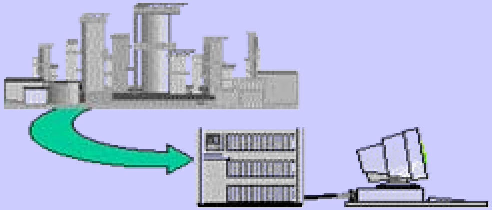
APS Forum
Balatonfüred, May 25-26th 2011

SOFT SENSORS APPLICATION IN PROCESS INDUSTRY



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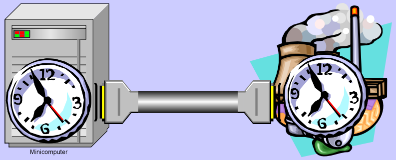
MEASUREMENT PROBLEMS

- Difficult to provide reliable, fast, on-line measurements to control product quality

- **The quality measure may only be available as a laboratory analysis or very infrequently on-line**

→ Lead to excessive **off-specification** of products

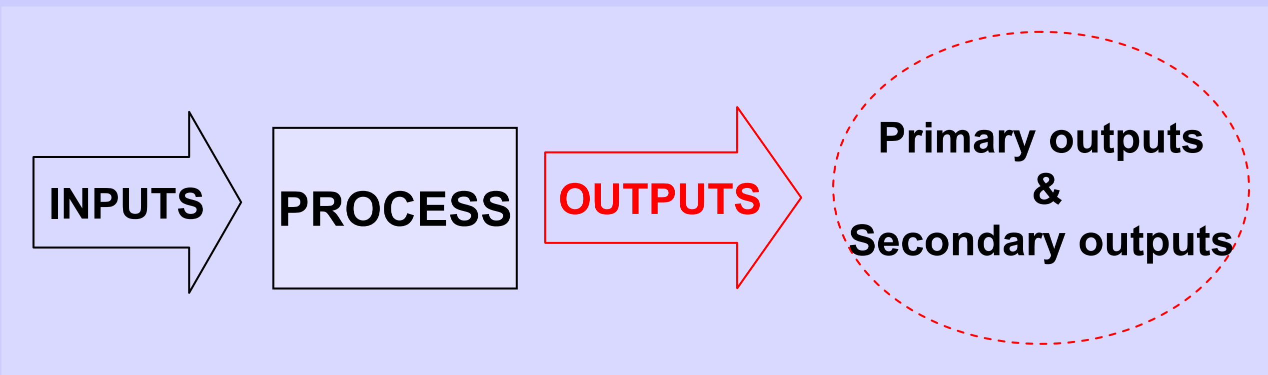
- **Reliability of on-line instruments**
(drifting, fouling, sample system failure etc.)

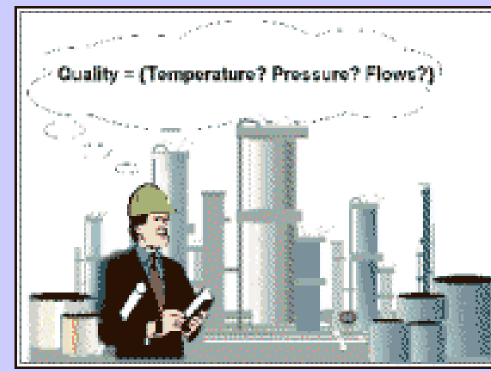


Automatic control and **optimisation** schemes **cannot be implemented.**

MEASUREMENT PROBLEMS

- Productivity is quantified by specifications upon which the product is sold - e.g. **purity**, **physical** or **chemical properties**
  → ***primary* variables** – difficult to measure on-line





- The other outputs (e.g. temperature, flow and pressure)
  → ***secondary variables*** - easily measured on-line

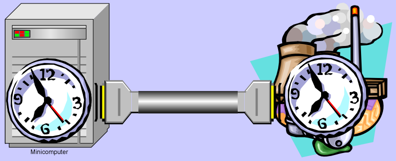
POSSIBLE SOLUTIONS

MANUAL CONTROL

- common approach to effecting control on the process is to control it **manually**

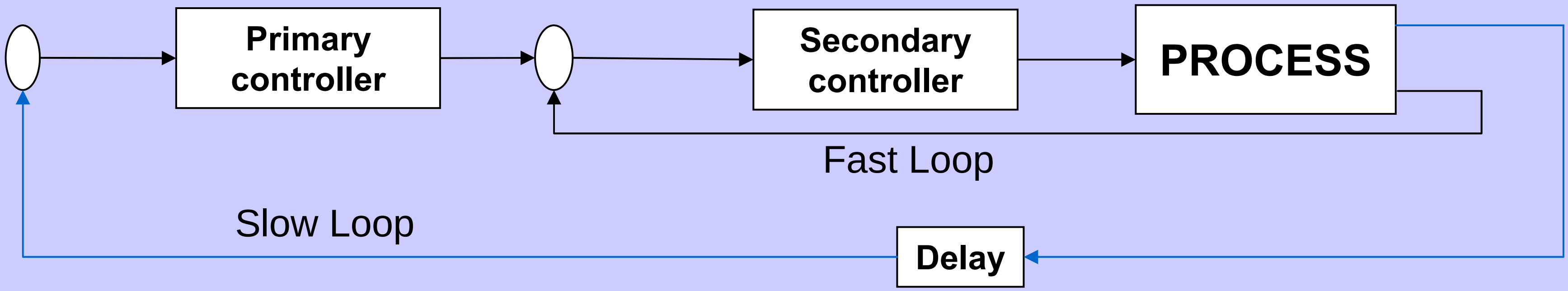
- Return of information for control purposes from laboratory is **slow** and **irregular**

- Its success depends on the operator's **training** and **experience**



POSSIBLE SOLUTIONS

PARALLEL CASCADE CONTROL



- The slow loop dictated by the delay of a measurement device

- Assumption:
  If the **secondary** variable is kept at some value,
  then the **primary** variable also be kept at some level

- Slow loop is used to correct (trim) the set-point of the secondary loop

Parallel Cascade Control

- often employed in the product composition control of **distillation columns**
- Two control loops:

  fast ***secondary*** loop - a **tray temperature**

  slow ***primary*** loop - **product compostion**

Drawbacks

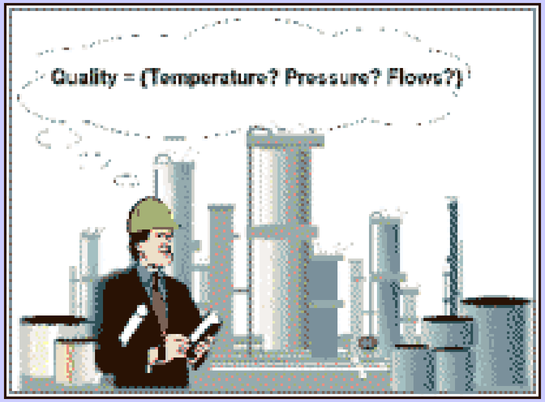
- **Disturbances** affecting the secondary variable may not affect the primary variable

- The relationship between the primary and secondary variables is **non-linear**, and can change depending on the **operating conditions**

POSSIBLE SOLUTIONS

INFERENTIAL MEASUREMENT

allows process quality, or a difficult to measure process variables, to be inferred from other easily made plant measurements such as pressure, flow or temperature.



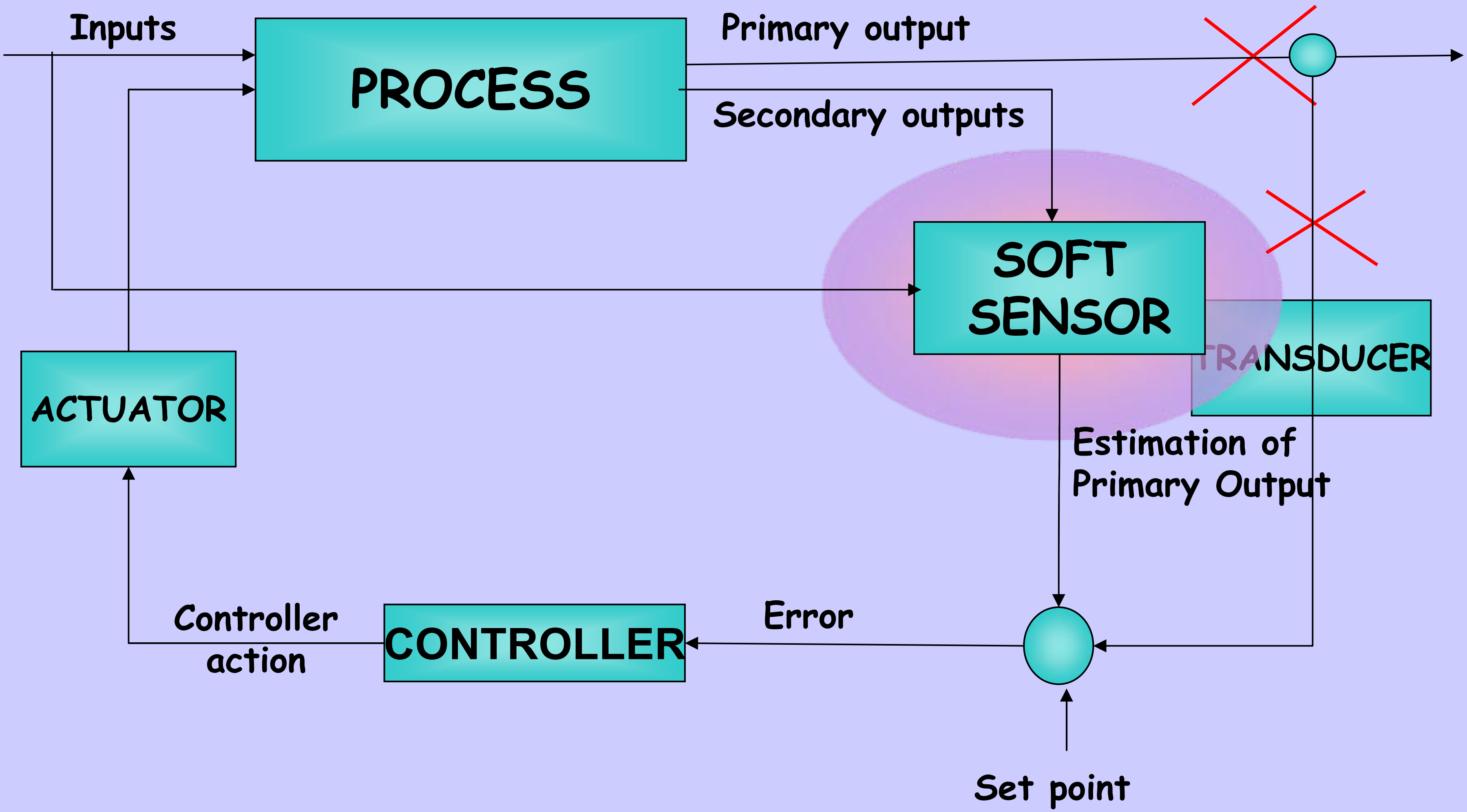
SOFT(WARE) SENSOR

Model which estimates unmeasurable process states based on easy to measure input and output variables.

KEY WORDS & SYNONYMS

software sensor, virtual soft sensor, smart sensor
virtual analyzer, inferential control

SOFT SENSOR AND INFERENTIAL CONTROL



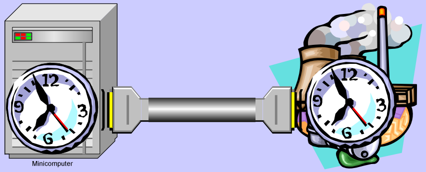
Criteria for soft sensor application

Inferential variable must satisfy the following criteria:

- Good **relationship** to true **controlled variable** for changes in the potential **manipulated variable**

- **Insensitive** to changes in **operating conditions** and unmeasured disturbances

- **Dynamics** must be acceptable for use in **feedback control**



Types of models for soft sensor developing

First principle models

- Based on balance and phenomenological equations
- Process knowledge required
- Comparatively expensive

Data driven models

- Identified using process data
- Comparatively inexpensive

Model structures and idenfication techniques

	Steady state	Dynamic
Models	• Multiple Linear Regression • PCA and PLS • Neural Networks	• Finite Impulse Response • ARX, ARMAX, OE, BJ, … • …
Identification	• Least Squares • Backpropagation • Numerical optimization	• Least Squares • Subspace identification • Prediction error methods • Numerical optimization

SOFT SENSOR MODEL DEVELOPMENT

SYSTEM IDENTIFICATION METHODS

Regressors	Linear model	Nonlinear model
u(k-i)	FIR	NFIR
u(k-i), y(k-i)	ARX	NARX
u(k-i), ŷ(k-i)	OE	NOE
u(k-i), y(k-i),e(k-i)	ARMAX	NARMAX
u(k-i), y_s(k-i),e(k-i) i e_s(k-i)	BJ	BJ

$$y(k)= f[u_1(k-1),\ldots,u_1(k-n_1),u_2(k-1),\ldots,u_2(k-n_2),\ldots,u_m(k-1),\ldots,u_m(k-n_m)]$$
$$y(k)= f[y_1(k-1),\ldots,y_1(k-n_1),y_2(k-1),\ldots, y_2(k-n_2),\ldots, y_m(k-1),\ldots,y_m(k-n_m)]$$

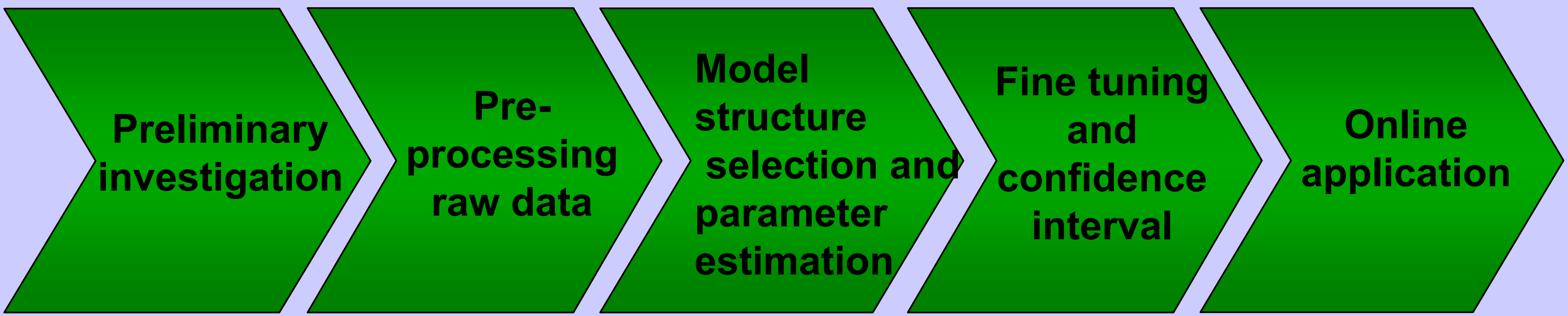
FIR – **F**inite **I**mpulse **R**esponse model
ARX – **A**uto **R**egresive model with e**X**ogenons inputs
OE – **O**utput **E**rror model
ARMAX – **A**uto **R**egresive **M**oving **A**verage model with e**X**ogenons inputs
BJ – **B**ox - **J**enkins model

DEVELOPING DATA-DRIVEN MODELS

- Feasibility
- Requirements
- Experiences

- Integration of knowledge
- Linear / non linear
- Steady-state / dynamic

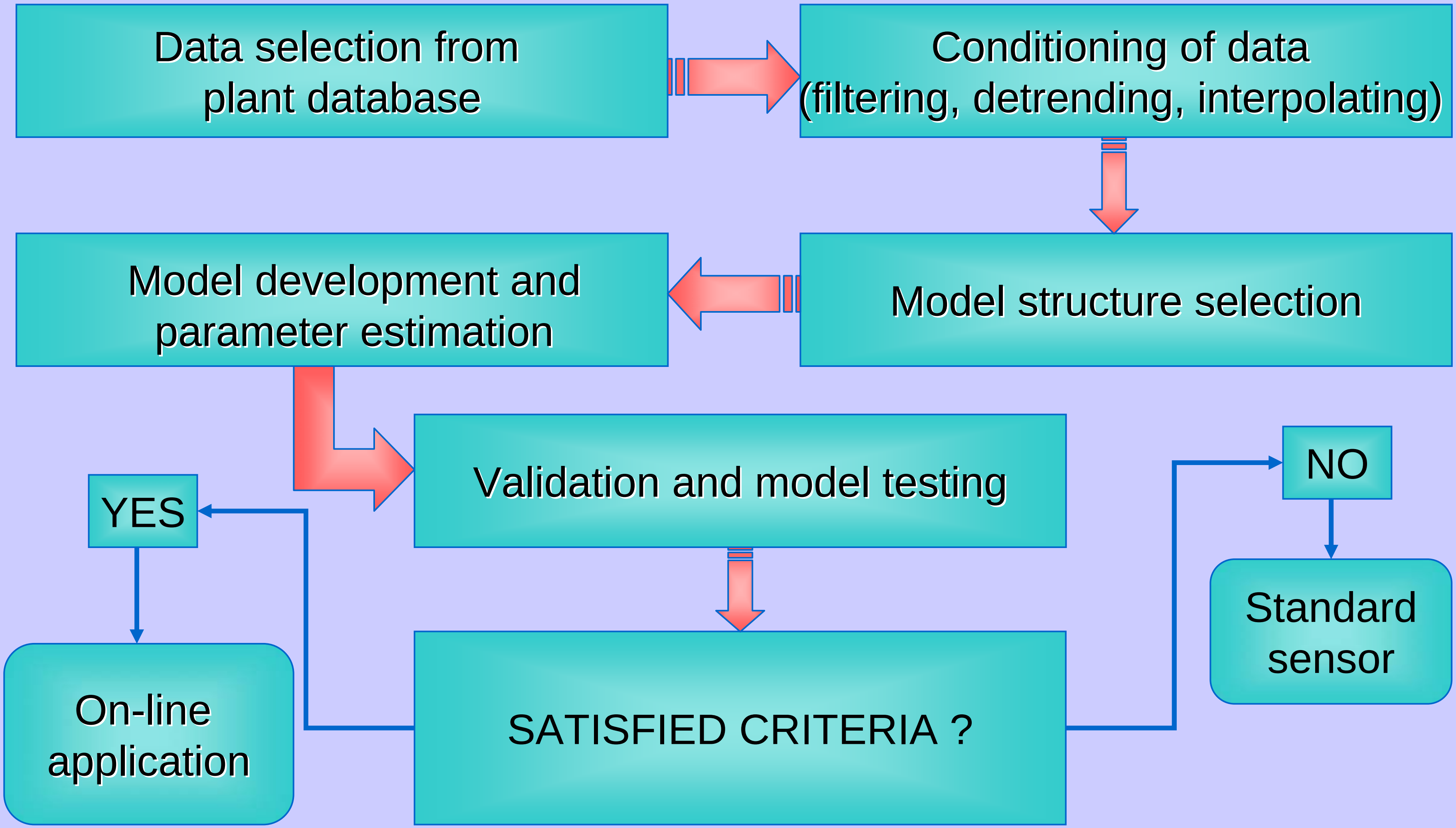
- Noise
- Disturbances
- Maintenance



- Validation
- Interpolation
- Outlier detection

- Analysis
- Sensitivity analysis

SOFT SENSOR DESIGN PROCEDURE



INDUSTRIAL APPLICATION

Back Up of Measuring Devices

during failures, maintance, services etc.

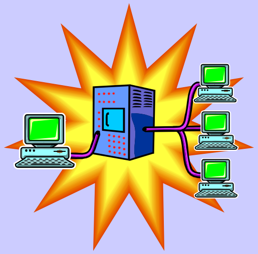
- **harsh working environment** and robust measuring hardware

- an inferential model for substituting **unavailable measuring equipment**

- two possible choice of model structure:

  - **MA** or **NMA** models which do not require past samples of the output variable (FIR)

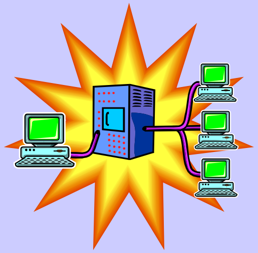
  - **AR** as infinite-step-ahead predictors



INDUSTRIAL APPLICATION

Reducing the Measuring Hardware Requirements

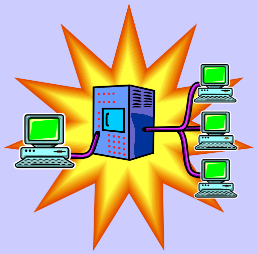
- software tools which substitute measuring hardware devices
- **NMA** models should be preferred to **AR** structures
- the problem is lack of any redundancy



INDUSTRIAL APPLICATION

Real-time Estimation for Monitoring and Control

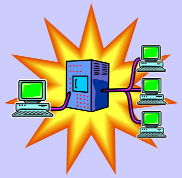
- long analyze time delay and transportation delay
- delay in the time in which data are presented to operator
- allows the use of **ARX** and **NARX** model structures for finite step-ahead prediction



INDUSTRIAL APPLICATION

Sensor Validation, Fault Detection and Diagnosis

- part of the supervision functions in the control systems
- comparing information collected from the system with the corresponding information from a **redundant source**



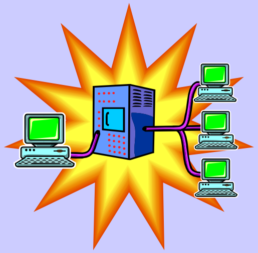
- **the main goals:**

  - early **detection of faults**
  - provide a **decision support system** for scheduled, preventive or predictive maintenance and repair
  - base for the development of fault-tolerant systems

INDUSTRIAL APPLICATION

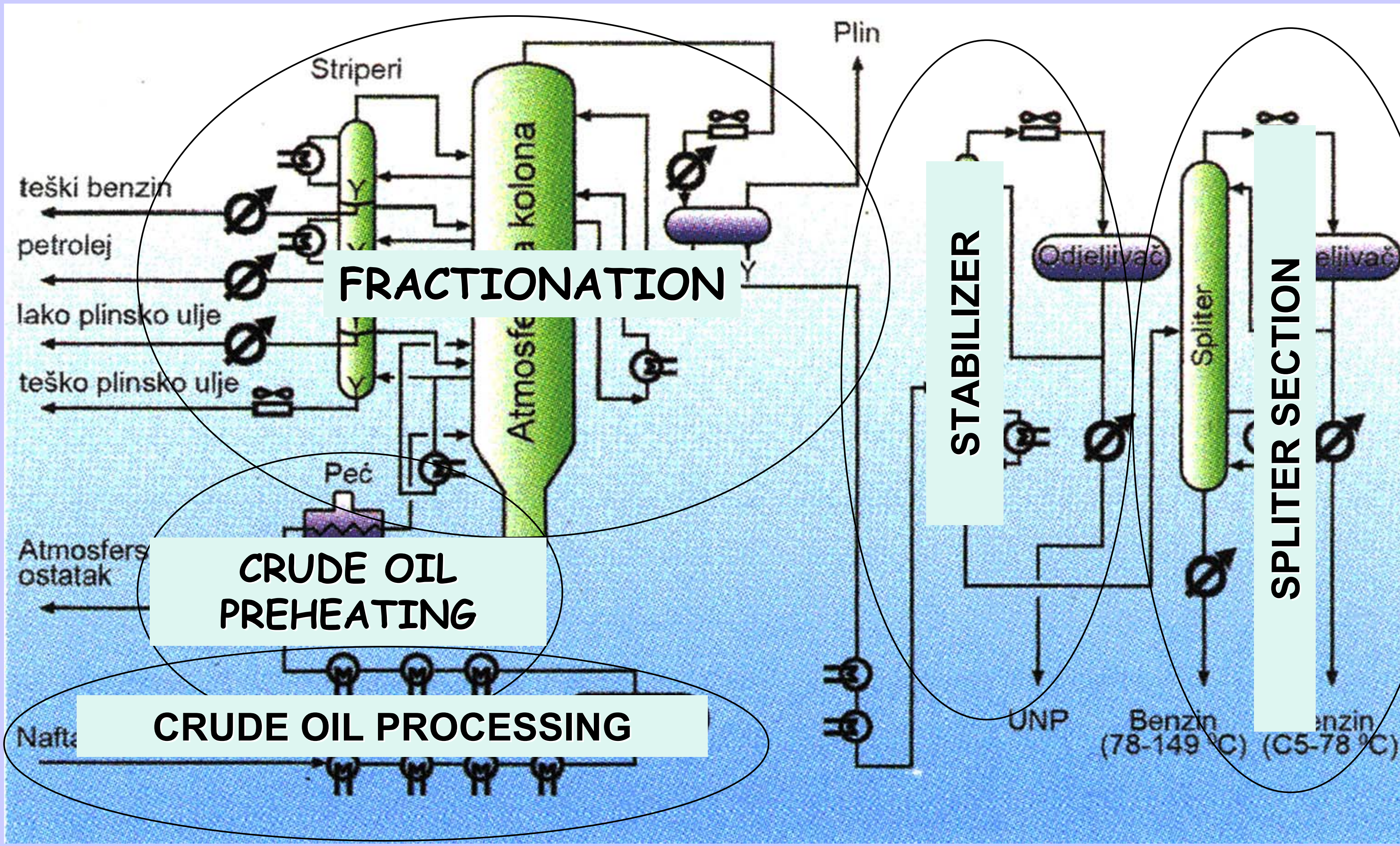
What-if-Analysis

- models that predict the system output to suitable input trends for a given time span
- simulation of the system dynamics to input trends of interest
- **NARX** models with finite time span used in simulations

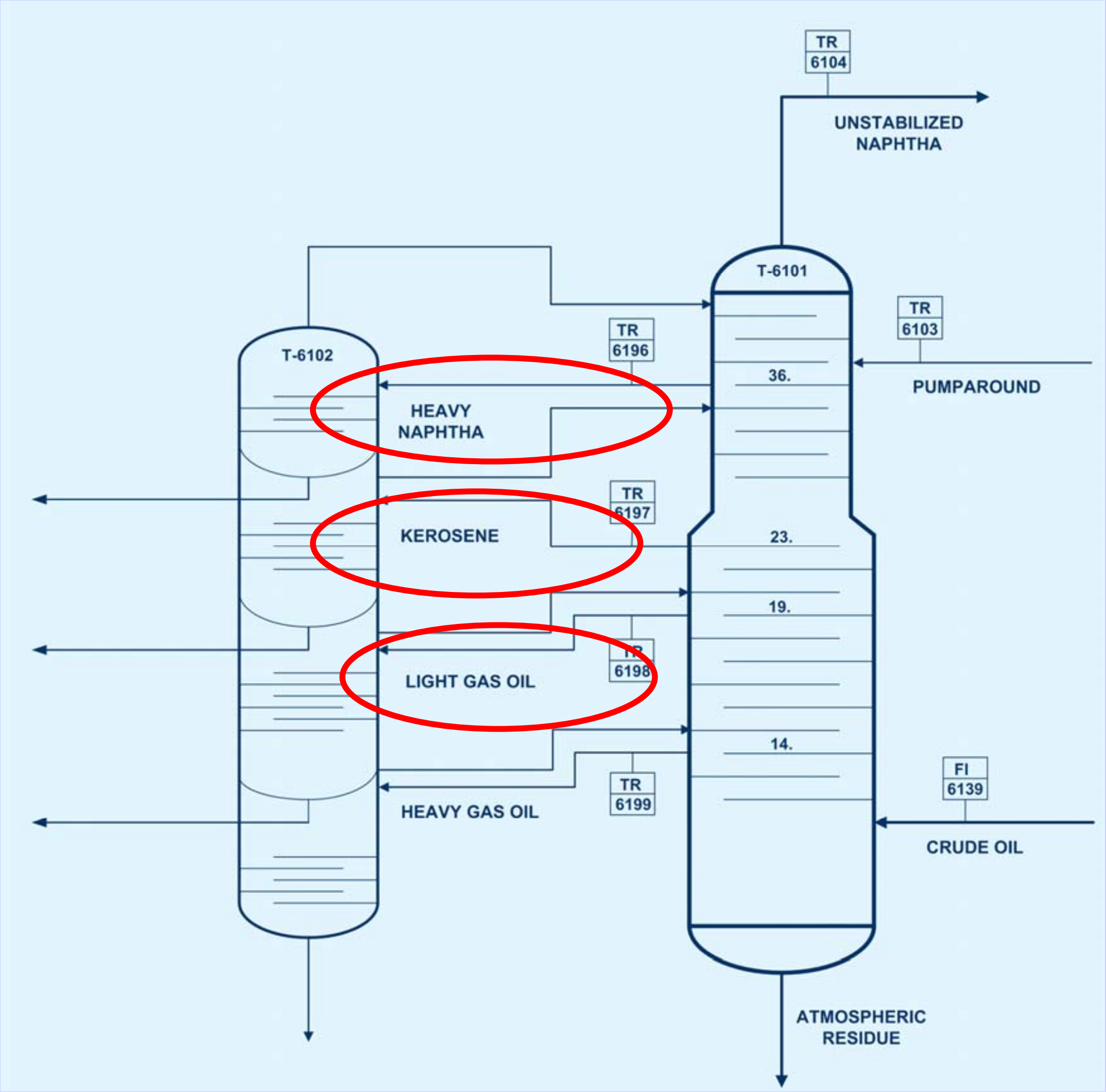


Case Study
CRUDE DISTILLATION UNIT
INA-SISAK REFINERY

CRUDE DISTILLATION UNIT



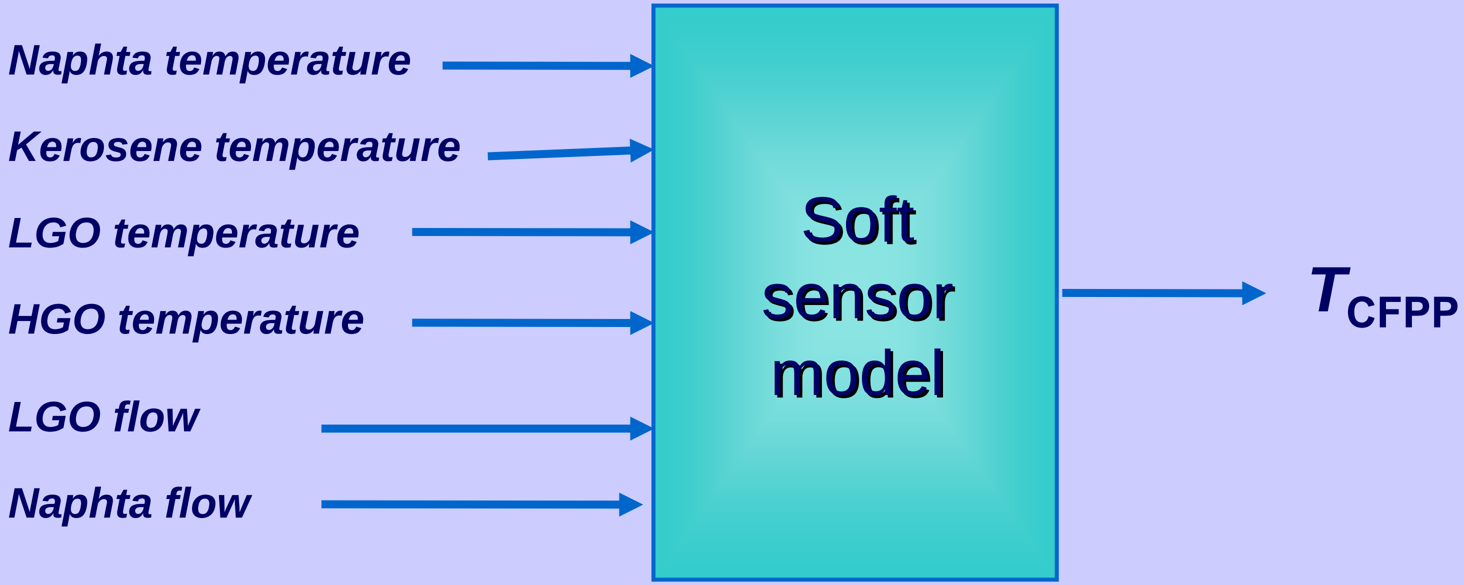
DIESEL FUEL SOFT SENSOR MODELS



DIESEL FUEL SOFT SENSOR MODELS

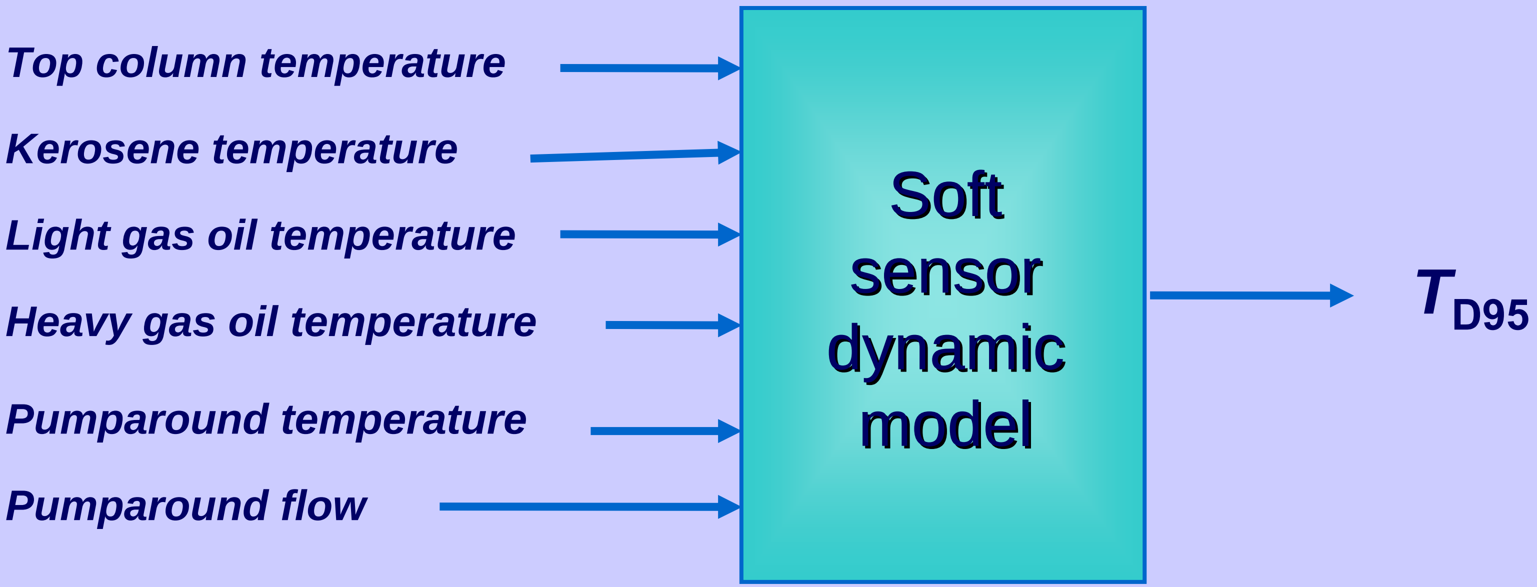
- Developed models for:
  - **Cold filter pluging point** estimation (CFPP)
  - **Distillation end point** estimation (D95)
- Models are developed using:
  - multiple linear regression
  - neural networks (MLP, RBF)

Neural network model structure for CFPP



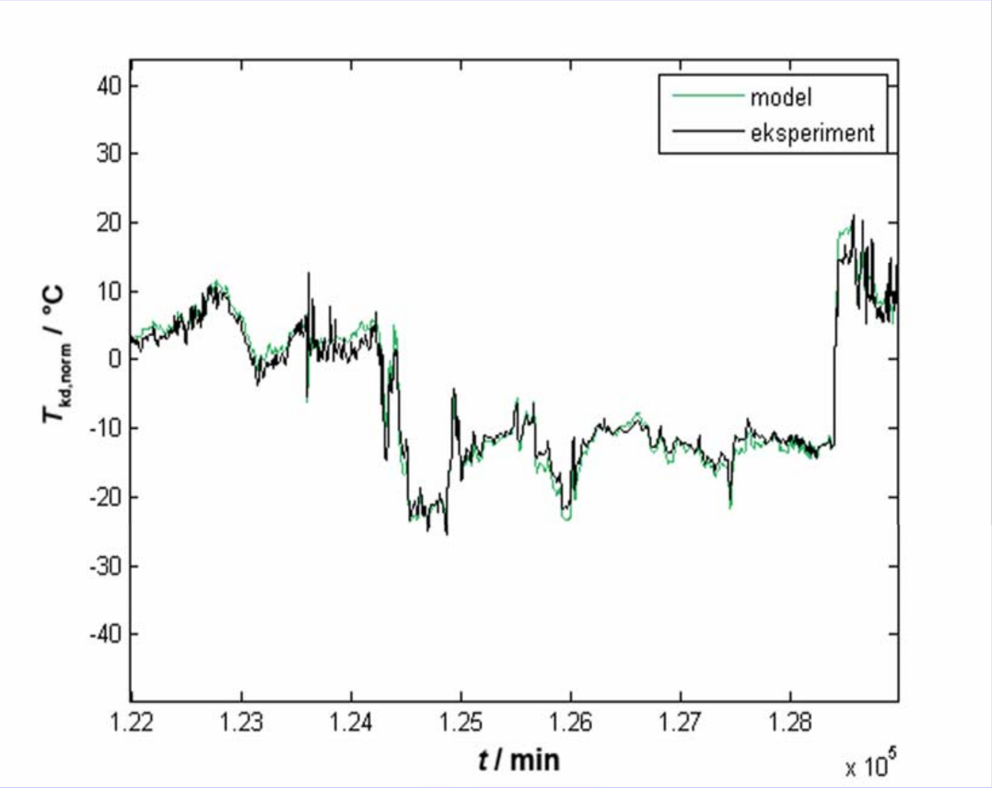
Multilayer perceptron neural network

SOFT SENSOR FOR DISTILLATION END POINT



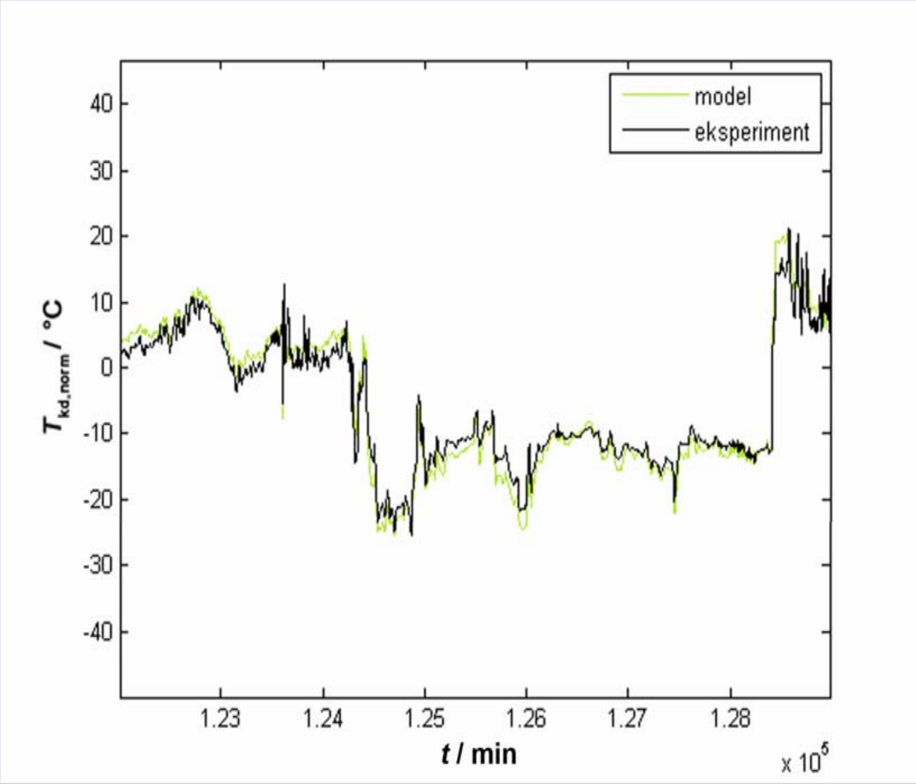
RESULTS – linear dynamic model (D95)

ARMAX model



FIT PRED.	*FPE*	MODEL PARAMETER
89,46	1,58	na = 3, nb = 3, nc = 6, nk = 0

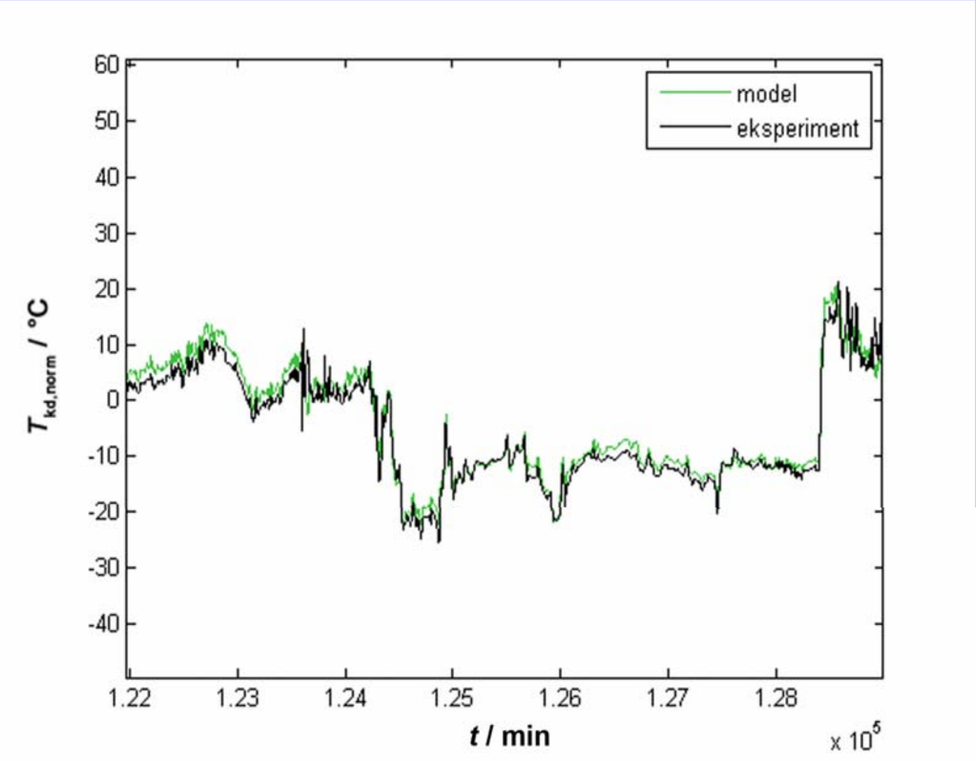
OE model

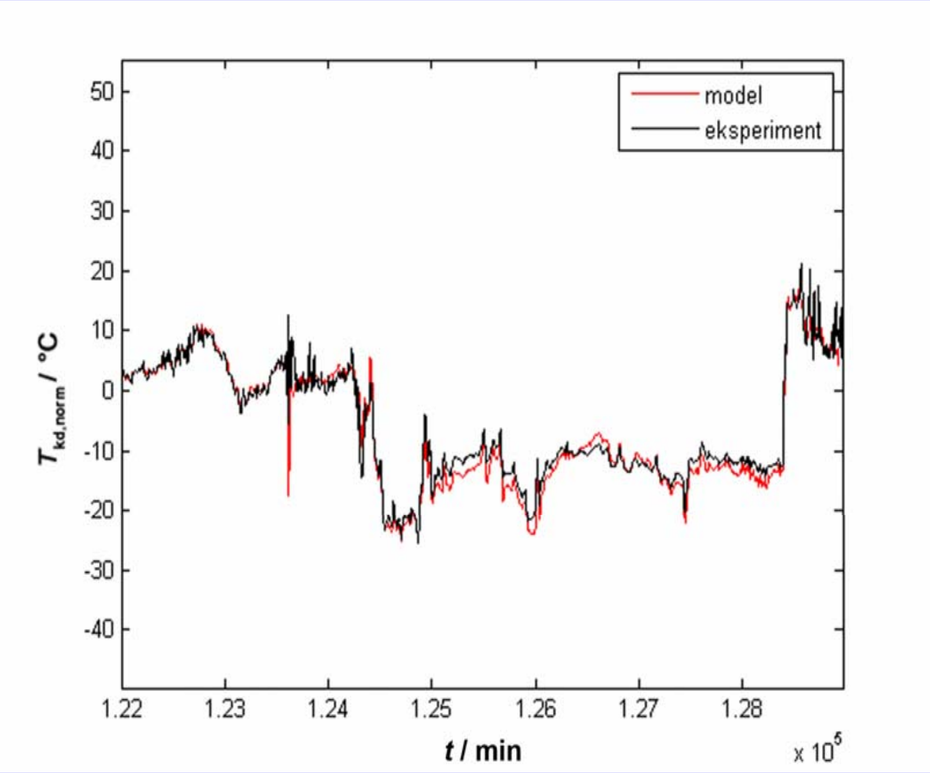


FIT PRED.	*FPE*	MODEL PARAMETER
83,50	6,09	nb = 2, nf =6, nk=0

RESULTS - Nonlinear dynamic models (D95)

HW and NARX model with sigma neural networks



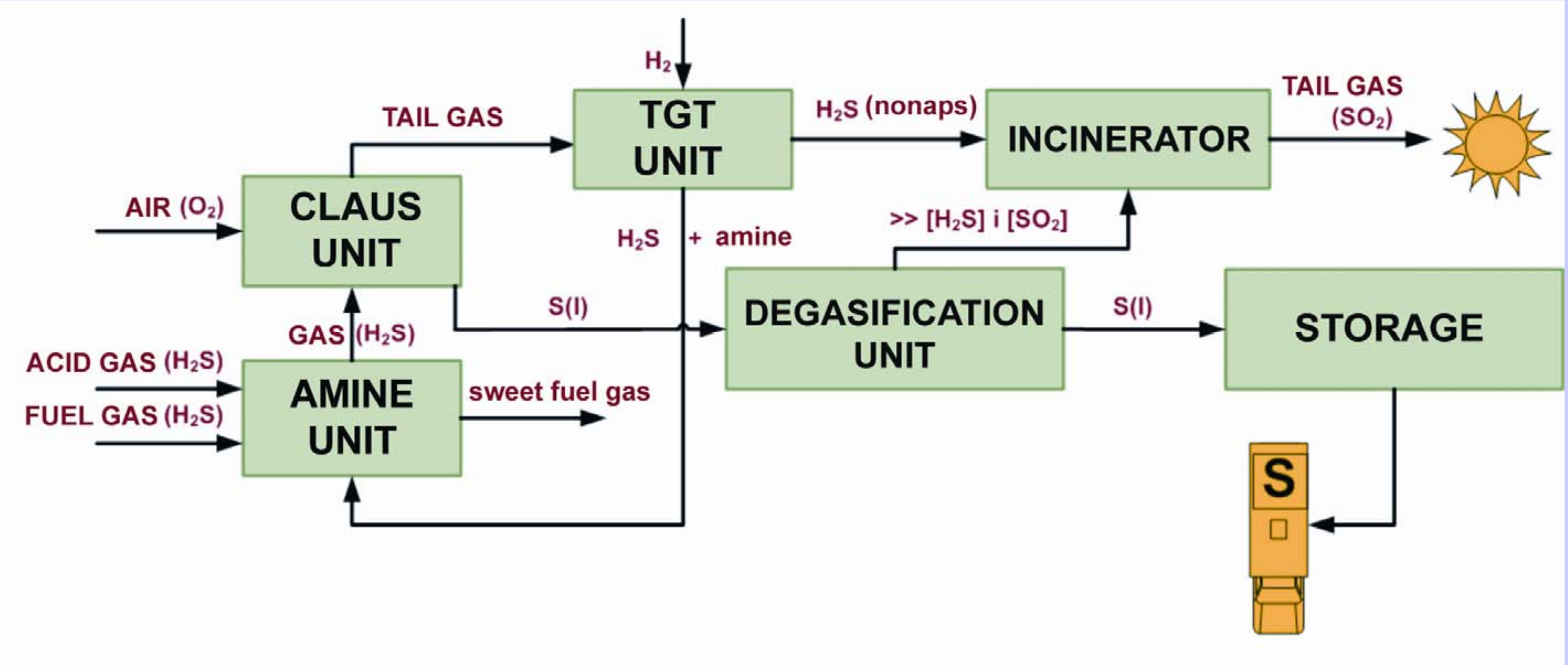


FIT PRED.	*FPE*	MODEL PARAMETER
81,07	4,97	nb = 2, nf =3, nk=0

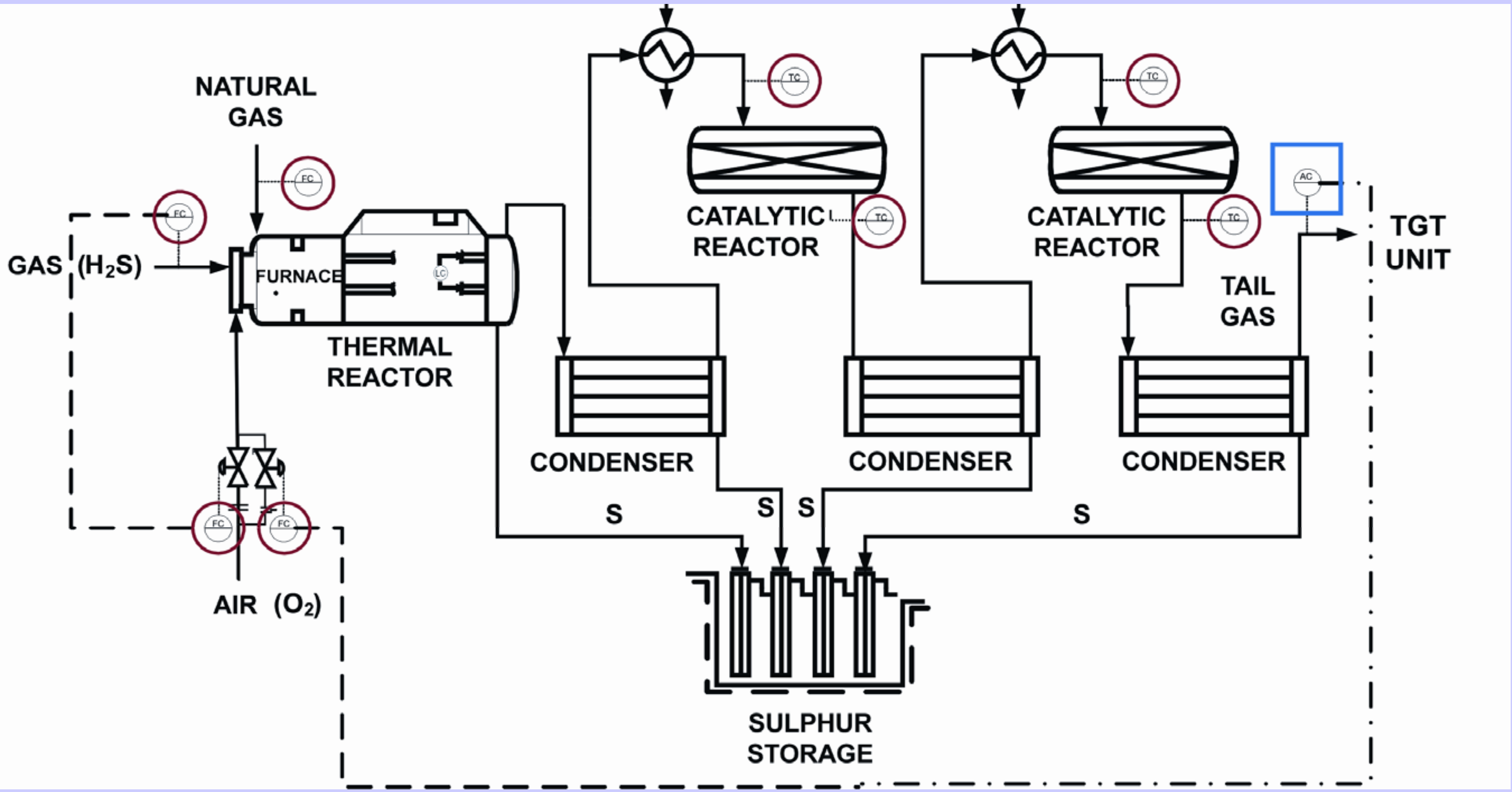
FIT PRED.	*FPE*	MODEL PARAMETER
88,73	1,09	na = 7, nb =6, nk=0

SULPHUR RECOVERY UNIT (SRU)
INA - SISAK RAFINERY

SULPHUR RECOVERY UNIT



CLAUS SECTION



SIMPLIFIED REACTION MECHANISM:

$H_2S + 1.5O_2 \longrightarrow H_20 + SO_2$

$2H_2S + SO_2 \longrightarrow 3S + 2H_2O$

H_2S and SO_2 ANALYZER

Type of analysis: UV photometry

Accuracy: ± 2% (SO_2 i H_2S) P.O.

Response: 90% < 15 s

Outputs - vol.% SO_2

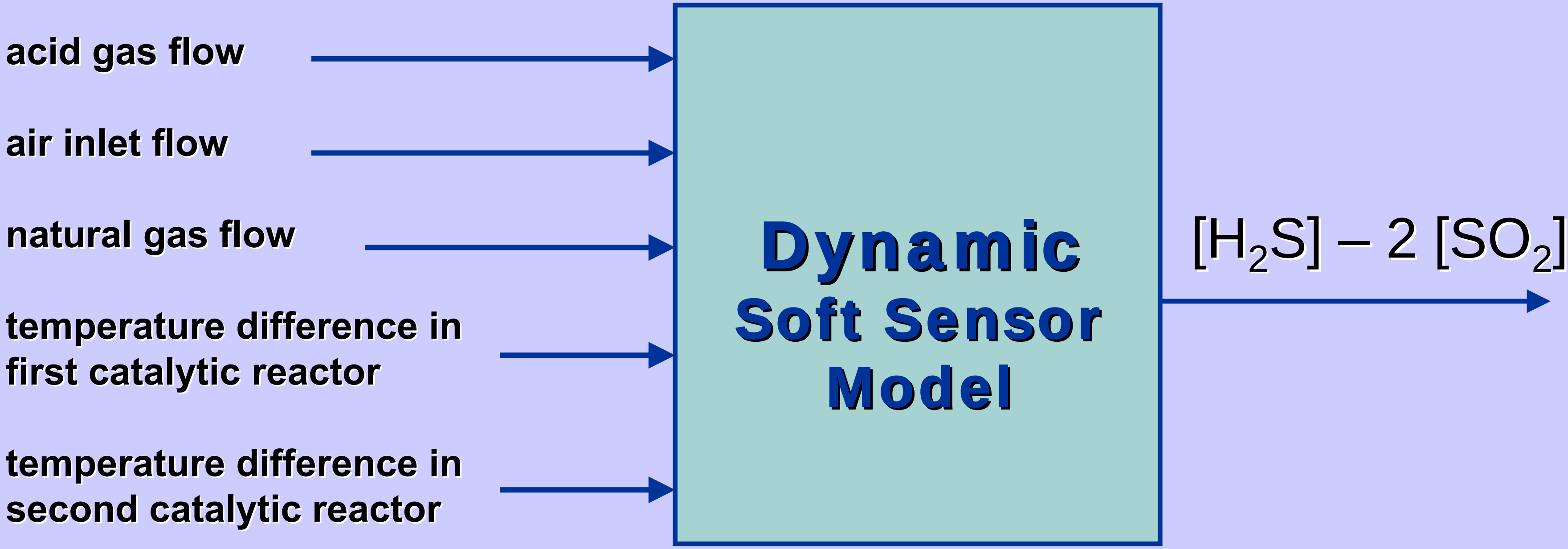
- vol.% H_2S
- vol.% surplus SO_2, H_2S

Out of service

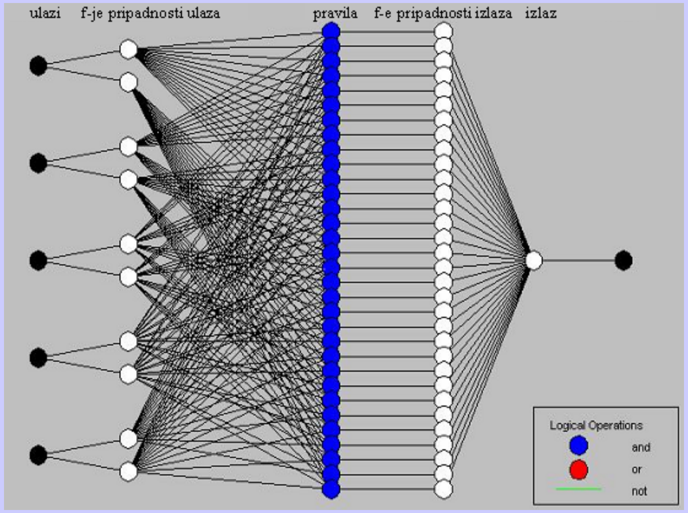
– **problems with the sampling system**

– **problems with the analyzer**

SOFT SENSOR FOR PROCESS CONTROL

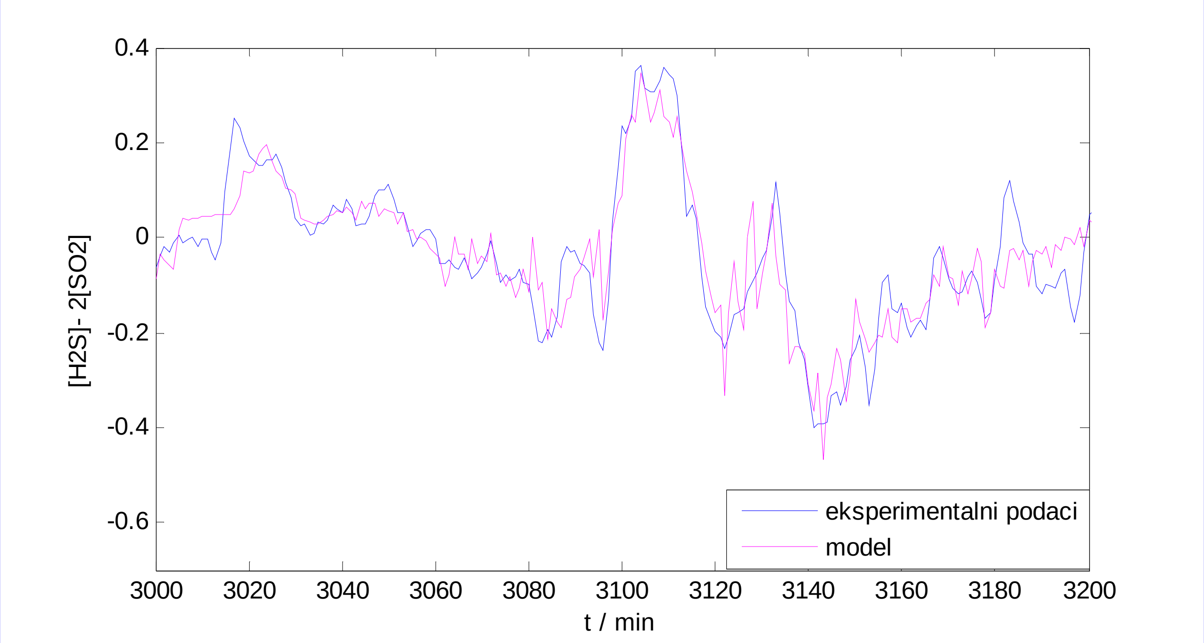


SOFT SENSOR FOR CLAUS PROCESS



NEURO-FUZZY MODEL

- combined neural network and fuzzy logic
- each of five inputs has two membership function
- by combining 2^5 fuzzy rules are obtained



model validation

CONCLUSION

BENEFITS OF SOFT SENSORS

- Feedforward information from inferential measurement
- More consistent production
- Better process control
- Increased scope for process optimization

CONCLUSION

- Data-driven soft sensors help to improve the operation of chemical processes and to drive them towards optimality.

- The necessary infrastructure (DCS, PIMS, LIMS) is needed

- The number of reported applications of data-driven models is growing.

- In most industrial cases linear and steady-state models are applied.

- Continuous exchange between academia and industry is permanently required in order to develop new application.

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SOFT SENSORS APPLICATION IN PROCESS INDUSTRY

THANKS FOR YOUR ATTENTION !

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