

A Yokogawa Commitment to Industry

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Data Reconciliation Techniques

By using a NIR Analyzer with
Chemometrics Software in Fuel
Property Analysis.

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Data Reconciliation Techniques Part 1

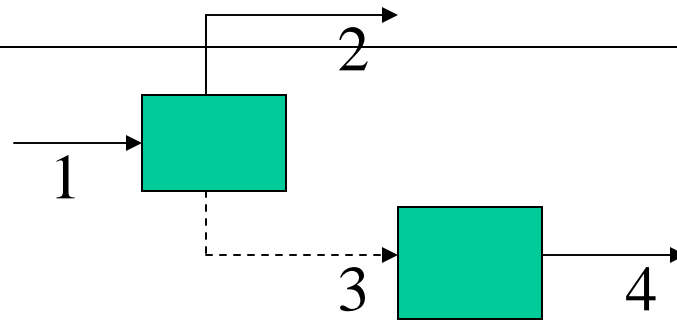
Topics on Data Reconciliation is based on works of
V.V. Veverka & F.Madron



Yokogawa Corporations India & Japan



➤ Data Reconciliation



$$F_1 - F_2 - F_3 = 0$$

$$F_3 - F_4 = 0$$

$$F(\underline{x}, \underline{y}, \underline{c}) = 0$$

X – Measured

Y – Unmeasured

C - Constant

$$x_i^+ = x_i + e_i$$

x_i – Measured Data

e_i – Error Characterized by SD σ

- Measured
 - Redundant – Can be calculated from other measured variable
 - Non-redundant
- Unmeasured
 - Observable – Can be uniquely calculated from other measured variable
 - Non-observable



➤ For Redundant Systems

$$f(\underline{x}, \underline{y}, \underline{c}) \neq 0$$

$$\hat{x}, \hat{y}$$

$$f(\hat{x}, \hat{y}, \hat{c}) = 0$$

and

$$\hat{X} = \Sigma \left[\frac{x_i - x^+}{\sigma} \right]^2 \Rightarrow \min$$

Least Sq. Soln.

→ Reconciled Value



➤ For redundant Systems

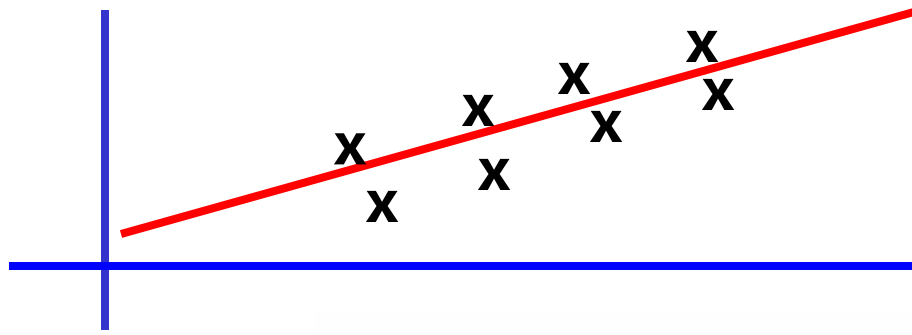
$$\frac{\sigma_{\text{reco}}}{\sigma_{\text{meas}}} \leq 1$$

Reconciliation

Provides
Info

- Possible Gross Errors
- Accuracy of Results
- Propagation of Measurement Errors

Regression / Reconciliation



Regression ← → Reconciliation
Data reconciled on least Squares (Measured data) Data reconciled on least Squares (Measured data)

Parameter Estimation

Propagation of Measurement Error

Reconciliation

Gross Error Elimination

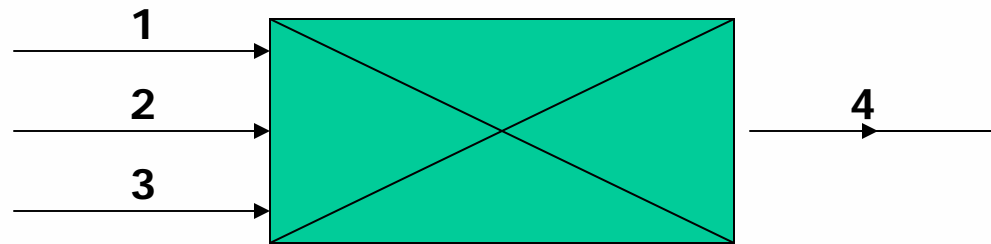
Measurement Design

❖ Data Reconciliation

Following are the Special Cases of Reconciliation:

- ❖ Classical Balancing
- ❖ Simulation
- ❖ Regression

➤ Applications in Blending

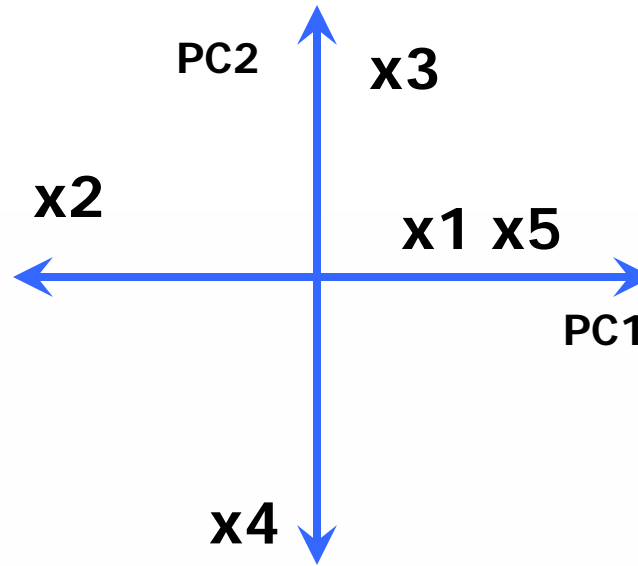


Static
Mixer

$$F_1 + F_2 + F_3 - F_4 = 0$$

(Mass Balance on
Measured / Observed Data)

Gross Error Detection thru Outlier Definition By Principal Component Analysis (PCA)



Loading Plot

Case 1 : Variables x1 & x2 are negatively correlated

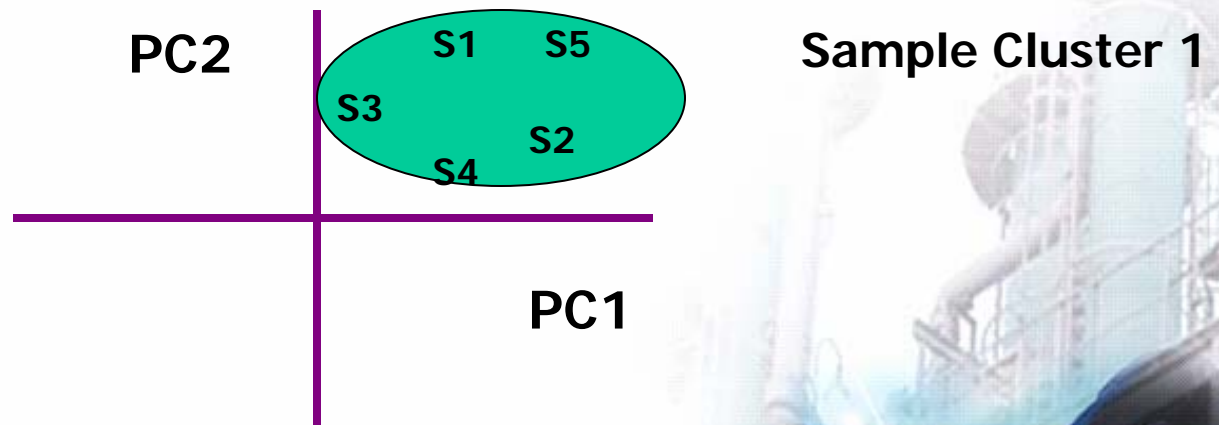
Case 2 : Variables x1 & x5 are positively correlated

Case 3 : Variables x3 & x4 are negatively correlated.

- The Variables are plotted on two orthogonal axes, Principal components 1 and 2 known as PC1 and PC2
- Case 3 Type Variables will not influence on Case 1 and Case 2 Variables

Interrelations between Samples & Variables determined by Score Plot – Sample Cluster 1

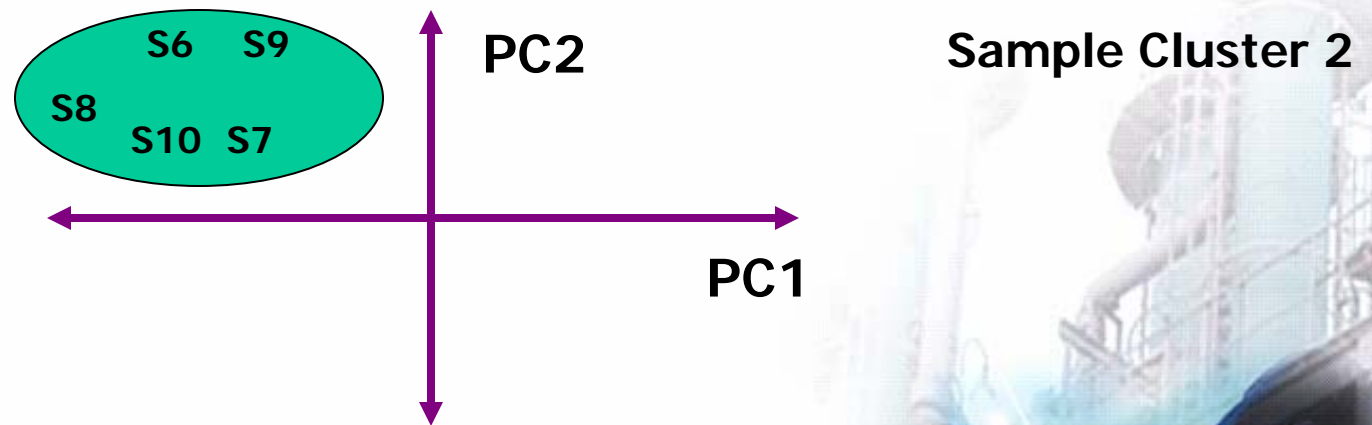
	x1	x2	x3	x4	x5
S1	H	L			H
S2	H	L			H
S3	H	L			H
S4	H	L			H
S5	H	L			H



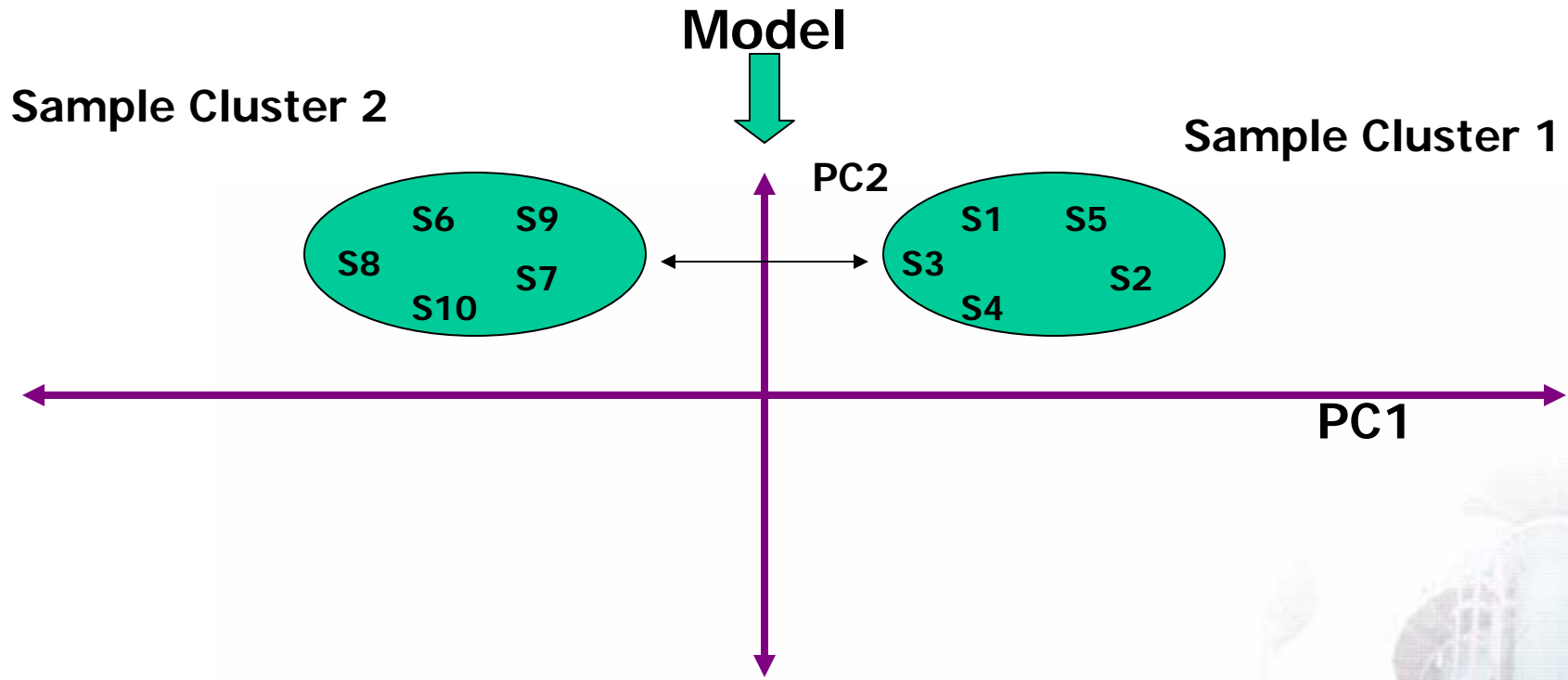
For all samples lying to the right of the Plot, the variables x1 and x5 will be high

Interrelations between Samples & Variables determined by Score Plot – Sample Cluster 2

	x1	x2	x3	x4	x5
S6	L	H			L
S7	L	H			L
S8	L	H			L
S9	L	H			L
S10	L	H			L



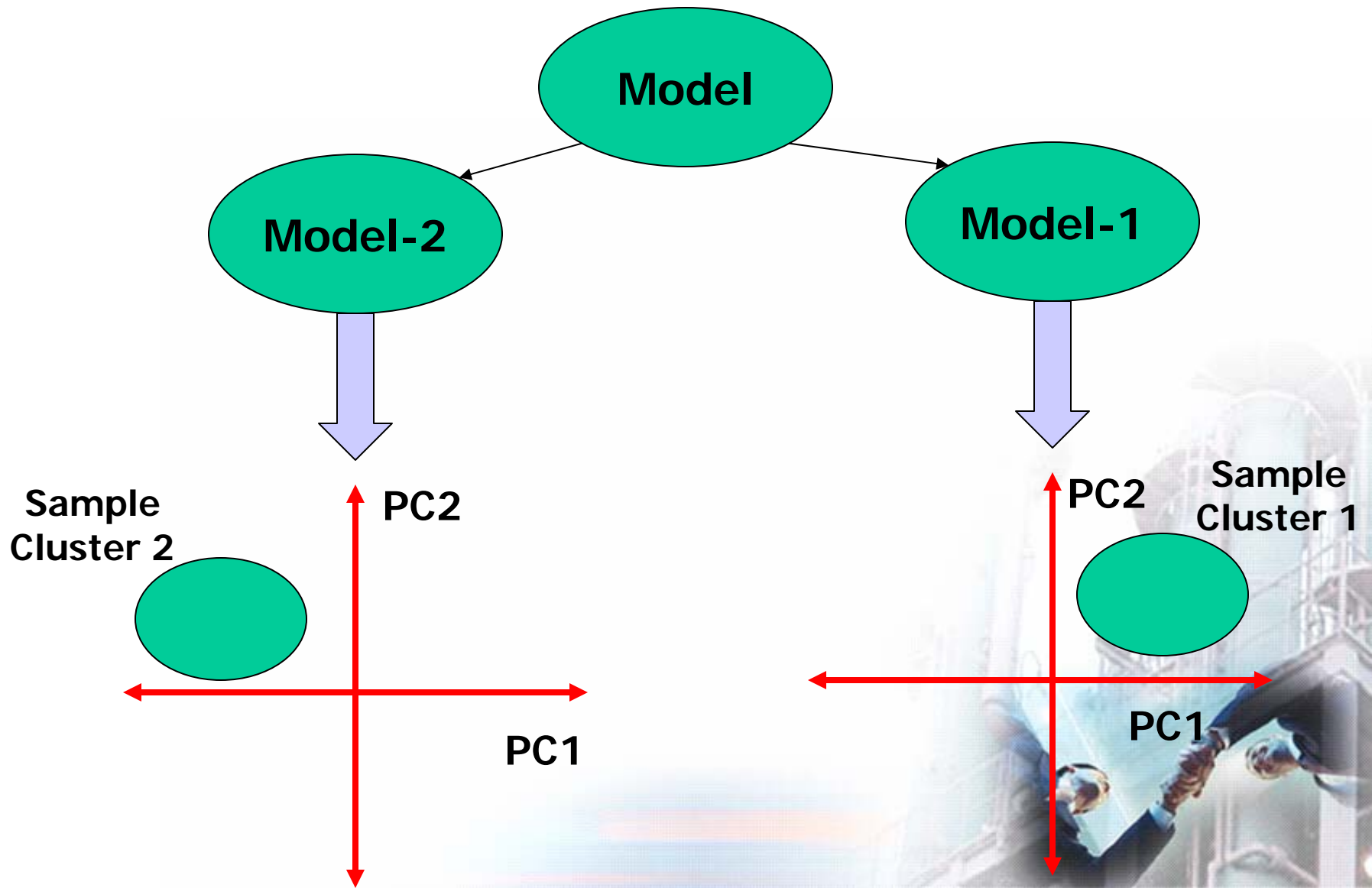
For all samples lying to the left of the Plot, the variables x2 only, will be high



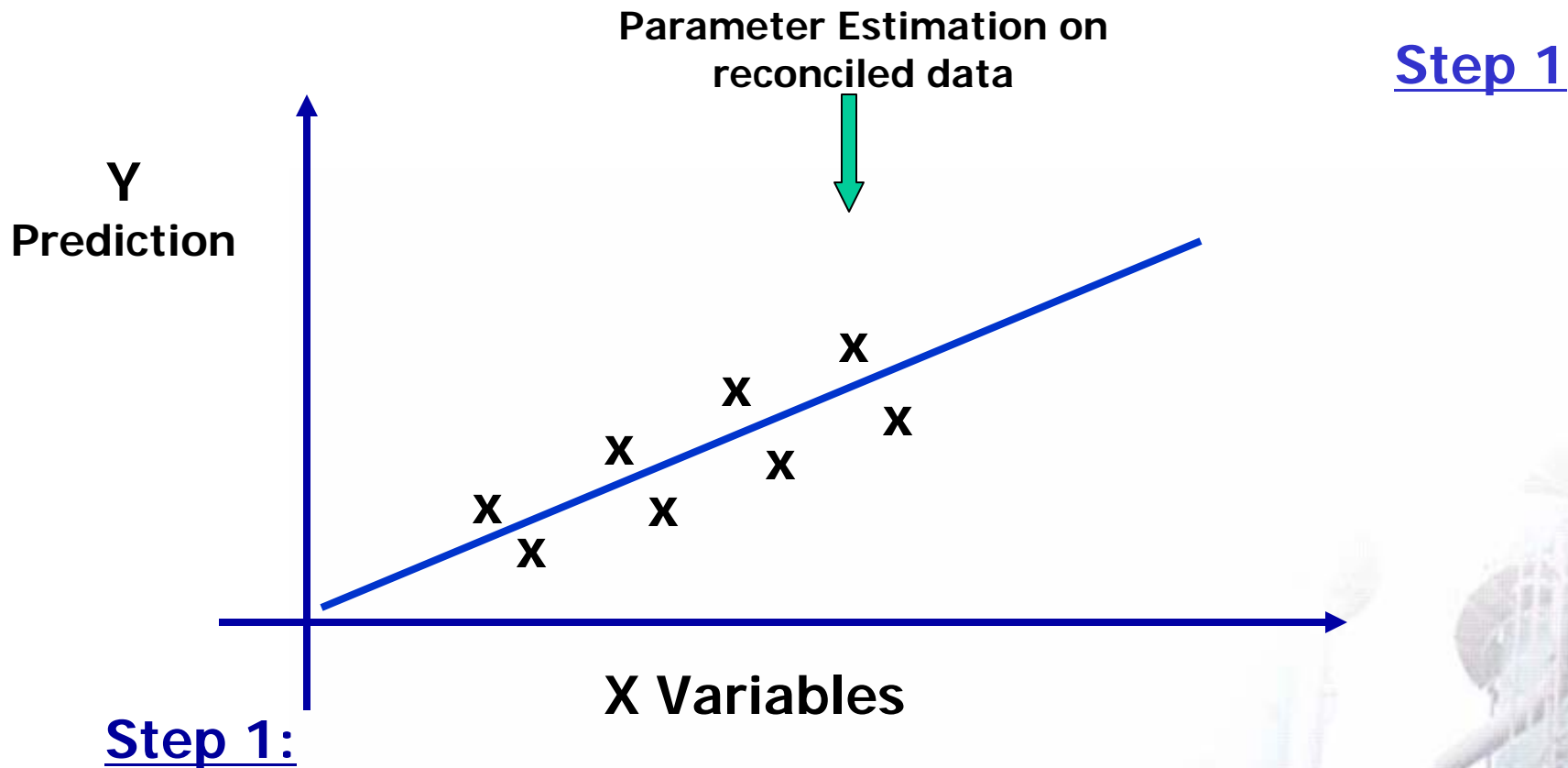
- ❖ These two sample clusters are outlying to each other.
- ❖ Outliers are a major cause of Gross Errors

Gross Error Elimination
through Outlier Elimination

❖ Data Reconciled thru' Gross Error Elimination by removal of Outliers



❖ Data Reconciliation – Step 1



Regression performed on reconciled data from a sample set of known values (Measured Y / Known X).
Regression performed by least square techniques

❖ Data Reconciliation – Step 2 & Step 3

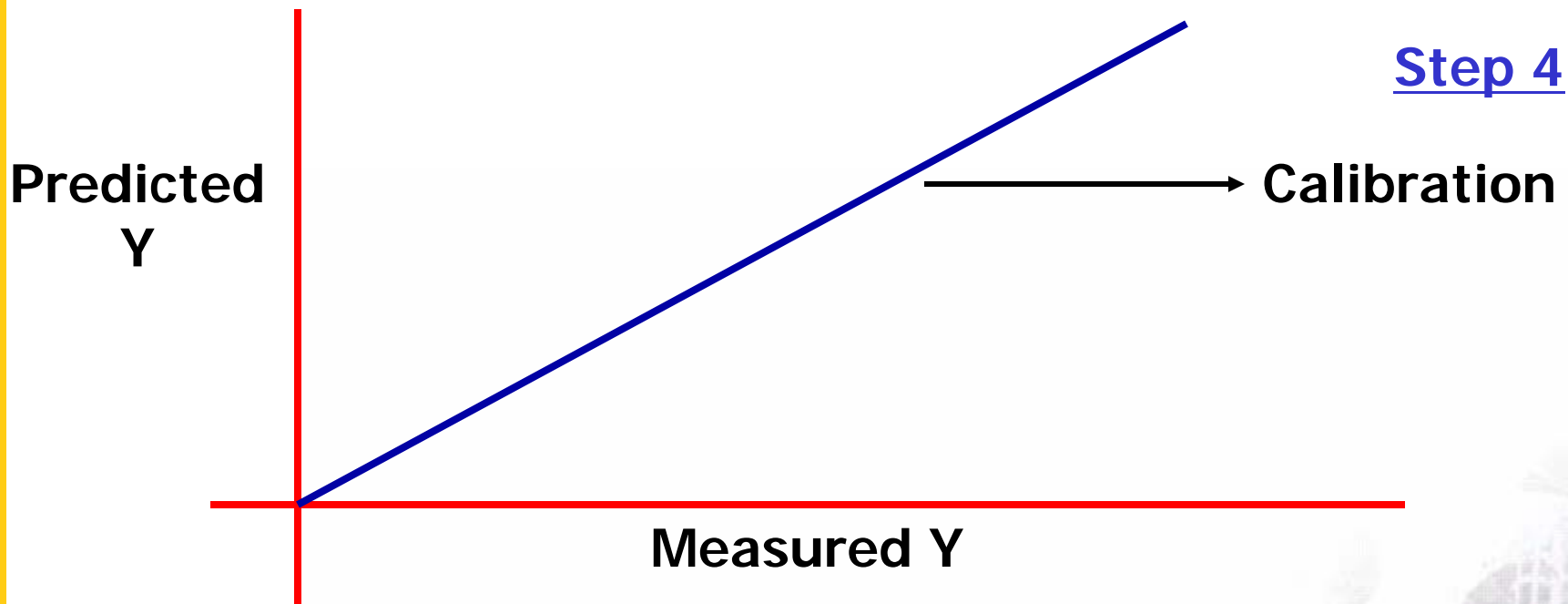
Step 2 :

Regression Co-efficients are calculated

Step 3 :

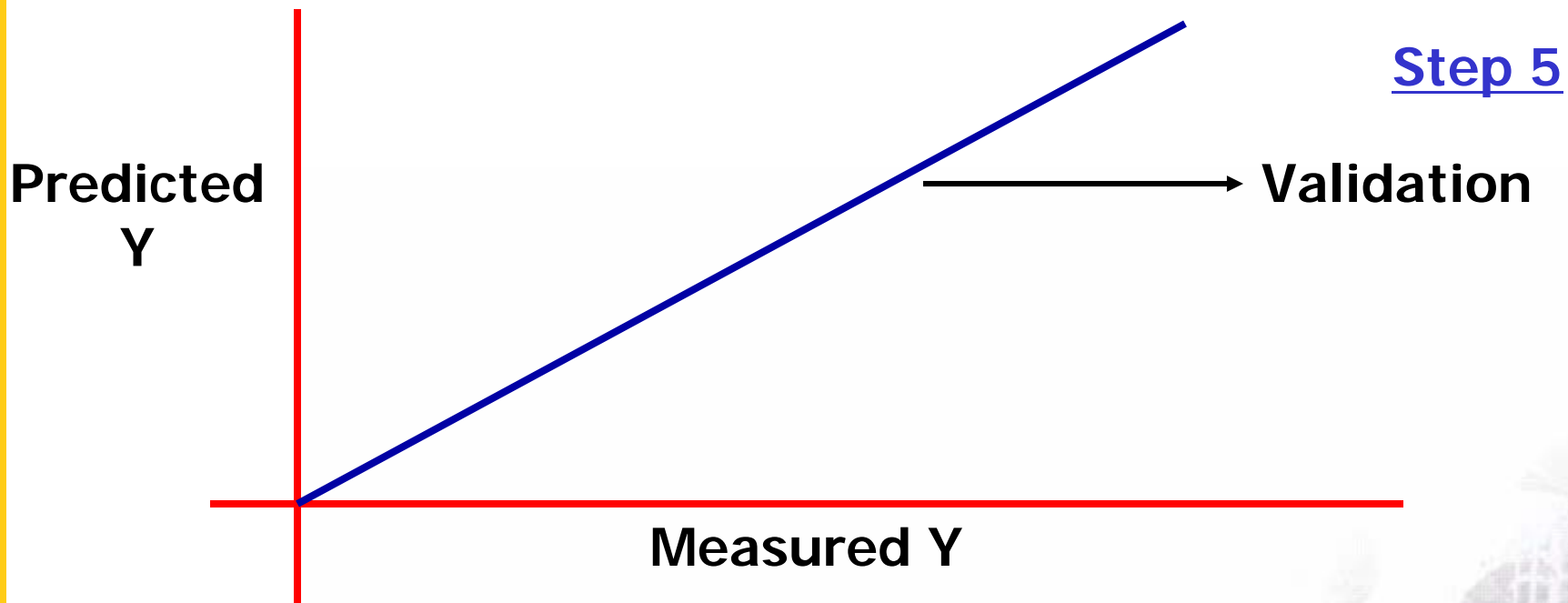
Calibration is performed from these calculated co-efficient to generate predictions (Predicted Y)

❖ Data Reconciliation – Step 4



The regressed line is tabulated on Measured Y v/s Predicted Y. SD error is RMSEC.

❖ Data Reconciliation – Step 5



The Calibrated Model is validated on the known sample set by Cross-validation technique.
SD error is RMSEV.

❖ Data Reconciliation – Step 6

Step 6

Unknown Sample from similar sample population is predicted from the Calibration Set.

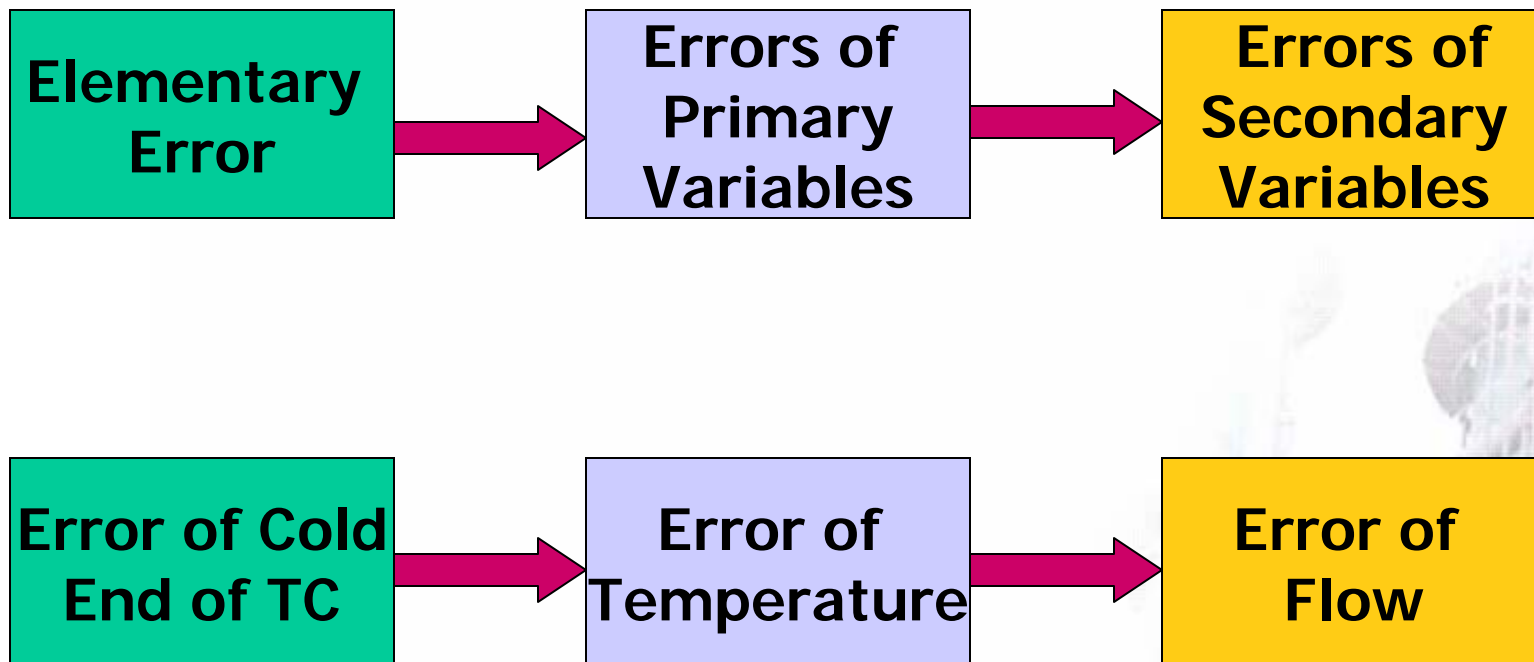
Gross error can also generate due to: [Step 7](#)

1. Process leaks. Typical is measurement design constraint as :

- Crude Type
- Energy Effcy
- Separation Effcy
- Treatment Effcy
- Catalytic and Rxns Effcy

Gross error can also generate due to: [Step 7](#)

2. Propagation of Measurement Error as :

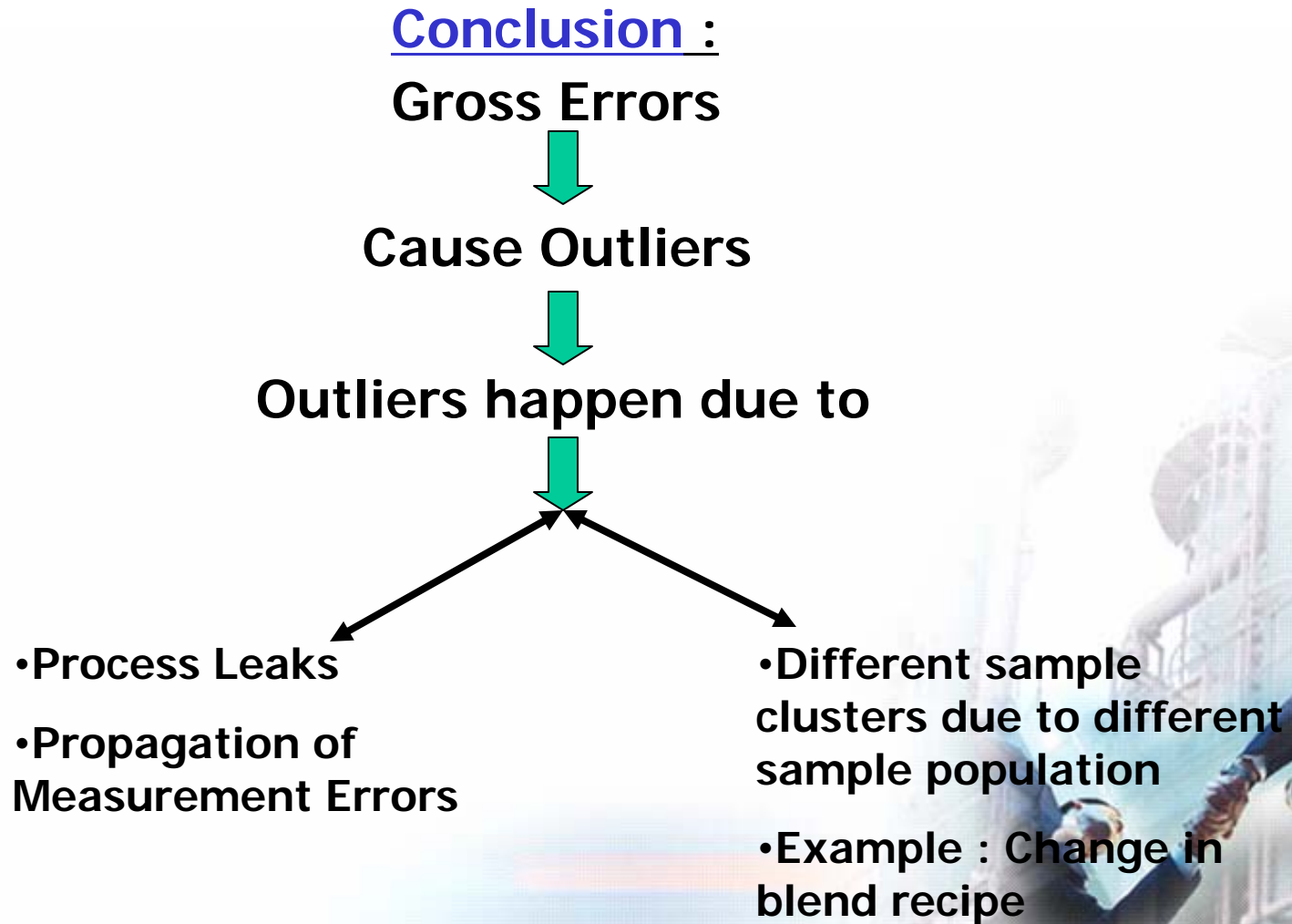


Ref. F.Madron, Data Reconciliation.

❖ Data Reconciliation thru' Gross Error Elimination – Step 8

To Eliminate gross errors in Steps 1 – 5, number of samples in a set should be large enough to be statistically significant

Step 8



➤ Benefits :

- NIR repeatability $\leq 2 \times$ RMSE \leq ASTM repeatability.
- NIR can achieve lower blending target octane numbers than traditional ASTM analyzers.
- Outlier alarm can be triggered if NIR value exceeds the threshold value of Blend target values.
- Process operators can take action to analyze outliers.
- Leads to predicted tank quality estimation.
- Saves on tank reblend.
- Saves on repeated manual analysis for final property values; multiple physical property analysis within scan time of few minutes
- Fast control decision if interfaced in control loop.
- Cost savings to users. NIR as a process optimization can lead to six sigma process control.
- OPEX reduction thru' improvements in 3Es (Energy, Environment, Emissions).

Thank you very much for your attention.

Comments : ?

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