DATA RECONCILIATION AND INSTRUMENTATION UPGRADE. OVERVIEW AND CHALLENGES

PASI 2005.
Cataratas del Iguazu, Argentina

Miguel Bagajewicz
University of Oklahoma
• A large number of people from academia and industry have contributed to the area of data reconciliation.
• Hundreds of articles and three books have been written.
• More than 5 commercial software exist.

• Although a little younger, the area of instrumentation upgrade is equally mature.
• One book has been written.
OUTLINE

• OBSERVABILITY AND REDUNDANCY
• DIFFERENT TYPES OF DATA RECONCILIATION
  - Steady State vs. Dynamic
  - Linear vs. Nonlinear

• GROSS ERRORS
  - Biased instrumentation, model mismatch and outliers
  - Detection, identification and size estimation

• INSTRUMENTATION UPGRADE
• SOME EXISTING CHALLENGES
• INDUSTRIAL PRACTICE
Simple Process Model of Mass Conservation

Material Balance Equations

\[
\begin{align*}
    f_1 - f_2 - f_3 &= 0 \\
    f_2 - f_4 &= 0 \\
    f_3 - f_5 &= 0 \\
    f_4 + f_5 - f_6 &= 0 \\
    f_6 - f_7 &= 0 \\
    f_7 - f_8 - f_9 &= 0 \\
    f_8 - f_{10} &= 0 \\
    f_9 - f_{11} &= 0
\end{align*}
\]
Variable Classification

Variables

\[
\begin{align*}
\text{Measured (M)} & \quad f_1 \\
\text{Unmeasured (UM)} & \quad f_2 \\
\text{Observable (O)} & \quad f_3 \\
\text{Unobservable (UO)} & \quad f_4 \\
\end{align*}
\]
Variable Classification

Variables

- Measured (M)
- Non-redundant (NR)
- Redundant (R)
- Observable (O)
- Unobservable (UO)
- Unmeasured (UM)
Conflict among Redundant Variables

\[
\begin{align*}
& f_1 - f_7 = 0 \\
& f_1 - f_8 - f_{11} = 0
\end{align*}
\]

Material Balance Equations
Conflict Resolution

\[
\begin{align*}
\text{Min} & \quad [\tilde{f}_R - f_R^+]^T Q_R^{-1} [\tilde{f}_R - f_R^+] \\
\text{s.t.} & \quad E_R \tilde{f}_R = 0
\end{align*}
\]

Data reconciliation in its simplest form

Analytical Solution

\[
\tilde{f}_R = \left[ I - Q_R E_R^T \left( E_R Q_R E_R^T \right)^{-1} E_R \right] f_R^+
\]
Precision of Estimates

If \( z = \Gamma x \), and the variance of \( x \) is \( Q \), then the variance of \( z \) is given by:

\[
\tilde{Q} = \Gamma Q \Gamma^T
\]

\[
\tilde{f}_R = \left[ I - Q_R E_R^T (E_R Q_R E_R^T)^{-1} E_R \right] f_R^+
\]

\[
\tilde{f}_{NR} = f_{NR}^+
\]

\[
\tilde{f}_O = C_{RO} \tilde{f}_R + C_{NRO} \tilde{f}_{NR}
\]

\[
\tilde{Q}_{R,F} = Q_{R,F} - Q_{R,F} C_R^T (C_R Q_{R,F} C_R^T)^{-1} C_R Q_{R,F}
\]

\[
\tilde{Q}_{NR,F} = Q_{NR,F}
\]

\[
\tilde{Q}_O = [C_{RO} C_{SRO}] \begin{bmatrix} \tilde{Q}_R \\ \tilde{Q}_{NR} \end{bmatrix} [C_{RO} C_{SRO}]^T
\]
Some Practical Difficulties

- Variance-Covariance matrix is not Known
- Process plants have a usually a large number of Tanks
- Plants are not usually at Steady State
- How many measurements is enough?
Estimation of the Variance-Covariance Matrix.

\[
\begin{align*}
\tilde{f}_{R,i} &= \frac{1}{n} \sum_{k=1}^{n} \tilde{f}_{R,i} |_k \\
\text{Cov}(\tilde{f}_{R,i}, \tilde{f}_{R,j}) &= \frac{1}{n-1} \sum_{k=1}^{n} (\tilde{f}_{R,i} |_k - \tilde{f}_{R,i})(\tilde{f}_{R,j} |_k - \tilde{f}_{R,j})
\end{align*}
\]

- Direct Approach
- Indirect Approach

**Direct Approach**

**Indirect Approach**

\[E_R f^+_R = r \quad \text{Cov}(r) = E_R Q_R E^T_R\]

1) Obtain \( r \)

2) Maximum likelihood estimate \( Q_R \)

However, this procedure is not good if outliers are present. Robust estimators have been proposed (Chen et al, 1997)

\[Almasy and Mah (1984),\]
\[Darouach et al., (1989) and\]
\[Keller et al (1992)\]
Tank Hold Up Measurements

Steady State formulations are used

Level at $t=t^0$

Level at $t=t^1$

Pseudo-Stream
The procedure is based on the following assumptions:

a) A normal distribution of measurement errors.
b) A single value per variable.
c) A “steady-state” system.

a) Substantiated by the central limit theorem.
b) Also valid for means.
c) No plant is truly at “steady-state”. Process oscillations occur. Therefore, it is said that it is valid for a “pseudo-steady state” system.

$$\text{Min } [ \tilde{f}_R - f_R^+ ]^T Q_R^{-1} [ \tilde{f}_R - f_R^+ ]$$

$$E_R \tilde{f}_R = 0$$
Reconciliation of averages is equal to the average of reconciled values using dynamic data reconciliation (Bagajewicz and Jiang, 2000; Bagajewicz and Gonzales, 2001).

That is, there is no need to adjust the variance-covariance matrix for process variations.
Dynamic Data Reconciliation

Linear Case (after cooptation):

\[
Min \sum_{i} \left\{ (\tilde{f}_{ri} - f_{ri}^+)^T Q_{rf}^{-1} (\tilde{f}_{ri} - f_{ri}^+) + [\tilde{V}_{ri} - V_{ri}^+]^T Q_{rv}^{-1} [\tilde{V}_{ri} - V_{ri}^+] \right\}
\]

\[
B \frac{d\tilde{V}_R}{dt} = A\tilde{f}_R
\]

\[
C\tilde{f}_R = 0
\]

When B=I, the Kalman filter can be used.
Dynamic Data Reconciliation

Min $\sum_{i} \{ \tilde{f}_{Ri} - f_{Ri}^{+} \}^T Q_{Rf}^{-1} [\tilde{f}_{Ri} - f_{Ri}^{+}] + [\tilde{V}_{Ri} - V_{Ri}^{+}]^T Q_{RV}^{-1} [\tilde{V}_{Ri} - V_{Ri}^{+}] \}$

$B \frac{d\tilde{V}_{R}}{dt} = A\tilde{f}_{R}$

$C\tilde{f}_{R} = 0$


$B (\tilde{V}_{R,i} - \tilde{V}_{R,i}) = A\tilde{F}_{R,i}$

$C\tilde{F}_{R,i} = 0$

An algebraic system of equations follows.

Integral Approach: Jiang and Bagajewicz, 1997.

$f_{R} \approx \sum_{k=0}^{s} \alpha_{k}^{R} t^{k}$

$B_{R} [V_{R} - V_{R0}] = B_{R} \sum_{k=0}^{s} \omega_{k+1}^{R} t^{k+1} = A_{R} \sum_{k=0}^{s} \alpha_{k+1}^{R} t^{k+1}$

The technique estimates the coefficients of polynomials.
Nonlinear Data Reconciliation

\[
\text{Min} \sum_{k=0}^{N} \left[ \tilde{x}_M(t_k) - z_{M,k} \right]^T Q^{-1} \left[ \tilde{x}_M(t_k) - z_{M,k} \right]
\]

\[
\frac{d\tilde{x}_1}{dt} = g_1(\tilde{x}_1, \tilde{x}_2)
\]

\[
g_2(\tilde{x}_1, \tilde{x}_2) = 0
\]

Applied in practice to steady state models with material, component and energy balances. In the dynamic case, orthogonal collocation was used (Liebmann et al, 1992) or linearization (Ramamurthi et al., 1993) or use of DAE (Albuquerque and Biegler, 1996).
Gross Errors
Types of Gross Errors

- Biases
- Leaks (Model departures)
- True outliers
Hypothesis Testing

Global Test (Detection)

\[ \gamma = r (E_R Q_R E_R^T)^{-1} r \]

\[ \begin{align*}
H_0 : & \quad \mu_R^T (E_R Q_R E_R^T) \mu_R = 0 \\
H_1 : & \quad \mu_R^T (E_R Q_R E_R^T) \mu_R \neq 0
\end{align*} \]

Distribution: Chi-Squared

Nodal Test (Detection and Identification)

\[ Z_i^N = n^{1/2} \frac{|r_i|}{\sqrt{(E_R Q_R E_R^T)_{ii}}} \]

\[ \begin{align*}
H_0 : & \quad \mu_r = 0 \\
H_1 : & \quad \mu_r \neq 0
\end{align*} \]

Distribution: Normal

Maximum Power versions of this test were also developed. Rollins et al (1996) proposed an intelligent combination of nodes technique.
Hypothesis Testing

Principal Component (Tong and Crowe, 1995)

$W_r : \text{matrix of eigenvectors of } (E_R Q_R E_R^T)$

$\Lambda_r : \text{matrix of eigenvalues of } (E_R Q_R E_R^T)$

$p_r = W^T r \quad p_r \sim N(0, I)$

\[
\begin{cases}
H_0 : W^T \mu_r = 0 \\
H_1 : W^T \mu_r \neq 0
\end{cases}
\]

Distribution : Normal
Hypothesis Testing

Measurement Test

\[ Z_{\chi}^{LCT} = \frac{\tilde{f}_i - f_i^+}{\sqrt{(\tilde{Q}_R)_{ii}}} \]

\[
\begin{align*}
H_0 : \phi_i - f_i &= 0 \\
H_1 : \phi_i - f_i &\neq 0
\end{align*}
\]

Distribution : Normal

This test is inadmissible. Under deterministic conditions it may point to the wrong location.
Hypothesis Testing

Generalized Likelihood ratio

\[
\lambda = \sup_{\forall i} \frac{\Pr\{r | H_1\}}{\Pr\{r | H_0\}}
\]

\[
\lambda = \sup_{\forall b,i} \frac{\exp\{-0.5(r - bAe_i)^T (E_R Q E_R^T)^{-1} (r - bAe_i)\}}{\exp\{-0.5r^T (E_R Q E_R^T)^{-1} r\}}
\]

\[
\begin{cases}
H_0 : \mu_r = 0 \\
H_1 : \mu_r = bAe_i
\end{cases}
\]

Distribution: Chi-Squared

Leaks can also be tested.
Multiple Error Detection

Serial Elimination
  Apply recursively the test and eliminate the measurement

Serial Compensation
  Apply recursively the test, determine the size of the gross error and adjust the measurement

Serial Collective Compensation
  Apply recursively the test, determine the sizes of all gross error and adjust the measurements
Multiple Error Detection

Unbiased Estimation
One shot collective information of all possible errors followed by hypothesis testing. Bagajewicz and Jiang, 2000, proposed an MILP strategy based on this.

Two distributions approach
Assume that gross error have a distribution with larger variance and use maximum likelihood methods (Romagnoli et al., 1981) (Tjoa and Biegler, 1991) (Ragot et al., 1992)

EQUIVALENCY THEORY

- Exact location determination is not always possible, regardless of the method used.
- Many sets of gross errors are equivalent, that is, they have the same effect in data reconciliation when they are compensated.
BASIC EQUIVALENCIES

In a single unit a bias in an inlet stream is equivalent to a bias in an output stream.

\[ S_1 \rightarrow \square \rightarrow S_2 \]

<table>
<thead>
<tr>
<th></th>
<th>S₁</th>
<th>S₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Case 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reconciled data</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Estimated bias</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Case 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reconciled data</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Estimated bias</td>
<td>-1</td>
<td></td>
</tr>
</tbody>
</table>
BASIC EQUIVALENCIES

In a single unit a bias in a stream is equivalent to a leak

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>Leak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
<td>4</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Case1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reconciled data</td>
<td>4</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>Estimated bias/leak</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Case2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reconciled data</td>
<td>4</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Estimated bias/leak</td>
<td>4</td>
<td>4</td>
<td>-1</td>
</tr>
</tbody>
</table>
EQUIVALENCY THEORY

For the set $\Lambda = \{S_3, S_6\}$ a gross error in one of them can be alternatively placed in the other without change in the result of the reconciliation. We say that this set has Gross Error Cardinality $\Gamma(\Lambda) = 1$. ONE GROSS ERROR CAN REPRESENT ALL POSSIBLE GROSS ERRORS IN THE SET.
GROSS ERROR DETECTION

TWO SUCCESSFUL IDENTIFICATIONS:

- Exact location
- Equivalent location

THIS MEANS THAT THE CONCEPT OF POWER IN LINEAR DATA RECONCILIATION SHOULD BE REVISITED TO INCLUDE EQUIVALENCIES
## COMMERCIAL CODES

<table>
<thead>
<tr>
<th>Package</th>
<th>Nature</th>
<th>Offered by</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IOO (Interactive On-Line Opt.)</strong></td>
<td>Academic</td>
<td>Louisiana State University (USA)</td>
</tr>
<tr>
<td><strong>DATACON</strong></td>
<td>Commercial</td>
<td>Simulation Sciences (USA)</td>
</tr>
<tr>
<td><strong>SIGMAFINE</strong></td>
<td>Commercial</td>
<td>OSI (USA)</td>
</tr>
<tr>
<td><strong>VALI</strong></td>
<td>Commercial</td>
<td>Belsim (Belgium)</td>
</tr>
<tr>
<td><strong>ADVISOR</strong></td>
<td>Commercial</td>
<td>Aspentech (USA)</td>
</tr>
<tr>
<td><strong>RECONCILER</strong></td>
<td>Commercial</td>
<td>Resolution Integration Solutions (USA)</td>
</tr>
<tr>
<td><strong>PRODUCTION BALANCE</strong></td>
<td>Commercial</td>
<td>Honeywell (USA)</td>
</tr>
<tr>
<td><strong>RECON</strong></td>
<td>Commercial</td>
<td>Chemplant Technologies (Czech Republic)</td>
</tr>
</tbody>
</table>

While the data reconciliation in all these packages is good, gross error detection has not caught up with developments in the last 10 years.

Global test and Serial Elimination using the measurement test seem to be the gross error detection and identification of choice.
INSTRUMENTATION UPGRADE
(The inverse engineering problem)

Given

Data Reconciliation (or other) monitoring Objectives

Obtain:

Sensor Locations

(number and type)
INSTRUMENTATION DESIGN

Minimize Cost (Investment + Maintenance)

s.t.

- Desired precision of estimates
- Desired gross error robustness
  Detectability, Residual Precision, Resilience.
- Desired reliability/availability
**Design of Repairable Networks**

**EXAMPLE: Ammonia Plant**

![Diagram of network](image)

Table 3: Optimization results for the simplified ammonia process flowsheet

<table>
<thead>
<tr>
<th>Repair Rate</th>
<th>Measured Variables</th>
<th>Instrument Precision (%)</th>
<th>Cost</th>
<th>Precision(%)</th>
<th>Precision Availability(%)</th>
<th>Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S1 S4 S5 S6 S7 S8</td>
<td>3 1 1 1 1 3 2</td>
<td>2040.2</td>
<td>0.8067</td>
<td>0.9841</td>
<td>0.9021</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.2893</td>
<td>1.2937</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>S4 S5 S6 S7 S8</td>
<td>3 3 1 3 1</td>
<td>1699.8</td>
<td>0.9283</td>
<td>1.9712</td>
<td>0.9222</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.9928</td>
<td>2.0086</td>
<td>0.9062</td>
</tr>
<tr>
<td>4</td>
<td>S4 S5 S6 S7 S8</td>
<td>3 3 1 3 3</td>
<td>1683.7</td>
<td>1.2313</td>
<td>1.9712</td>
<td>0.9636</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.9963</td>
<td>2.0086</td>
<td>0.9511</td>
</tr>
<tr>
<td>20</td>
<td>S4 S5 S6 S7 S8</td>
<td>3 3 1 3 3</td>
<td>1775.2</td>
<td>1.2313</td>
<td>1.9712</td>
<td>0.9983</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.9963</td>
<td>2.0086</td>
<td>0.9969</td>
</tr>
</tbody>
</table>

- **There is a minimum in cost as a function of the repair rate. This allows the design of maintenance policies.**
Upgrade

Upgrade consists of any combination of:

- Adding instrumentation.
- Replacing instruments.
- Relocating instruments (thermocouples, sampling places, etc).
Upgrade

Example

Reallocation and/or addition of thermocouples as well as a purchase of a new flowmeter improve the precision of heat transfer coefficients

<table>
<thead>
<tr>
<th>Case</th>
<th>$\sigma_{U_1}$</th>
<th>$\sigma_{U_2}$</th>
<th>$\sigma_{U_3}$</th>
<th>$\sigma_{U_1}$</th>
<th>$\sigma_{U_2}$</th>
<th>$\sigma_{U_3}$</th>
<th>$c$</th>
<th>Reallocations</th>
<th>New Instruments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.00</td>
<td>4.00</td>
<td>4.00</td>
<td>3.2826</td>
<td>1.9254</td>
<td>2.2168</td>
<td>100</td>
<td>$u_{T_1,2,6}$</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>2.00</td>
<td>2.00</td>
<td>2.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>2.00</td>
<td>2.00</td>
<td>2.20</td>
<td>1.3891</td>
<td>1.5148</td>
<td>2.1935</td>
<td>3000</td>
<td>-</td>
<td>$T_2, T_6$</td>
</tr>
<tr>
<td>4</td>
<td>1.50</td>
<td>1.50</td>
<td>2.20</td>
<td>1.3492</td>
<td>1.3664</td>
<td>2.1125</td>
<td>5250</td>
<td>-</td>
<td>$F_4, T_2, T_6$</td>
</tr>
<tr>
<td>5</td>
<td>2.40</td>
<td>2.30</td>
<td>2.20</td>
<td>2.0587</td>
<td>1.8174</td>
<td>2.1938</td>
<td>1500</td>
<td>-</td>
<td>$T_6$</td>
</tr>
<tr>
<td>6</td>
<td>2.20</td>
<td>1.80</td>
<td>2.40</td>
<td>1.7890</td>
<td>1.6827</td>
<td>2.2014</td>
<td>1600</td>
<td>$u_{T_1,2,6}$</td>
<td>$T_6$</td>
</tr>
</tbody>
</table>
Latest Trends

+ Multiobjective Optimization (Narasimhan and Sen, 2001, Sanchez et al, 2000): Pareto optimal solutions (cost vs. precision of estimates are built)

+ Unconstrained Optimization (Bagajewicz 2002, Bagajewicz and Markowski 2003): Reduce everything to cost, that is find the economic value of precision and accuracy.
Unconstrained Optimization

Let $SN_0$ be an existing network, then an upgrade to network $SN$ has a Value defined as:

$$\text{Value} (SN) = \text{Profit} (SN) - \text{Profit} (SN_0)$$

Then the upgrade SND problem is defined as:

$$\text{Maximize} \quad \{ \text{Value} (SN) - \text{Cost} (SN) \}$$
Integrated Approach

Maximize \[ \sum_{i=1}^{3} \{ V_i(SN) \} - \text{Cost}(SN) \]

where \( V_i(SN) \) are the Value functions from the three perspectives

- \( i=1 \) Control Systems
- \( i=2 \) Material Accounting
- \( i=3 \) Fault Diagnosis
Material Accounting Perspective

Given an distribution \( g(\xi, \hat{\sigma}_{p,m}(SN_0)) \) one can calculate the probability that target production is not met.

This is quantified as the Downside Expected Production Loss:

\[
DEPL(\hat{\sigma}_p) = T \int_{-\infty}^{m^*} (m^* - \xi) g(\xi, \hat{\sigma}_p) d\xi \approx 0.2T\hat{\sigma}_p
\]

The above expression assumes process variability \( (\sigma_p)<<\hat{\sigma}_p \)
In the presence of biases we have:

\[
DEFL = \Psi^0 DEFL^0 + \sum_i \Psi^1_i DEFL^1_i + \sum_{i_1, i_2} \Psi^2_{i_1, i_2} DEFL^2_{i_1, i_2} + \ldots
\]

Portion of time in each state

Financial loss when **no** gross error is present

Financial loss when **one** gross error is present

Financial loss when **two** gross error are present
Control Perspective

- Conservative Operating Point
- Dynamic Operating Regions
- Backed-off Point
- Optimal Steady-State Point

CV’s

MV’s
Control Perspective

Dynamic Operating Regions for Different Sensor Networks

Minimally Backed-off Points

Optimal Steady-State Point
Faults Perspective

• Consider a set $F$ of possible faults $F=\{f_i\}$.

Define a set $A_i(SN)$ as the set of sensors in $SN$ that can observe fault $f_i$.

If $A_i(SN)$ is not empty then $f_i$ can be detected.

Assume immediate correction occurs for detected faults.

If all faults in $F$ can be detected, then no production losses or safety incidents will be expected.
Example

Assume the current network \((SN_o)\) consists of 6 sensors located at

\[ C_{Ai}, C_A, T, V, F, P \]

each having a precision of 2\%.
# Results (Control)

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C_A$, $P$</td>
<td>7,060</td>
<td>2,000</td>
<td>5,060</td>
</tr>
<tr>
<td>2</td>
<td>$C_A$, $T_c$, $P$</td>
<td>7,630</td>
<td>3,000</td>
<td>4,630</td>
</tr>
<tr>
<td>3</td>
<td>$P$</td>
<td>4,500</td>
<td>1,000</td>
<td>3,500</td>
</tr>
<tr>
<td>4</td>
<td>$T$, $P$</td>
<td>5,420</td>
<td>2,000</td>
<td>3,420</td>
</tr>
<tr>
<td>5</td>
<td>$C_A$, $T$, $T_c$, $V$, $P$</td>
<td>8,090</td>
<td>5,000</td>
<td>3,080</td>
</tr>
<tr>
<td>6</td>
<td>$T$, $T_c$, $V$, $P$</td>
<td>6,150</td>
<td>4,000</td>
<td>2,140</td>
</tr>
<tr>
<td>7</td>
<td>none</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Results (Material Accounting)

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C_{Ai}$</td>
<td>131</td>
<td>1000</td>
<td>-868</td>
</tr>
<tr>
<td>2</td>
<td>$F_{vg}$</td>
<td>127</td>
<td>1000</td>
<td>-872</td>
</tr>
<tr>
<td>3</td>
<td>$F_2$</td>
<td>77</td>
<td>1000</td>
<td>-922</td>
</tr>
<tr>
<td>4</td>
<td>All sensors</td>
<td>355</td>
<td>13,000</td>
<td>-12,644</td>
</tr>
</tbody>
</table>

In all cases the cost of adding sensors far exceeds the profit returned in the form of Upgrade Value.
## Results (Faults)

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$T_{ci}$, $T_i$</td>
<td>7,810</td>
<td>2,000</td>
<td>5,810</td>
</tr>
<tr>
<td>2</td>
<td>$F_c$, $T_c$, $T_i$</td>
<td>7,810</td>
<td>3,000</td>
<td>4,810</td>
</tr>
<tr>
<td>3</td>
<td>$T_c$, $T_{ci}$</td>
<td>4,720</td>
<td>2,000</td>
<td>2,720</td>
</tr>
<tr>
<td>4</td>
<td>$F_c$, $T_c$</td>
<td>4,720</td>
<td>2,000</td>
<td>2,720</td>
</tr>
</tbody>
</table>
### Integrated Perspective

<table>
<thead>
<tr>
<th>No</th>
<th>New Sensors</th>
<th>Value ($/yr)</th>
<th>Sensor Costs ($/yr)</th>
<th>Value - Sensor Costs ($/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C_A$, $P$, $T_{ci}$, $T_i$</td>
<td>14,930</td>
<td>4,000</td>
<td>10,930</td>
</tr>
<tr>
<td>2</td>
<td>$C_A$, $P$, $F_c$, $T_c$, $T_i$</td>
<td>15,525</td>
<td>5,000</td>
<td>10,525</td>
</tr>
</tbody>
</table>

**Case 1:** union of best networks from individual perspectives.

**Case 2:** union of second best networks.

- These are the best combinations given the tables presented.
- Exhaustive enumeration search is underway.
CHALLENGES

- **Academic**: Multiple Gross Error Identification
  Gross Errors for Nonlinear Systems.
  Unconstrained Methods. Solution Procedures

- **Industrial**: Dynamic data reconciliation.
  Gross Error Handling.
  Sensor Upgrades
CONCLUSIONS

• Data Reconciliation is an academically mature field.
• It is a must when parameter estimation (mainly for on-line optimization) is desired.
• Commercial codes are robust but lack of up to date gross error detection/location techniques.
• Instrumentation Upgrade methodologies have reach maturity
• Industry understands the need for upgrading, but academic efforts have not yet reached commercial status. They will, soon.