Improve Measurement with Soft Sensors for Process Industries

with

No Drilling, No Intrusion, and No Additional Cost

Biao Huang, PhD, PEng, Professor

Department of Chemical and Materials Engineering

University of Alberta

Presentation at ISA Fort McMurray 04/18/11

Outline

- Research program overview
- Soft sensor introduction
- Soft sensor principles
- Soft sensor applications

Our Research Programs

- An on-going NSERC strategic project in Optimization of Process Automation Systems
- Another major industrial research program in Process Systems Engineering and Control to start soon.

Challenges

- harsh operating environment - reliability of instruments.
- unique process such as oil sands – no common solutions.
- lack of key measurements, irregular and missing data, bad readings, and outliers – need of inferential sensors
- a large amount of routine operating data – lack of tools for efficient use.
- requirement of no or minimum disruptions to operation - minimally intrusive test or use of routine operating data.
- hard constraints, non-Gaussian distribution, and non-linearity – advanced estimation and control

Research Objectives

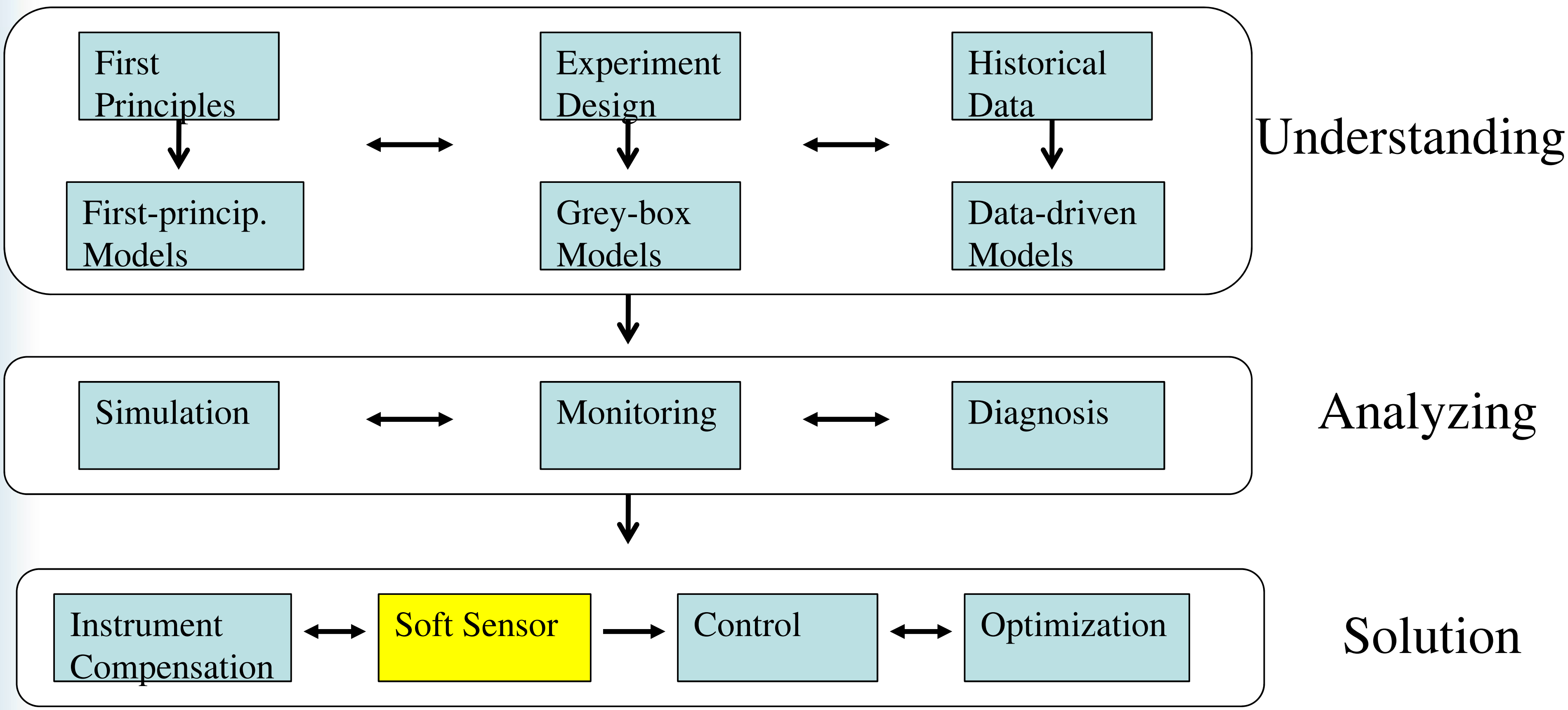
Objectives

Developing solutions for performance improvement of control systems within existing process control infrastructure for better

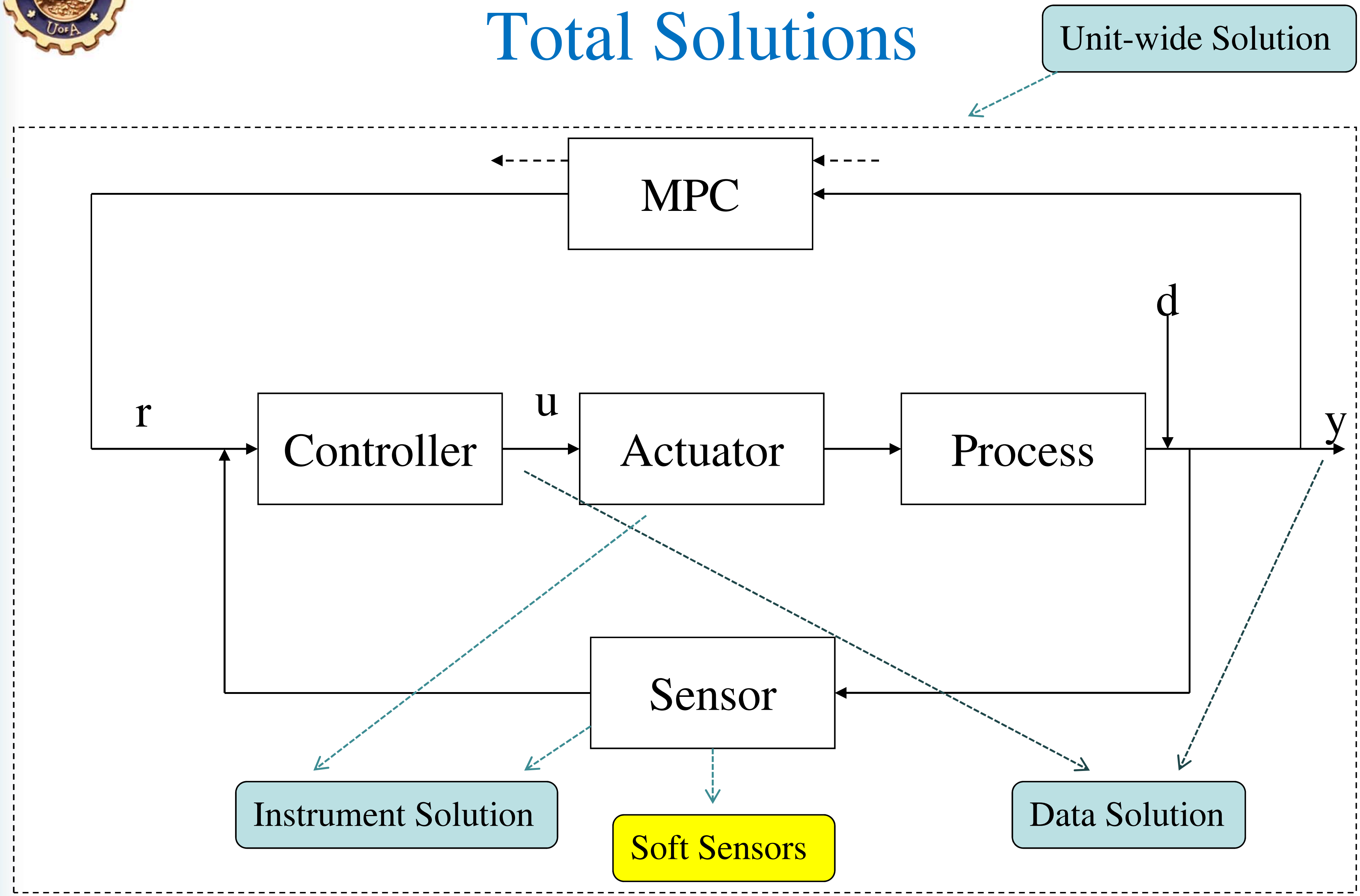
– monitoring and diagnosis
– instrumentation
– control
– unit-wide/plant-wide operations.

Scope and Methods

Scope and Approach



Total Solutions



This talk will focus on soft sensor solution

Soft Sensor Technology

Introduction

- Definition of soft sensor

  A mathematical model, correlating difficultly measured quality variables with the frequently and easily measured process variables.

- Purpose of soft sensor

  real-time predictions of the quality variables, monitor processes, design tighter control, fault detection and diagnosis.

- Properties of soft sensor

-- low cost alternative of expensive online analyzer

-- easily implemented on existing hardware and no additional investment

-- provide real-time estimation of quality variable, handling time delay and slow sampling rate of lab data

• Classification of soft sensor

(1) First principle or white-box model, obtained from the fundamental process knowledge.

Advantage:

-- good extrapolating property

Disadvantage:

-- requires a lot of process expert knowledge, effort and time to develop

(2) Data-driven or black-box model, multivariate statistical methods or artificial intelligence methods based on the data acquired during the process operation.

Advantage:

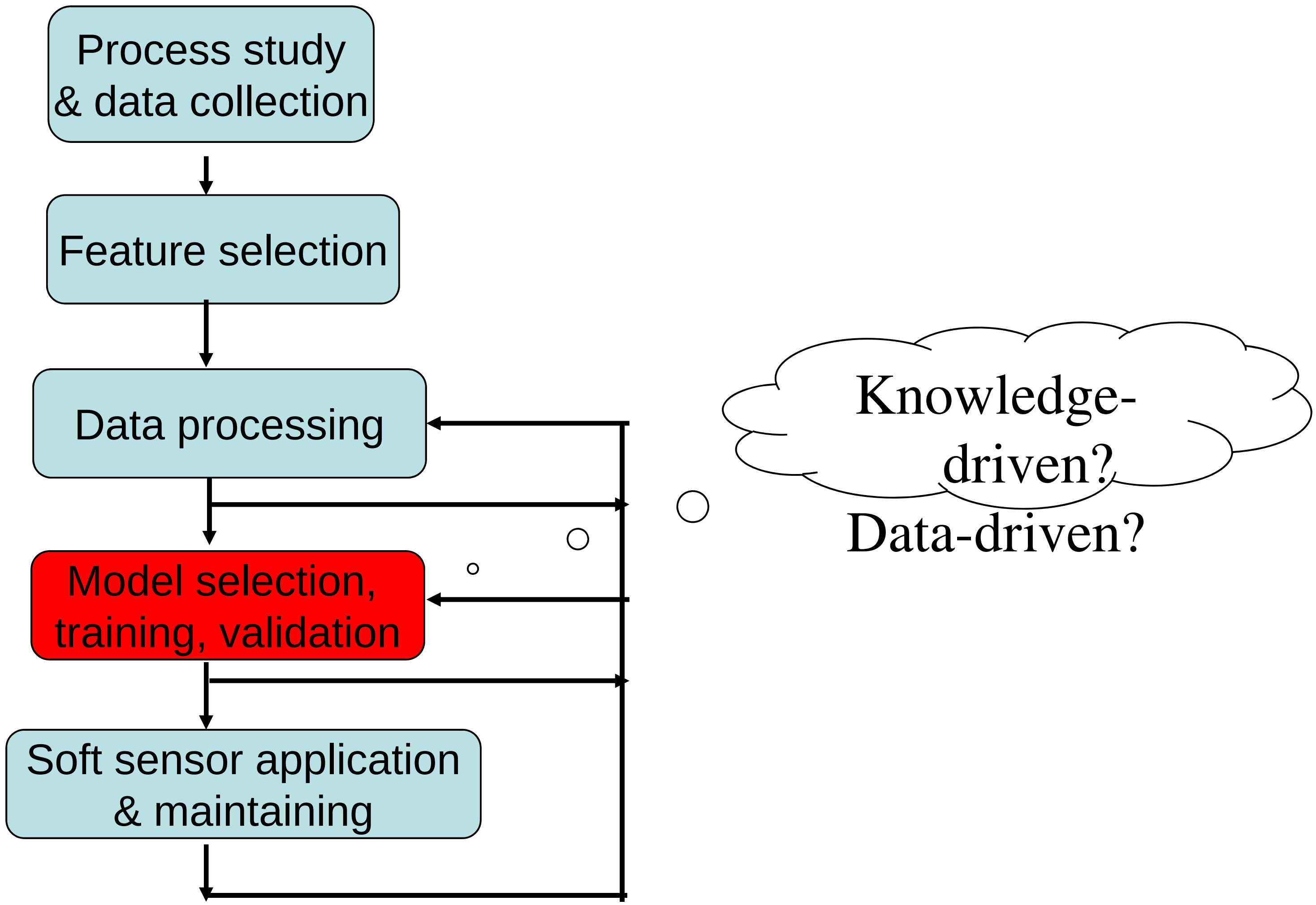
-- can be developed quick and cheap

Disadvantage:

-- depends on the quality of the historical data, deteriorate due to outliers, noises and missing data

(3) Hybrid model or grey-box model, combines the strength of both first principle model and data-driven model.

Soft Sensor Development



- Data collection and selection

-- sampling frequencies and locations of the hardware sensors

-- check if the input/output variable has enough variation – data quality assessment.

-- Select appropriate sections of the data; separate data for training and validation.

- Data pre-processing

(1) Missing data

-- *Cause*: abrasion or failure of hardware sensors, transmission errors, problems in accessing the database, missing data are inevitably existed in the recorded data with values like 0, inf and N/A.

-- *Handing of missing data*:

I. the mean value or the last observation before the missing one;

II. Case deletion;

III. Reconstruction by PCA, PLS, Maximum Likelihood,

Expectation Maximization and Bayesian theory.

(2) Drifting data

I. For process drift

-- *Cause*: Abrasion of mechanical components, and external influences like the purity variation and catalyst deactivation.

-- *Handling*: Recognize the drift, and take action to remove their cause or model it to compensate soft sensor.

II. For sensor drift

-- *Cause*: Abrasion of measurement devices.

-- *Handing*: Calibrate the measurement devices.

"Soft" solution: adaptive soft sensor based on recursive updates of the LS, PCA and PLS methods.

(3) Outliers

- Deviate from majority of data
- Can significantly affect soft sensor performance
- Should be detected and replaced by, for example, predicted value

(4) Measurement delays

-- *Cause*: transportation delay, measurements taken at the same time but at different locations.

-- *Handing*: synchronizing variables.

Uncertain delay such as lab sampling time is more difficult to handle and need advanced method such as Bayesian method

- Model selection, training and validation

(1) Model selection

-- *Structure selection*: based on the complexity of the process and the soft sensor objective.

I. linear or nonlinear model

II. static or dynamic model

III. First principles or dada driven

-- *Variable and regressor selection*

Regressor selection is essential for dynamic modeling.

I. Include the knowledge of process physics

II. Correlation Analysis

III. Using PLS or NPLS

(2) Model training

-- *linear model*:

LS, Prediction Error Method, Subspace Identification, Kalman Filter, EM, PCA, PLS…

-- *nonlinear model*:

Nonlinear version of LS, PCA, PLS; Extended KF, Artificial Neural Networks, Neuro-Fuzzy Systems, Support Vector Machines, Genetic Programming…

(3) Model validation

-- based on an independent data set.

-- residual tests

-- numerical method (MSE) and visual method.

- Soft sensor maintenance

The drifts of the process is a major problem, and need compensation either by adapting or re-developing the model.

Some adaptive approaches:

I. Moving window based techniques

II. Recursive version of LS, PCA, PLS…

III. Bayesian method

Good References

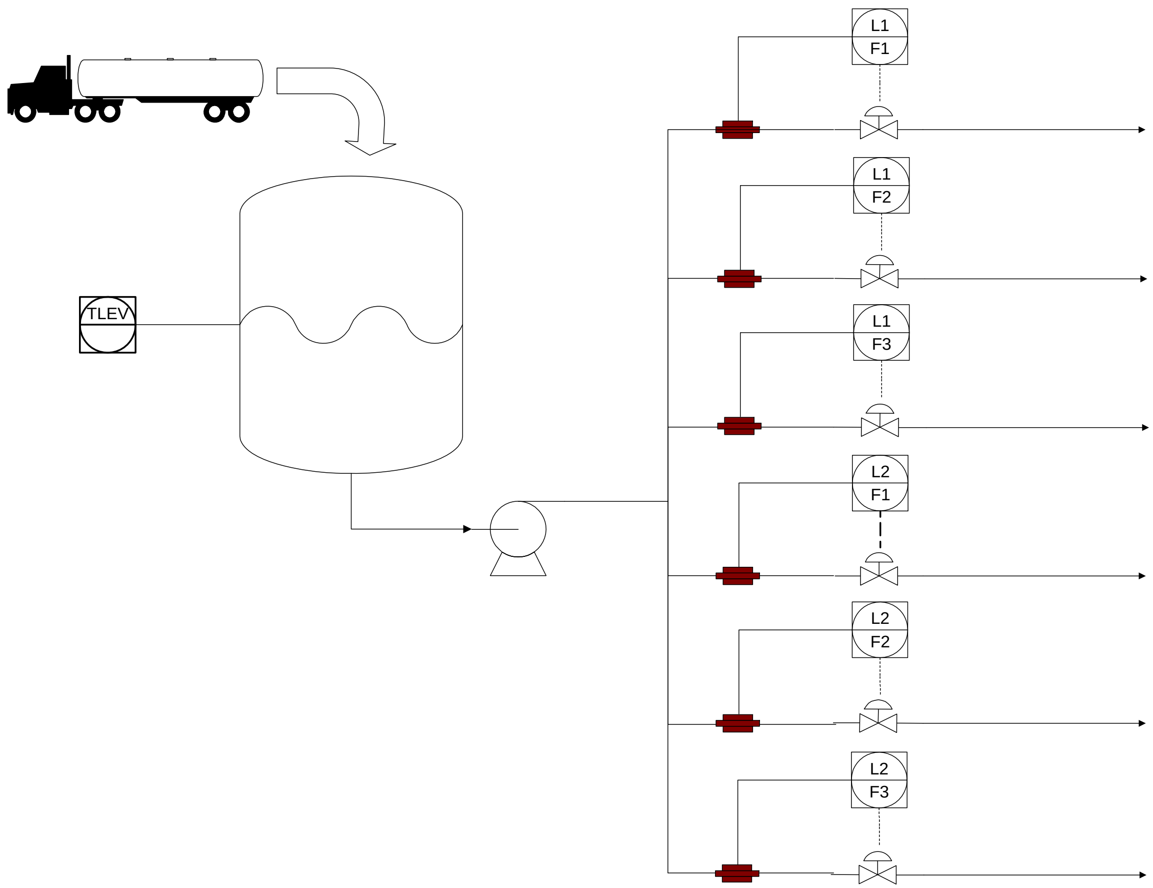
[1] Fortuna L, Graziani S, Rizzo A, Xibilia MG. Soft sensors for monitoring and control of industrial process. Springer, 2007.

[2] Kadlec P, Gabrys B, Strandt S. Data-driven soft sensor in the process industry. Computers and Chemical Engineering, 2009, 33 (4): 795–814.

[3] Kadlec P, Grbic R, Gabrys B. Review of adaptation mechanisms for data-driven soft sensor. Computers and Chemical Engineering, 2011, 35 (1): 1–24.

Soft Sensor Principles

Example: Tank Inventory System



Understanding the process

$$\rho \frac{dV}{dt} = F_{in} - \sum F_{out}$$

where,

ρ, is the density of the liquid

V, is the volume

F_{in}, is the inlet flow rate

F_{out}, is the outlet flow rate

Mathematical Redundancy

$$\rho V(t) - \rho V(t-1) = \left(F_{in}(t) - \sum F_{out}(t)\right)T$$

where T is sampling interval

$$V(t) = V(t-1) + \frac{\left(F_{in}(t) - \sum F_{out}(t)\right)T}{\rho}$$

Mathematical Redundancy

Add a noice term to consider modeling error and disturbance effect

$$V(t) = V(t-1) + \frac{\left(F_{in}(t) - \sum F_{out}(t)\right)T}{\rho} + w(t)$$

If $V(t-1), F_{in}(t), F_{out}(t)$ are known, $V(t)$ can be predicted - equivalent to another sensor (soft sensor).

On-line analyzer

Consider there is real-time volume measurement (on-line "analyzer") possibly inaccurate with bias and noise

$$V^m(t) = V(t) + b(t) + v^m(t)$$

Lab (camera in this case) samples

Consider there is a slower volume measurement through a camera (or lab analysis), accurate but slower

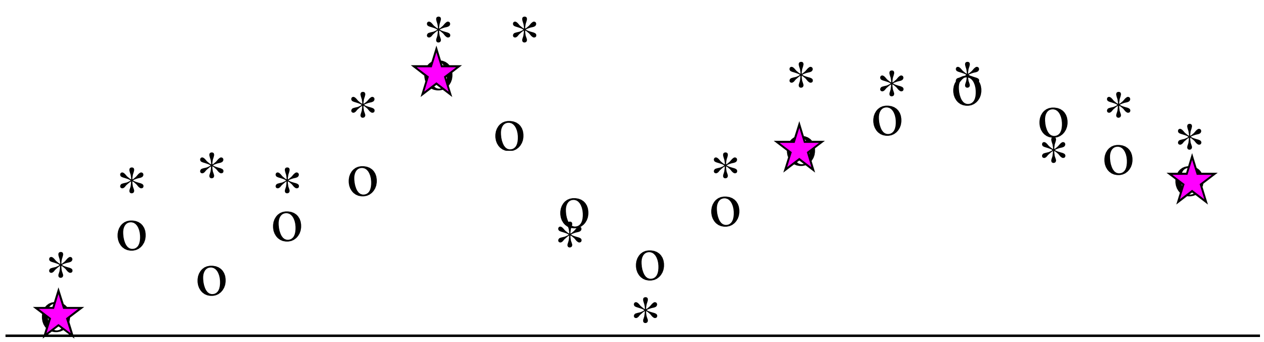
$$V^c(T) = V(T)$$

Putting together

$$\begin{cases} V(t) = V(t-1) + \dfrac{\left(F_{in}(t) - \sum F_{out}(t)\right)T}{\rho} + w(t) \\ V^m(t) = V(t) + b(t) + v^m(t) \\ V^c(T) = V(T) \end{cases}$$

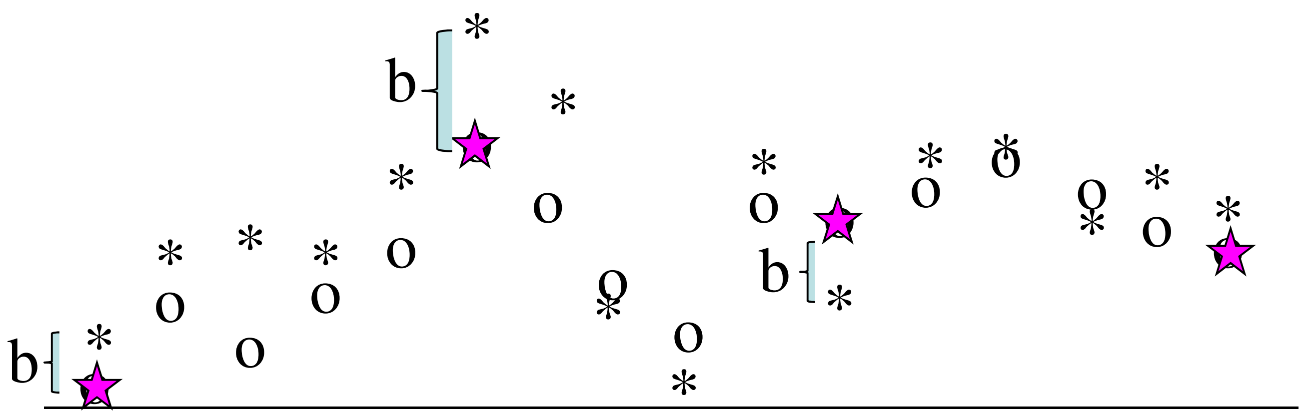
This is known as dynamic soft sensor model

Data trend



o real volume
* on-line hardware sensor (“analyzer”)
★ camera (“lab” analysis)

Conventional bias update



o real volume
* on-line hardware sensor
★ camera

Limitation of conventional approach

- Omit mathematical redundancy
- Omit measurement noise effect
- Assume bias is constant from one lab sample until the next lab sample

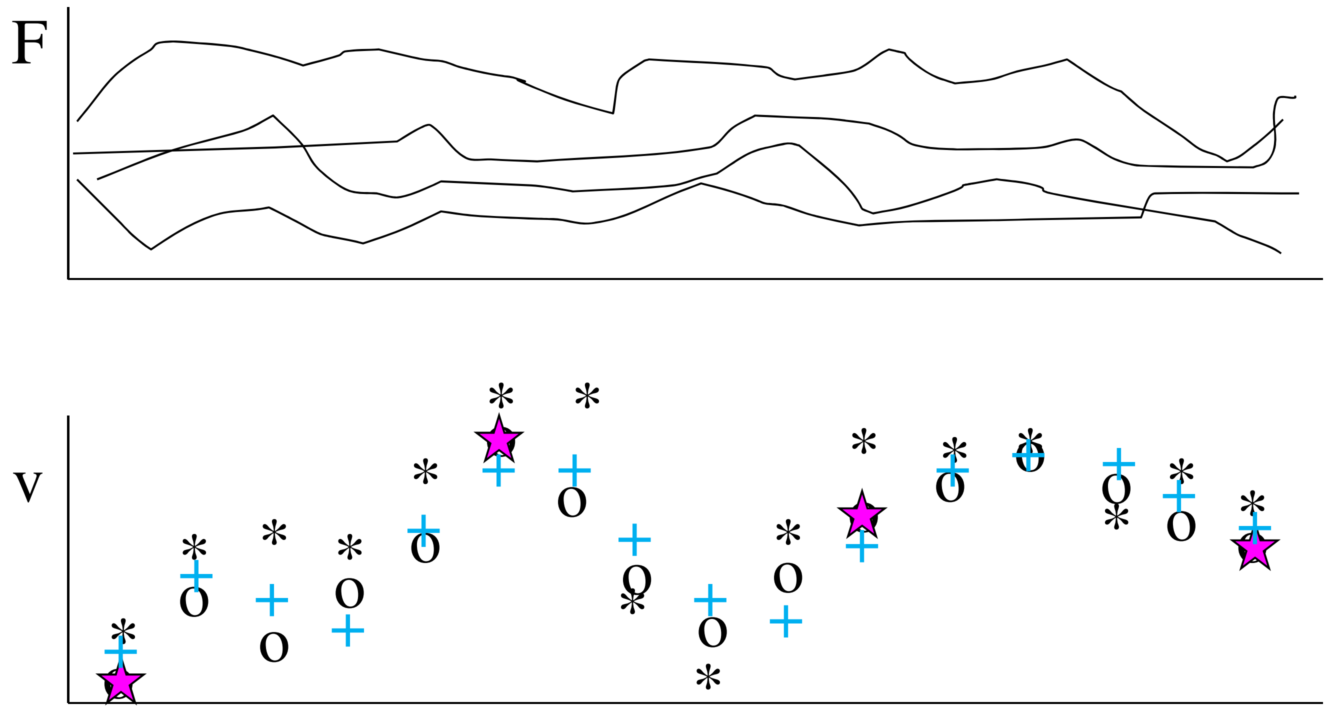
Data driven method: LS, PLS, SVR, etc

According to available variables: $V^c(t), V^m(t), F_{in}(t)$, 6 $F_{out}(t)$'s

Simply build a model to relate $V(t)$ to $V^m(t)$, $F_{in}(t)$, 6 $F_{out}(t)$'s

$$V^c(t) = \alpha_1 V^m(t-1) + \alpha_2 F_{in}(t) + \alpha_3 F_{out}^1(t) + \ldots$$

Data driven methods: LS, PLS, SVR, etc



o real volume
* on-line hardware sensor
★ camera
\+ predicted

Data-driven method

- Simple
- Often the first method to try
- Often use "too many" variables, poor robust
- Poor extrapolation performance
- Multi-rate problem is not optimally handled
- Bias update is separated

Bayesian Method

$$p(Query \mid All\, Observations) = kp(All\, Observations \mid Query)\, p(Query)$$

Posterior

Likelihood

Prior

Bayesian Method

- Infer query using all observations available
- Can incorporate prior information such as process knowledge, flowchart, etc.
- Automatically incorporate useful information and discard non-useful one
- Can provide confidence interval of the inference
- Solve query problem systematically and optimally

Bayesian Soft Sensor

- Can handle missing data, outlier, multi-rate, multi-mode, bias update, noise, etc simultaneously and optimally
- Can learn by itself progressively
- With appropriate design, no poorer performance than any of "existing" sensor – worst case scenario

Who is Bayes?

- Thomas Bayes, British mathematician, and Presbyterian minister(1702-1761)

Who is Bayes?

- Most significant contribution:
  - Proposed Bayes's rule in '*An Essay Towards Solving a Problem in the Doctrine of Chances*'
- Not known until his death
  - Was found after his death by Richard Price, and was published in 1763

Nowadays

Microsoft's competitive advantages is its expertise in "Bayesian networks"

Gates [LATimes, 28/Oct/96]

Bayesian Soft Sensor Applications

Sample industrial applications

- Oil sands froth treatment N2B ratio soft sensor
- Water content soft sensors
- Steam quality soft sensors for steam generator
- O2 soft sensor for H2 combustion tank
- N/C ratio soft sensor in the HP synthesis loop
- PSV tailing bitumen content soft sensor
- PSV interface soft sensor
- …

Beyond

- Each soft sensor is unique
- Developing soft sensor is challenging
- Working with practitioner together is key to success
- Successful soft sensor application is operationally and economically appealing
- We are working for many other soft sensors

Acknowledgement

Our current industrial partners/collaborators:

- Syncrude
- Suncor
- Suncor In-situ
- Sherritt
- Agrium

Acknowledgement

Students and PDFs who have contributed to the work:

- Xinguang Shao
- Yu Miao
- Da Zheng
- Shima Khatibisepher
- Jing Deng
- Li Xie
- Yu Zhao
- Yijia Zhu
- Xing Jin

Welcome more industries to participate in our R&D program

Contact: biao.huang@ualberta.ca
www.ualberta.ca/~bhuang