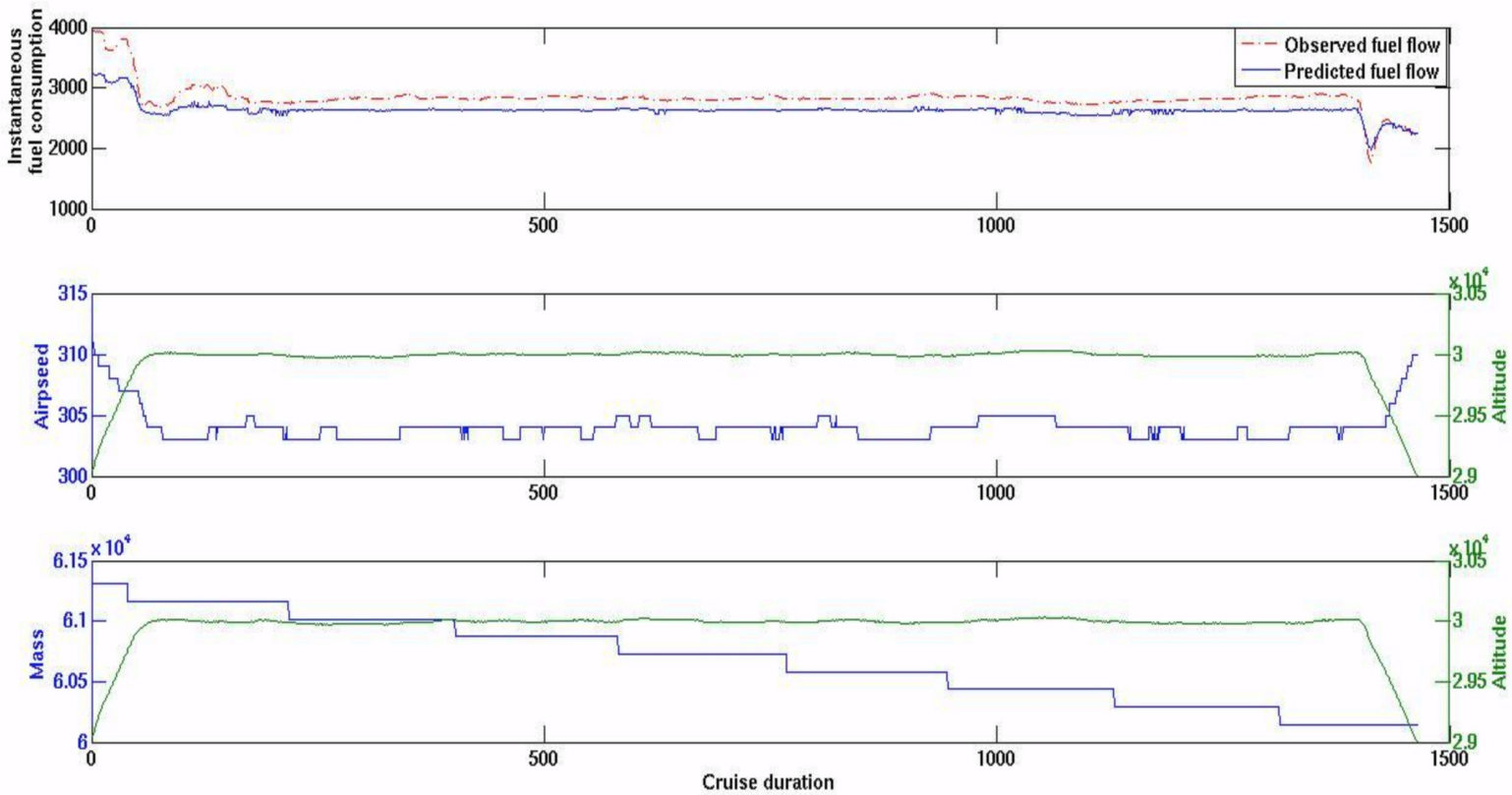

Top anomalous flight in terms of average mean squared error of predicted fuel flow

Anomalous fuel consumption example

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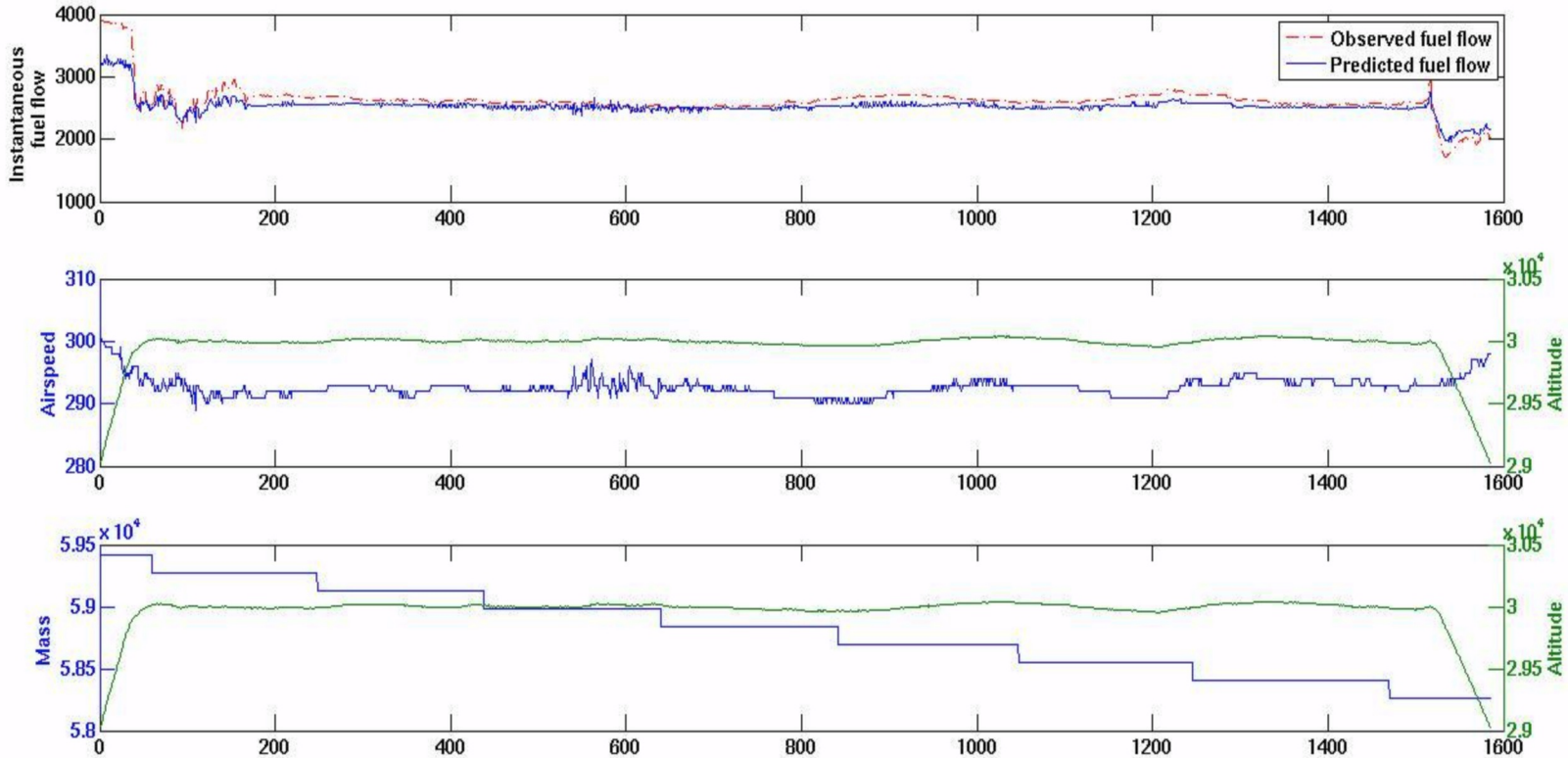

Lowest ranked anomalous flight in terms of average mean squared error of predicted fuel flow

Anomalies explained

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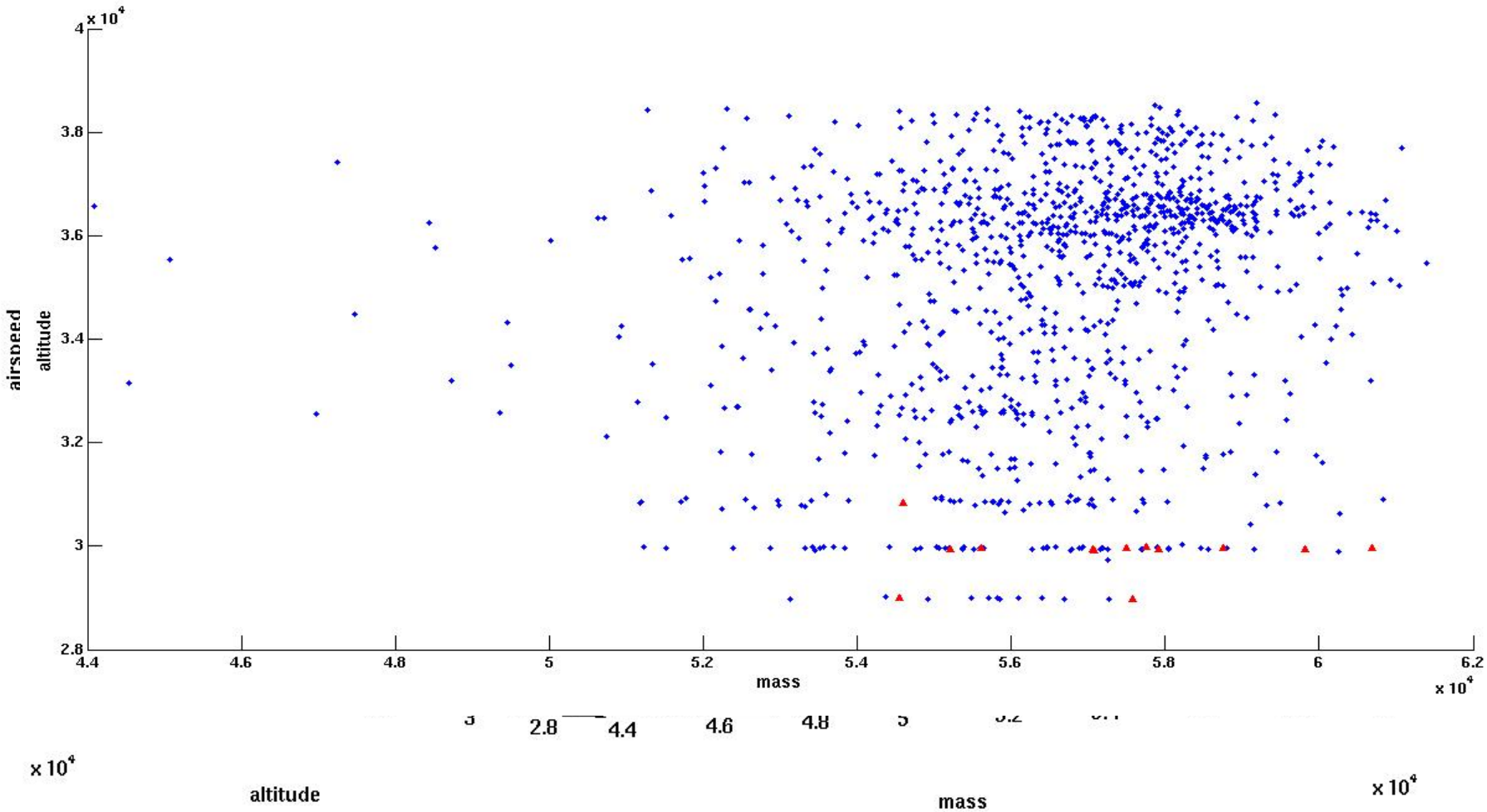

Anomalies are jointly distributed differently than nominal flights

Impact

- Perhaps the first technology to detect fuel consumption anomalies as a function of aircraft state
- Findings may be used to take timely, corrective maintenance measures on fleet
- It could even discover unknown flight configurations that use more fuel
- Has been used on Boeing simulation data for testing new flight procedures. Plan to compare against physics based fuel consumption models.

Milestones achieved

- TA1: Introduce Huber loss penalty and automatic feature selection for modeling fuel flow
  - Tested on Boeing simulation data, European commercial airline data
- TA2: Conduct validation on SWA data
  - Built infrastructure, awaiting data from SWA. Validated on European carrier data
- TA3: Can technology lead to improved efficiency?
  - Have identified aircraft configurations that lead more fuel consumption than others
- TA4: Dissemination
  - Published in OMAD 2014 workshop, part of SDM 2014

Dissemination

- Published initial results in Workshop on Optimization Methods for Anomaly Detection, 2014
- Manuscript in preparation for submission to ECML-PKDD 2014 conference

Summary and Future Work

Summary	Future Work
• Fuel consumption depends on state of aircraft. Anomalous behavior should be determined **relative to** state of the aircraft. • New loss function and distributed optimization method for it allows scaling of the virtual sensors technology to larger data set without any approximation • Method validated on European carrier data. Aircraft configurations have been identified that consume more fuel than others	• Validation on SWA data • Further study to investigate whether airport city pairs have an effect on fuel consumption during cruise phase • Extending study to analyze take off and landing phases • Incorporate aircraft modes • Perform study on Boeing simulation data to analyze new flight plans in test and compare performance against physics based fuel models