Nonlinear System Identification using Support Vector Regression

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Outline

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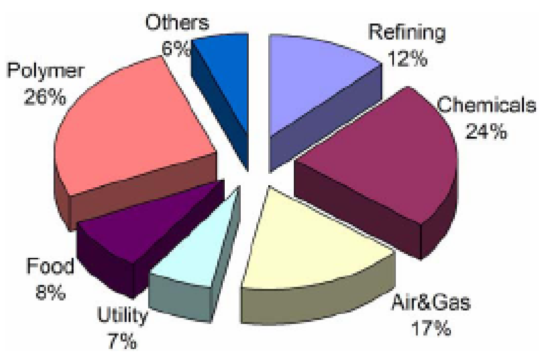
2. Nonlinearity in Process Industry
3. Support Vector Regression
4. Nonlinear System Identification: Case studies
   a. Melt Index Soft Sensor
   b. Nonlinear Dynamic System Identification of a pH neutralization process
5. Concluding Remarks

Objectives

- ❖Development of soft sensors based on the theory of Support Vector Regression (SVR) for application to nonlinear plants
- ❖Development of a methodology for nonlinear system identification from dynamic data using SVR

Nonlinearity in Process Industry

- Many industrial processes pushed to nonlinear operation windows
  - Increasingly tight product specifications
  - Higher Environmental & Safety considerations
  - Economic pressures
- Nonlinear Model Predictive control (NMPC) is becoming popular in the chemical industry due to increasing process nonlinearities
  - 125 NMPC applications reported in chemical industries in the past decade*



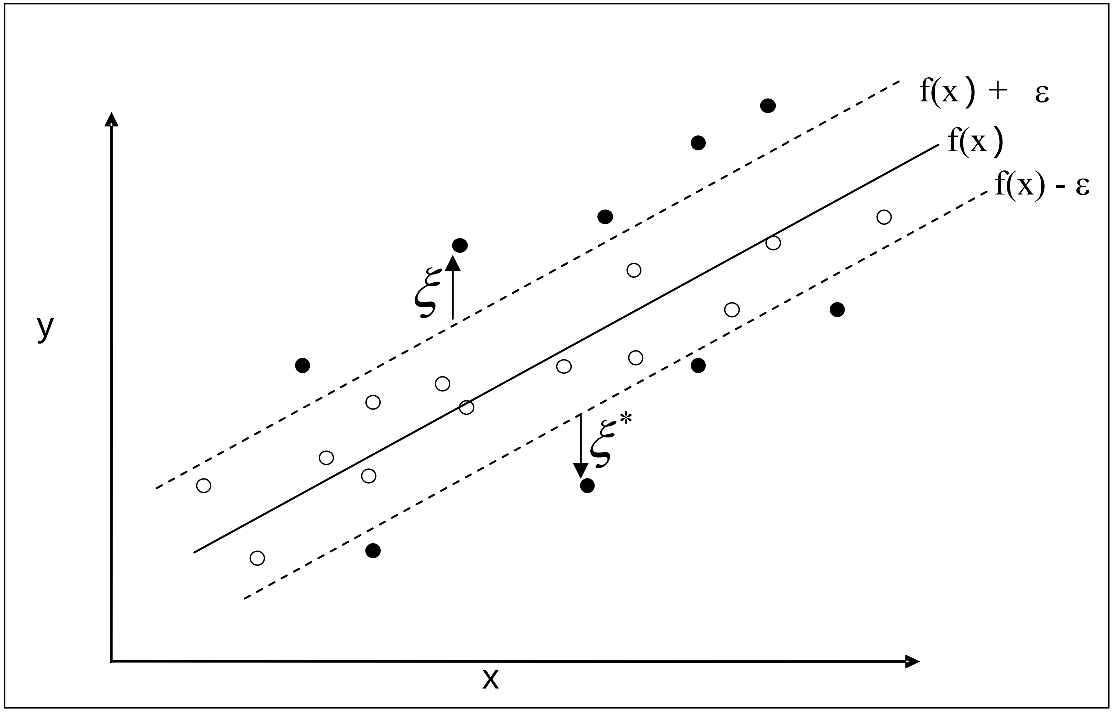
Breakdown of NMPC applications in Chemical Industry

*Courtesy:
'*Nonlinear Model Predictive Control: From Chemical Industry to Microelectronics*',Zoltán K. Nagy and Frank Allgöwer, 43rd IEEE Conference on Decision and Control,2004

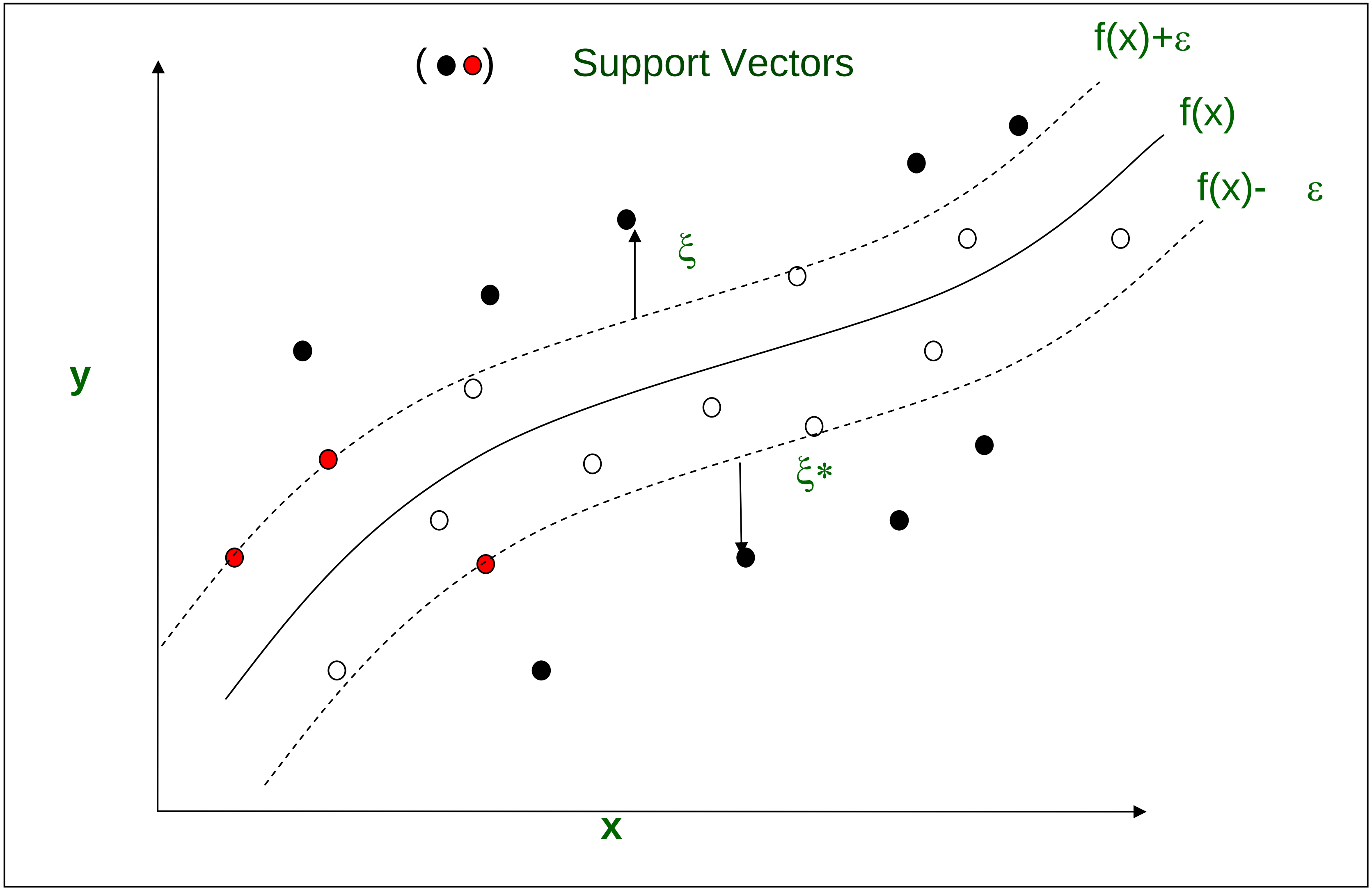
- SVR can be used to build data based nonlinear models

Support Vector Regression

- “Support Vector Regression Machines” proposed in 1996 by Vapnik, Harris Drucker, Chris Burges, Linda Kaufman and Alex Smola (*Advances in Neural Information Processing Systems 9, NIPS 1996, 155-161, MIT Press*)



Support vectors



Nonlinear regression by Kernels

- Examples:

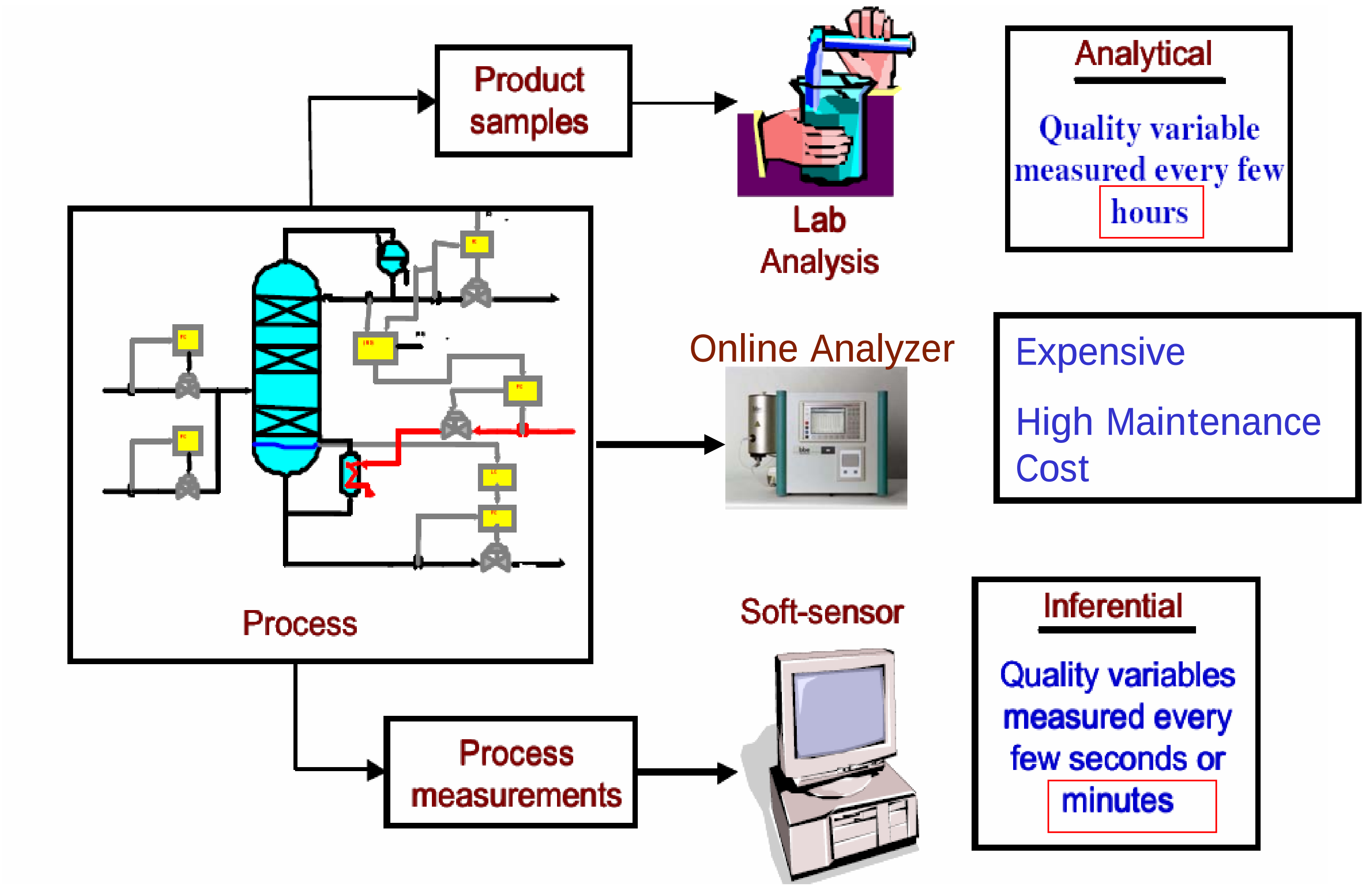
Linear	**$<x_i, x_j>$**
Polynomial	$(<x_i, x_j>+c)^p$
Sigmoid	$\tanh(c+\gamma <x_i, x_j>)$
Radial Basis function /Gaussian kernel	**$exp(-\gamma\|\|x_i-x_j\|\|^2)$**

- Choosing a Kernel depends on application

Nonlinear System Identification: Case studies

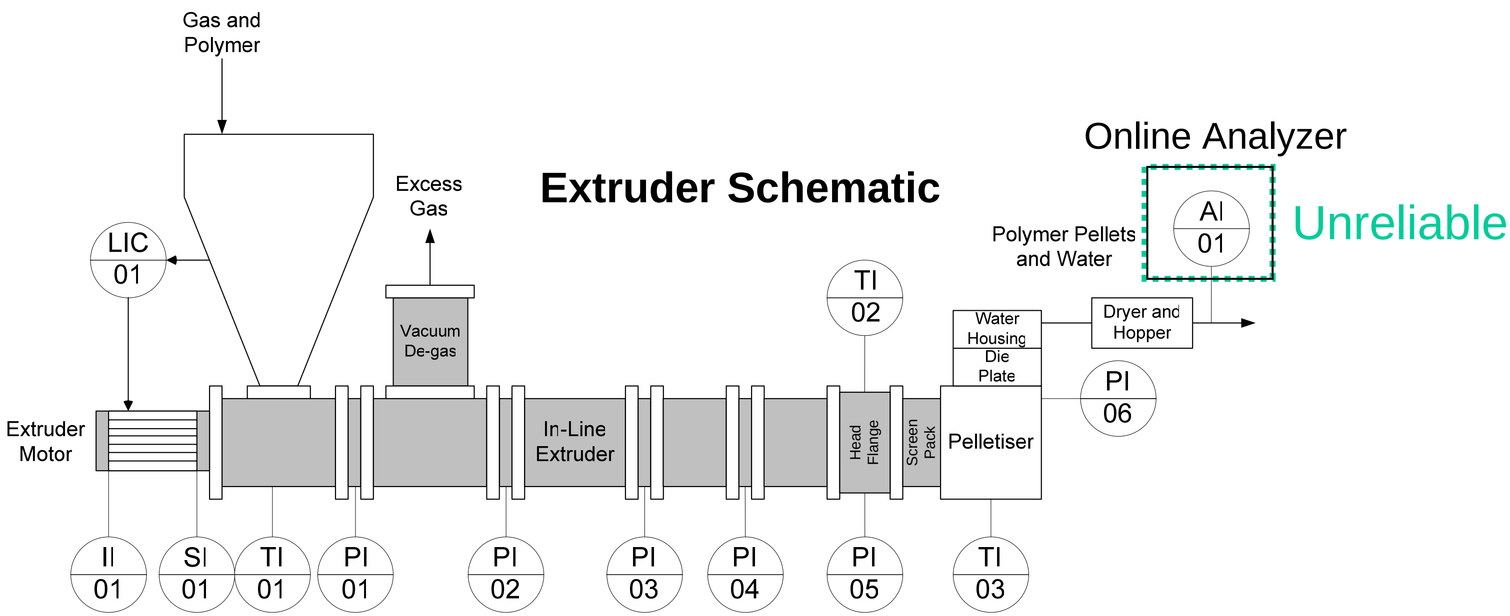
- MI Soft Sensor

What is a Soft Sensor?



Nonlinear System Identification: Case studies

- MI Soft Sensor
  - Nonlinear SVR can be used to build a soft sensor where the output has nonlinear relationship with the input
  - Eg: Melt Index of polymer is observed to be nonlinearly related to variables monitored in the extruder (Sharmin et al (2006), Alleyne et al (2006))

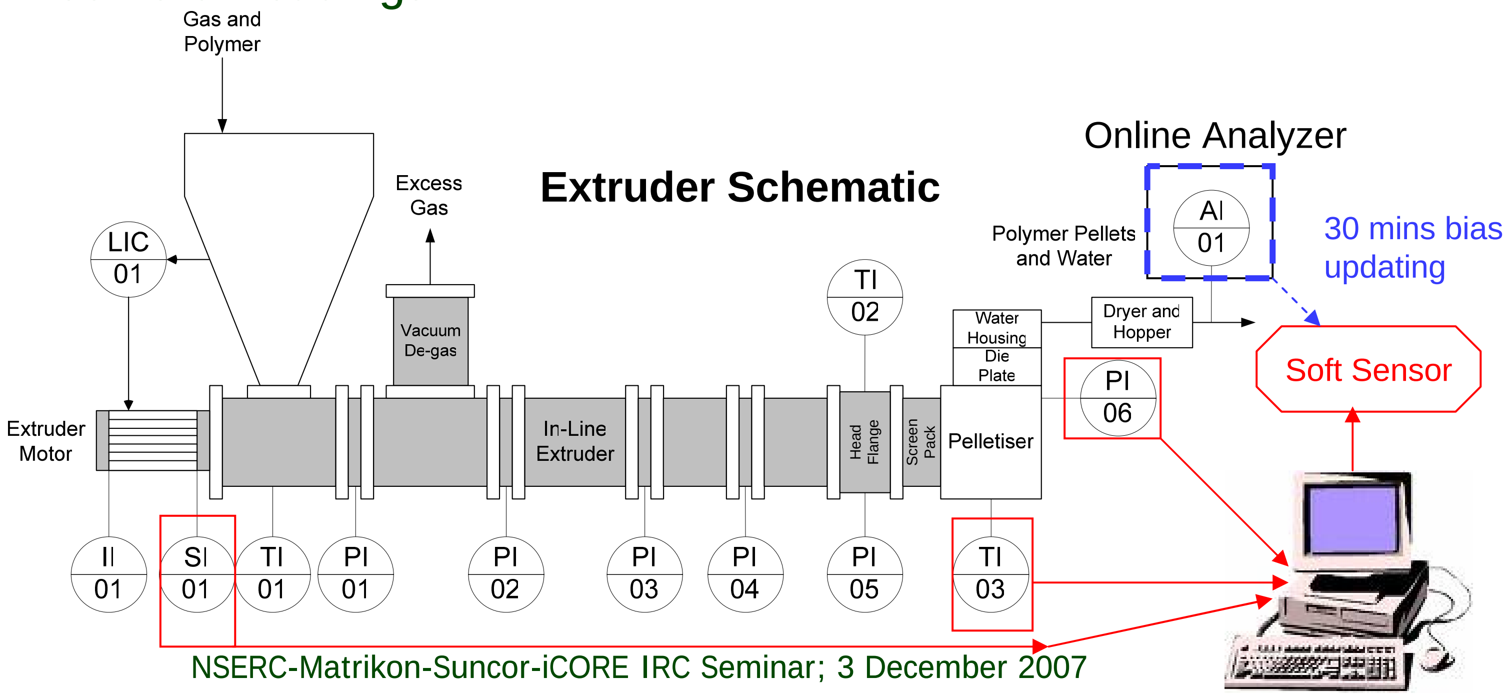


MI Soft Sensor (contd..)

- Application to MI data from EVA polymerization plant
  - Empirical Soft sensor previously implemented

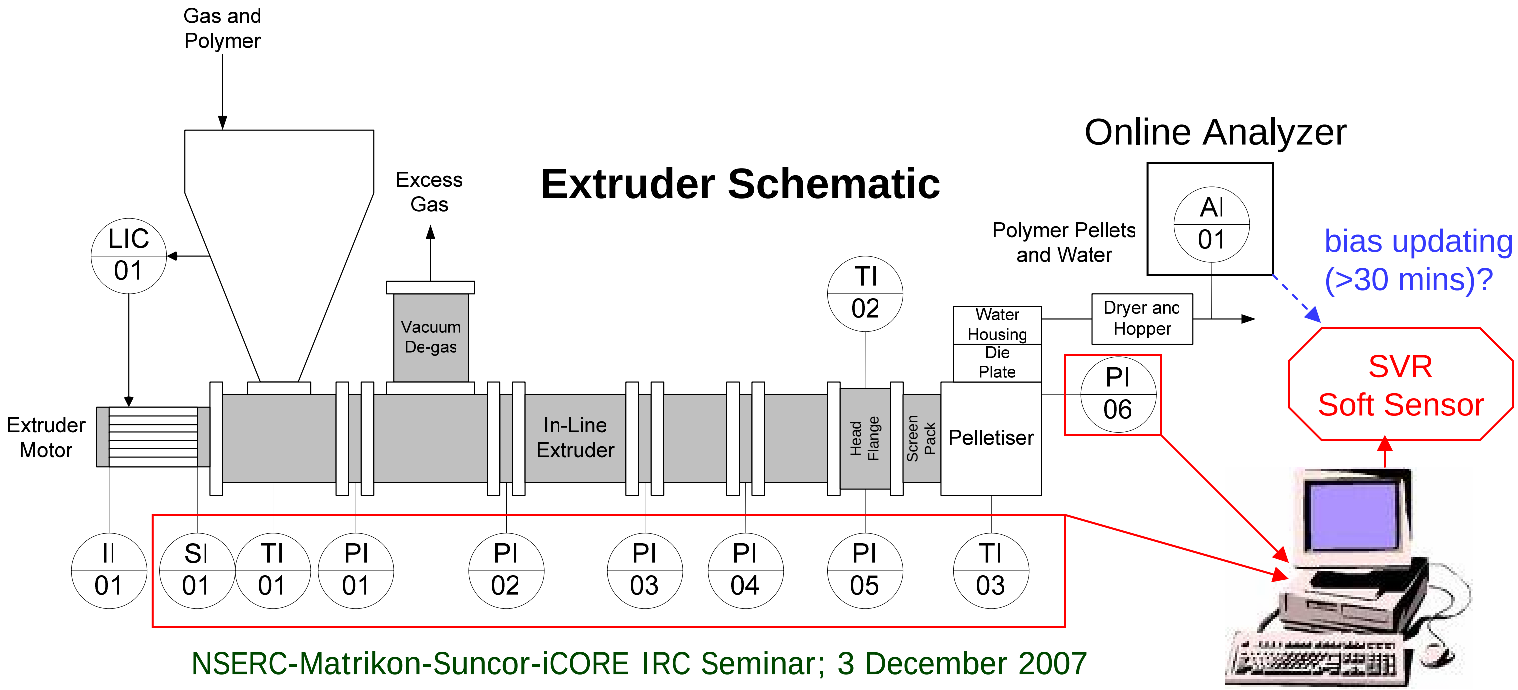
$$MI = \frac{\exp(a + b.S + c(\frac{S}{P^{\alpha}}) + d.P^{\alpha})}{T^{2}}$$

- Nonlinear Least square Regression (slow training, local minima, results highly dependent on initial guesses)
- Soft sensor required bias update every 30 mins using the online rheometer readings



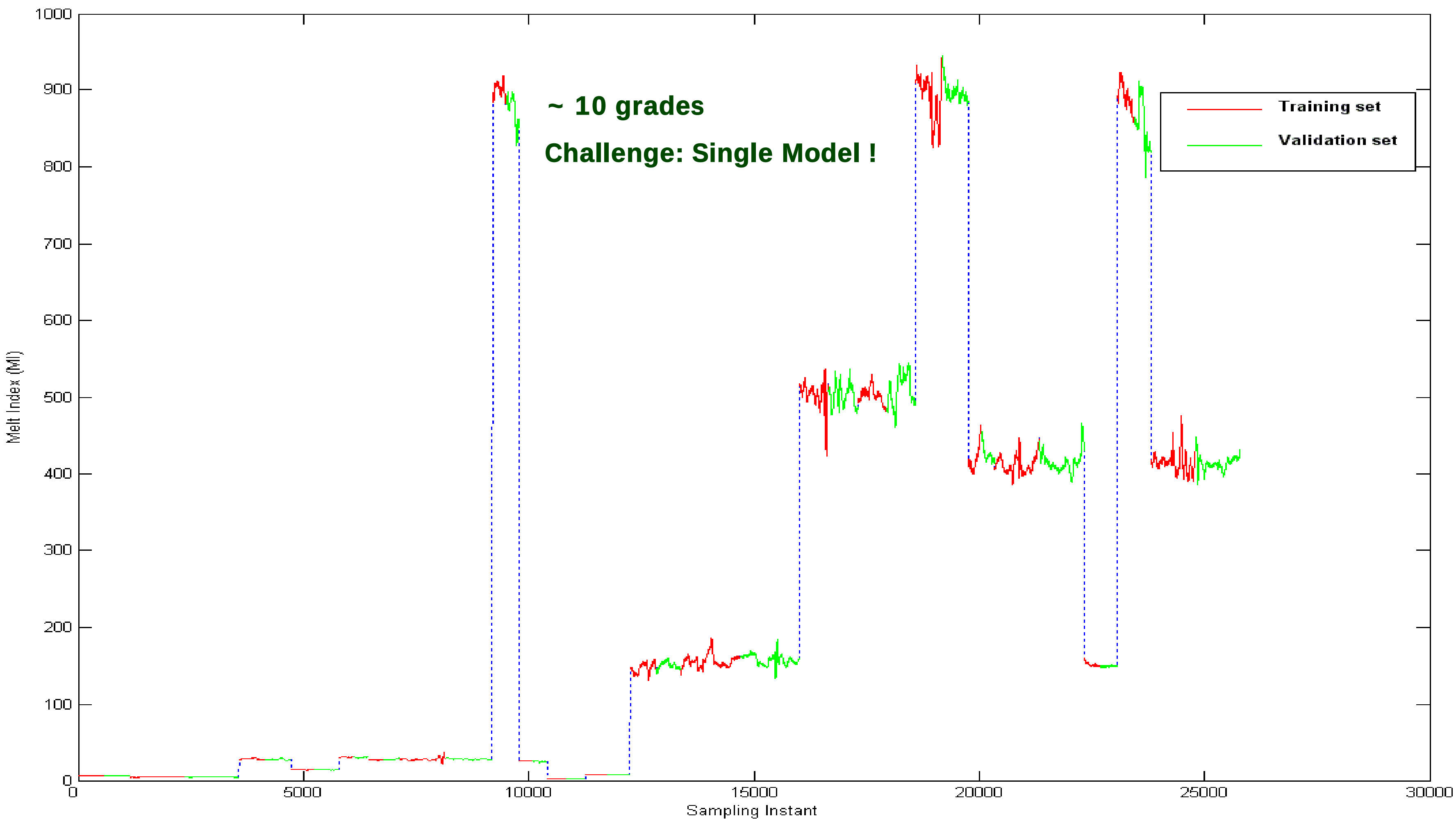
MI Soft Sensor (contd..)

- SVR based soft sensor
  - Implementation in MATLAB: LIBSVM Toolbox
  - Based on 10 variables measured at the extruder upstream of the online MI measurement
  - Input variables : 6 Pressures, 3 Temperatures, Extruder speed
  - Target variable : Y_i= log(MI)
  - Kernel choice : RBF kernel
  - All parameters tuned by trial and error method→ C=100, ε=0.3,γ =1e-6



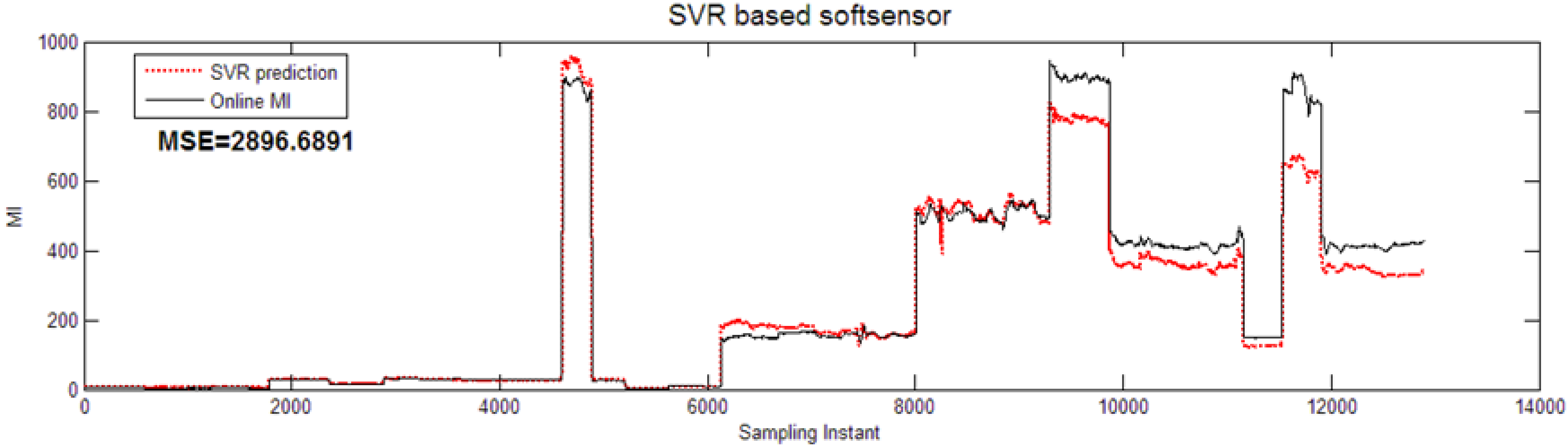
MI Soft Sensor (contd..)

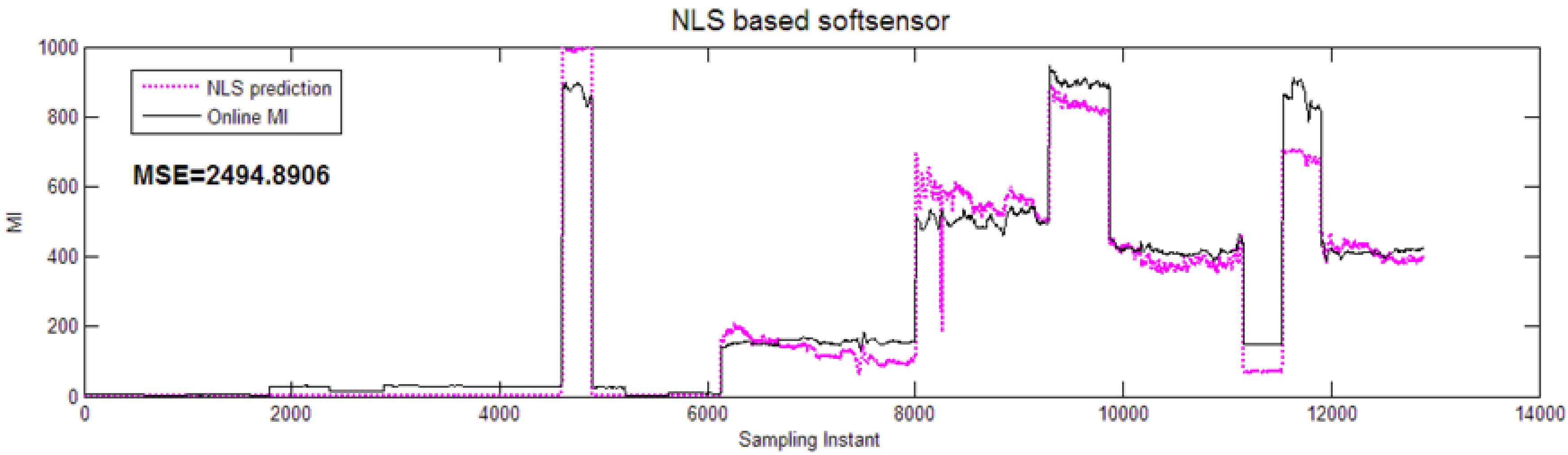
- MI data from EVA polymerization unit (AT Plastics, Edmonton)



MI Soft Sensor (contd..)

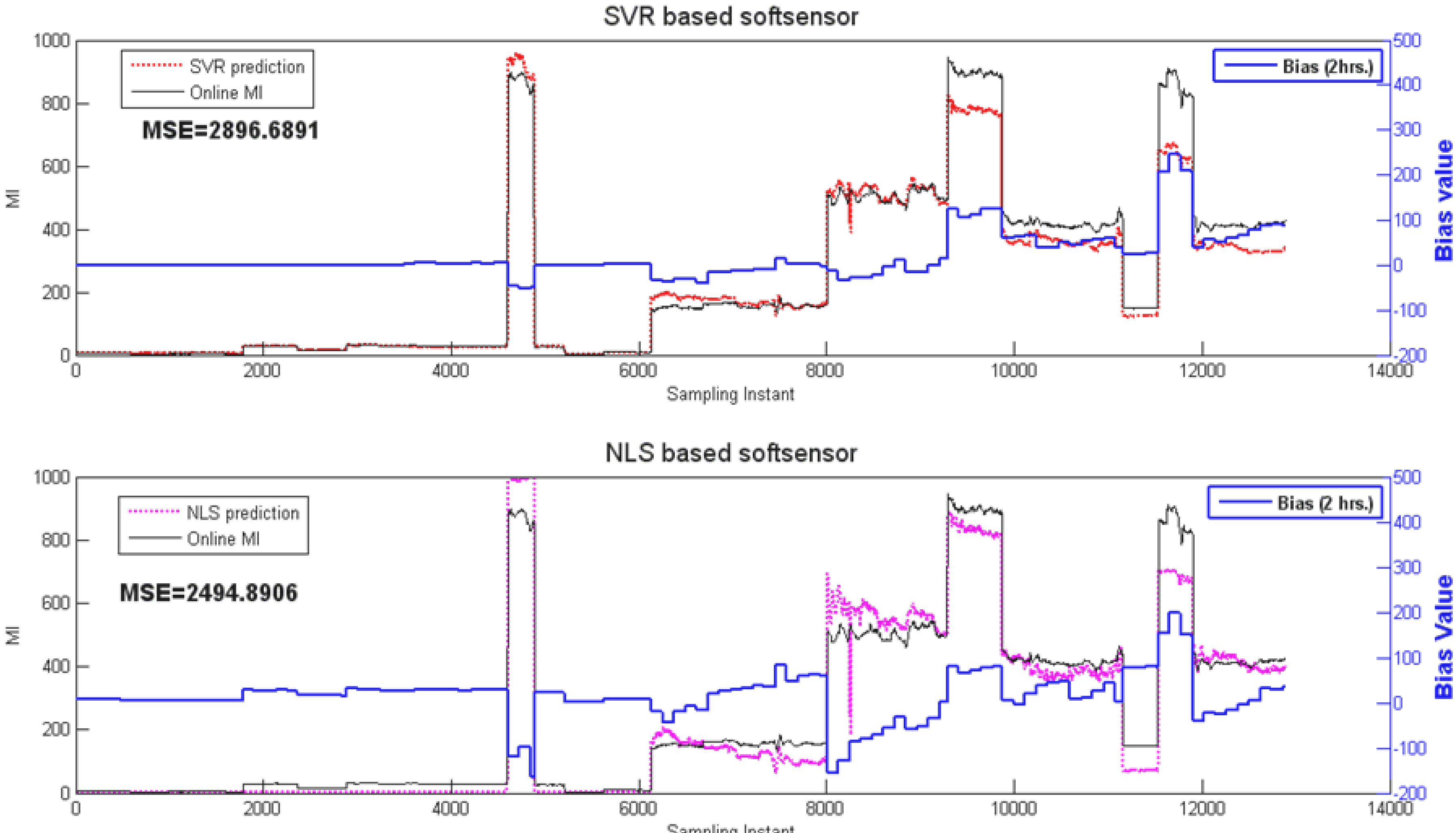
- Comparing the two models (without bias update):





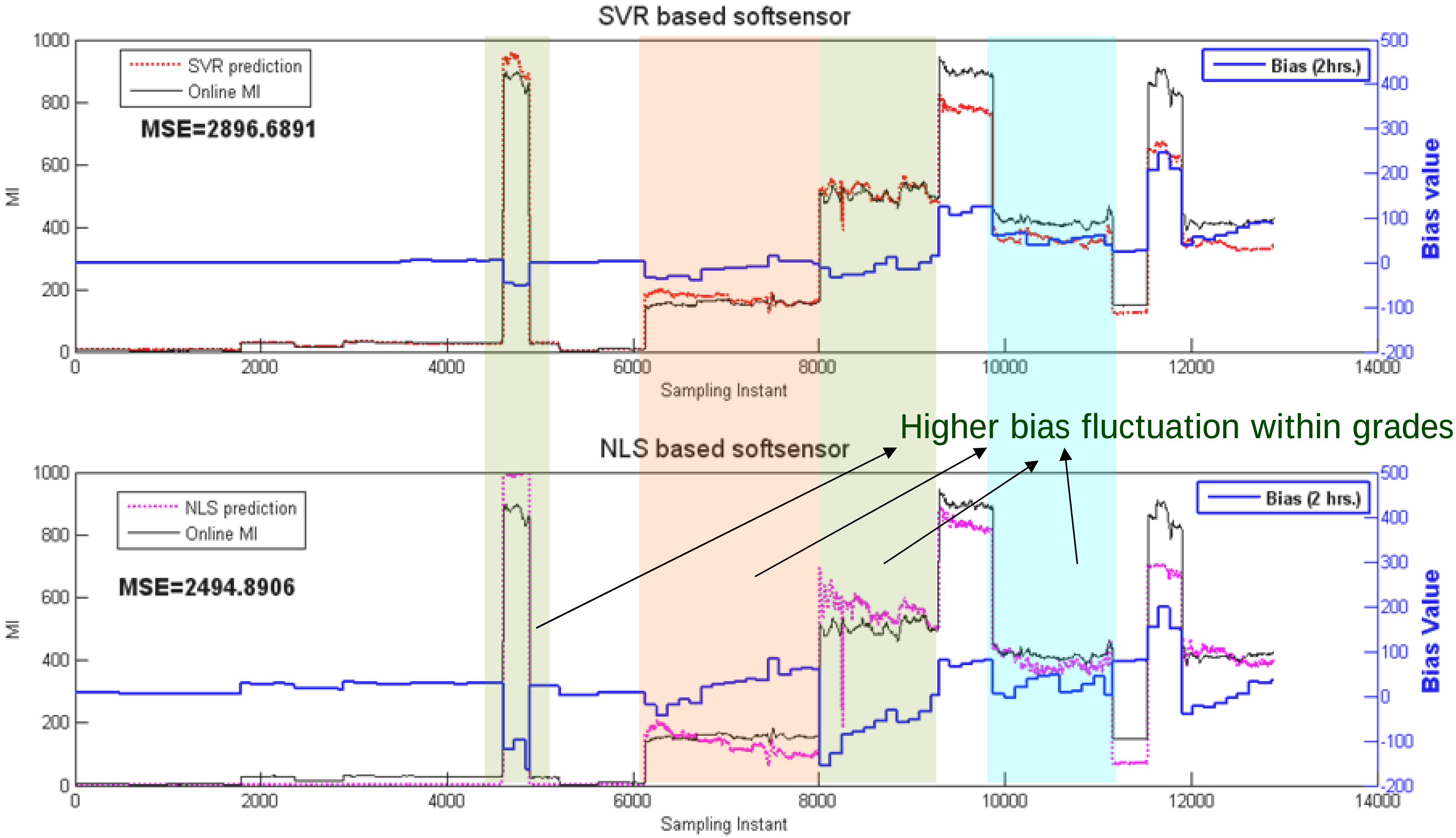
MI Soft Sensor (contd..)

- Comparing 2 hrs-bias values of the two models



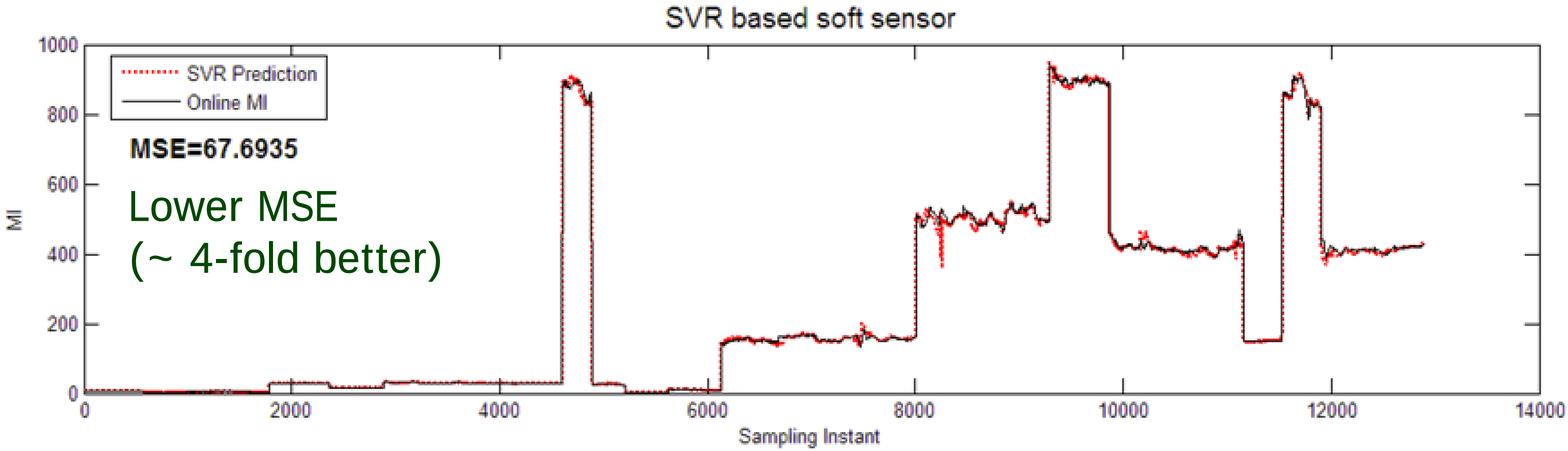
MI Soft Sensor (contd..)

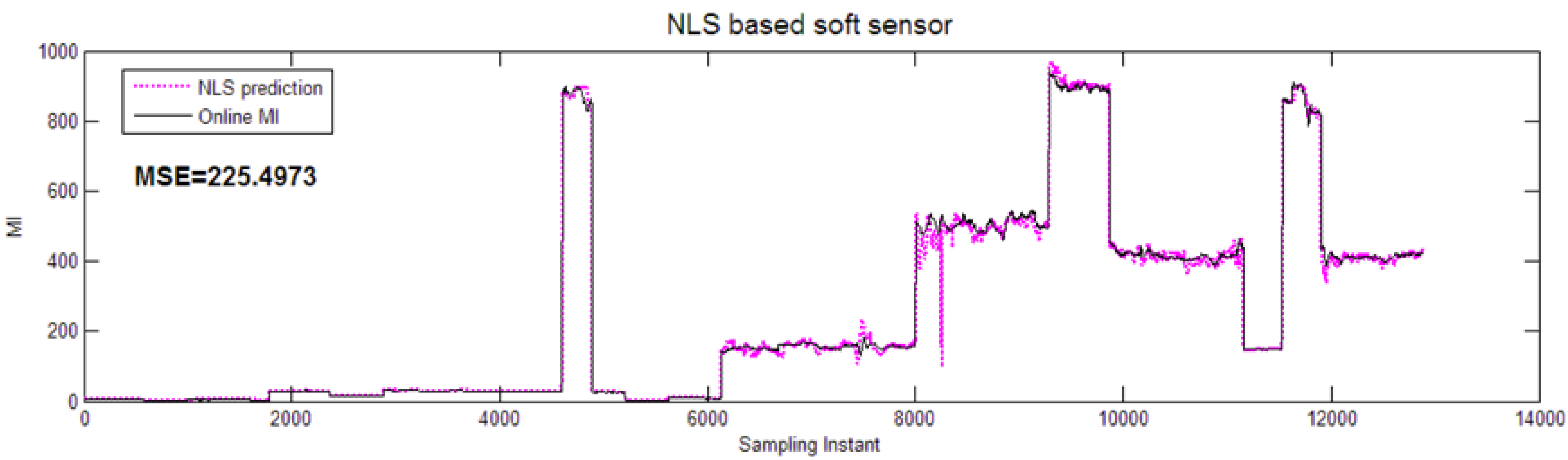
❖ Comparing 2 hrs-bias values of the two models



MI Soft Sensor (contd..)

❖ Comparing the two models (with 2hrs bias update):





MI Soft Sensor (contd..)

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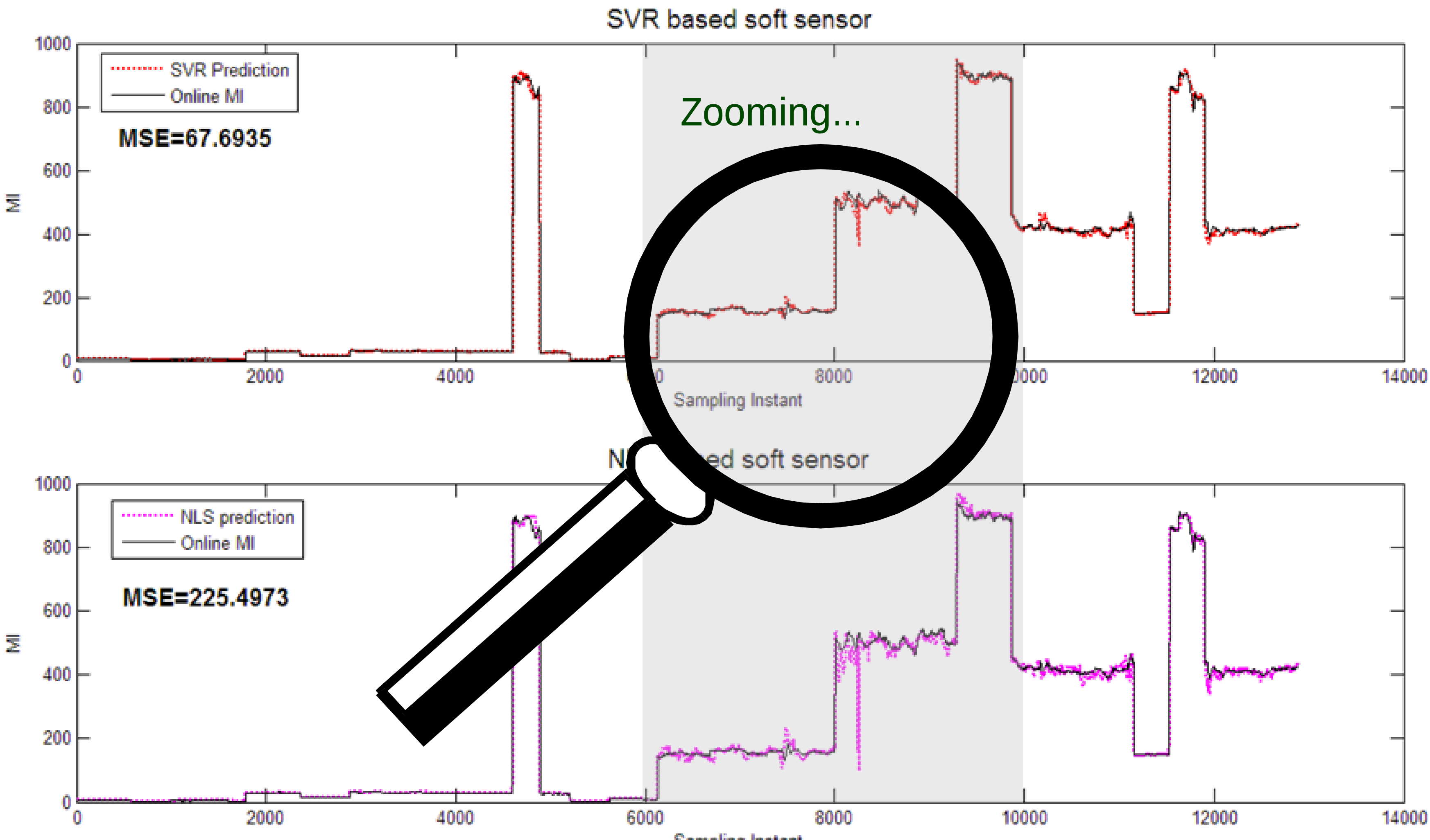

MI Soft Sensor (contd..)

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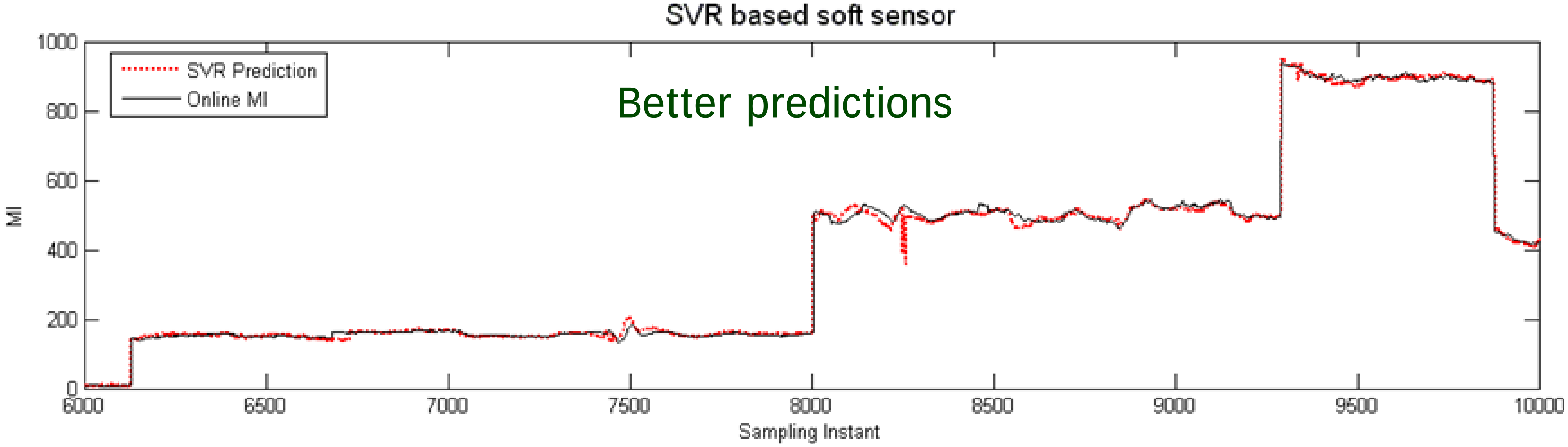
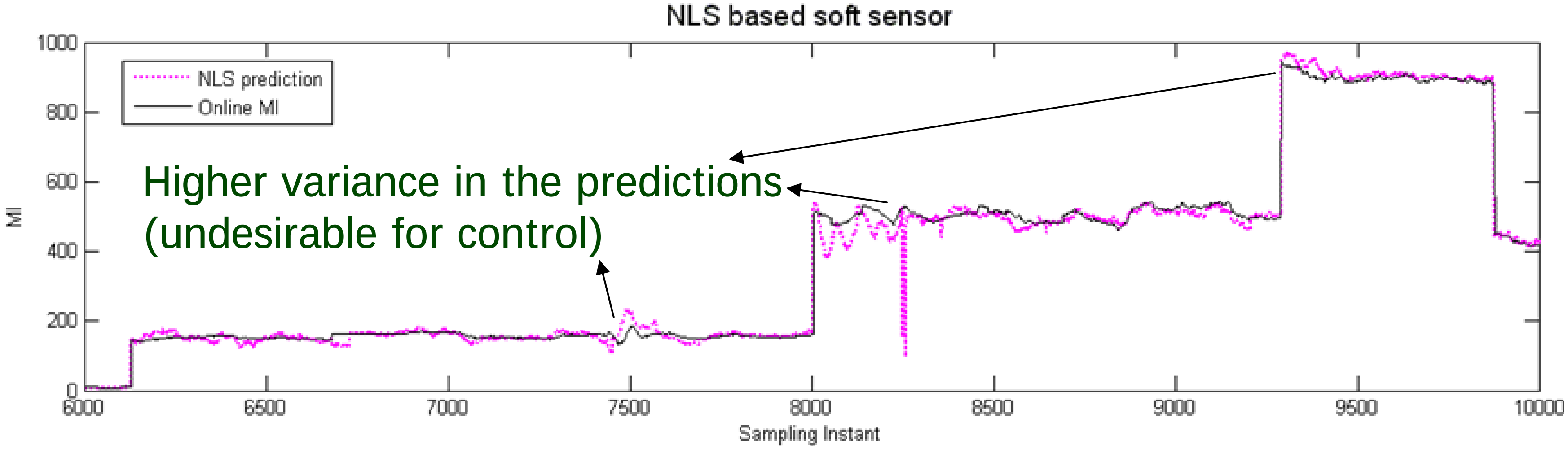
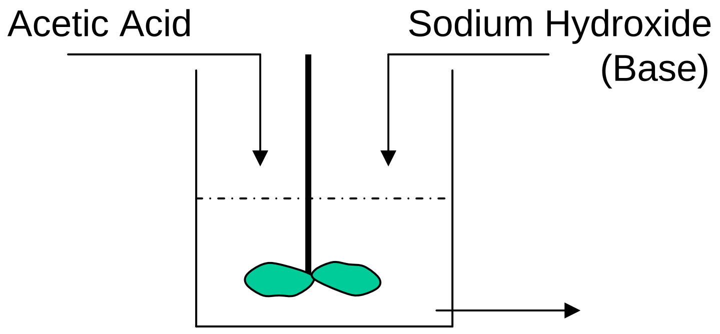
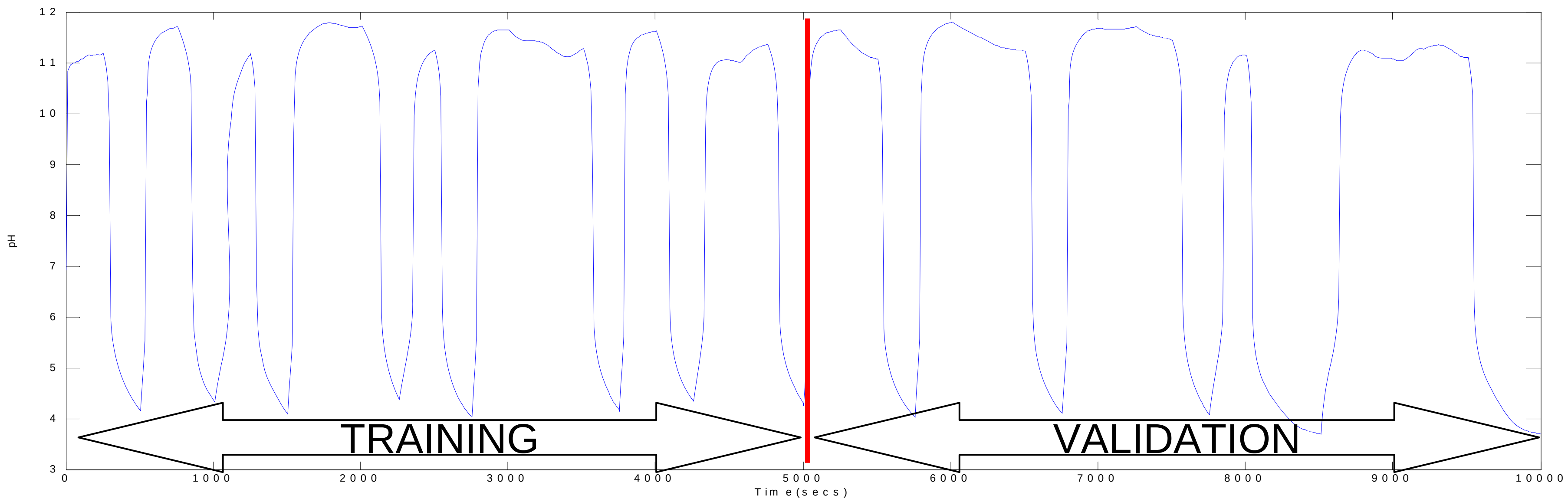




Nonlinear Dynamic System Identification

- pH neutralization process
  - Highly Nonlinear dynamic system
  - Inputs: Acid, Base flow rates
  - Output: pH of mixture





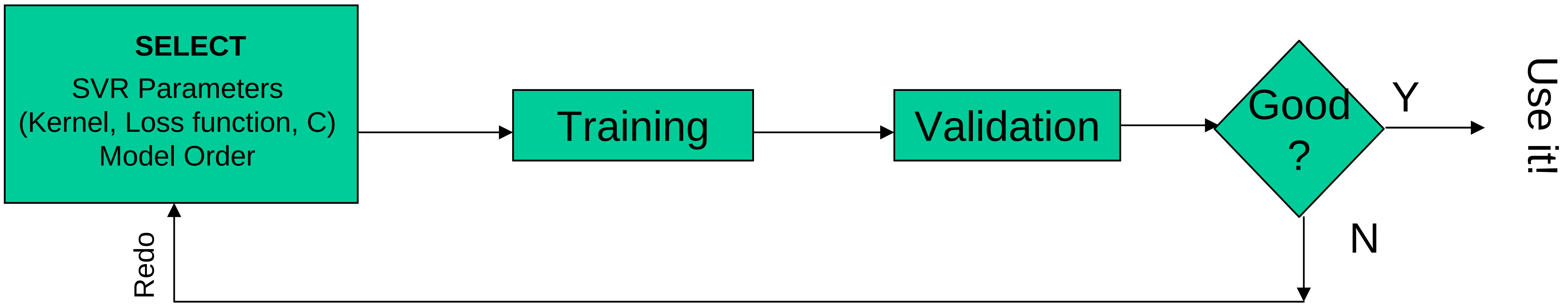
DaISy: Database for the Identification of Systems
Department of Electrical Engineering, ESAT/SISTA, K.U.Leuven, Belgium,
URL: http://homes.esat.kuleuven.be/~smc/daisy/

Nonlinear Dynamic System Identification (contd..)

- SVR based system identification
  - Assume Nonlinear ARX structure (NARX)

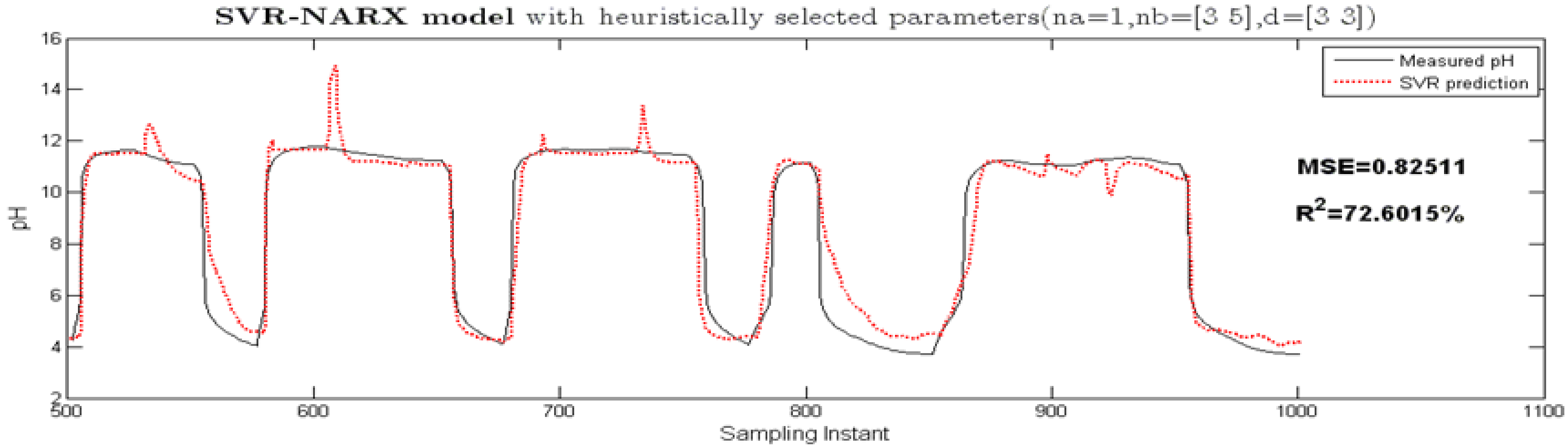
$$y(t) = f([y(t-1:t-na), u_1(t-d_1:t-d_1-nb_1+1), u_2(t-d_2:t-d_2-nb_2+1)]) + \varepsilon$$

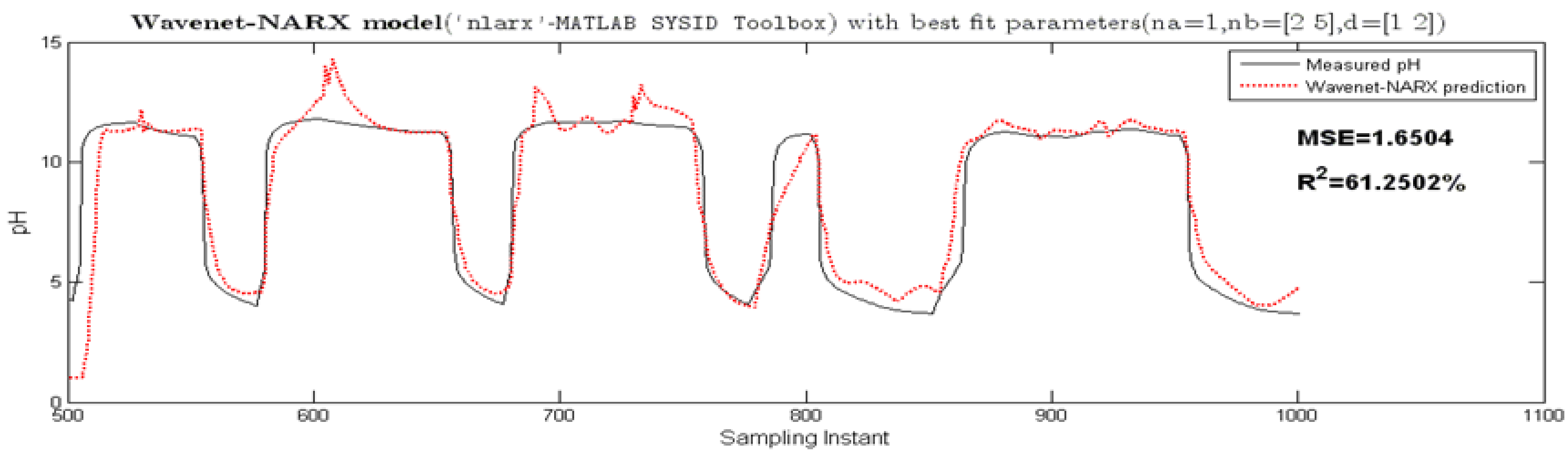
  - RBF Kernel
  - Model order selection (na, nbs), delay selection, SVR parameter tuning: By trial and error based on the validation data fit
  - Validation: Infinite horizon prediction on validation data set



Results

- Validation results:





Concluding Remarks

1. SVR is an efficient tool for non-linear regression

2. Case studies discussed:
   a. Soft sensor development based on SVR
      - MI Soft sensor: Accurately captures wide operating ranges of a nonlinear EVA polymerization plant

   b. Nonlinear Dynamic System Identification using SVR
      - pH neutralization: Illustrates effectiveness of SVR for developing nonlinear dynamic models based on process data

Acknowledgements

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2. CPC Group Members

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