Nonlinear System Identification using Support Vector Regression

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Outline

1. Objectives
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


- SVR can be used to build data based nonlinear models
Support Vector Regression

Support Vector Regression

Support vectors

\( f(x) + \varepsilon \)

\( f(x) \)

\( f(x) - \varepsilon \)

\( \xi \)

\( \xi^* \)
Support Vector Regression

Nonlinear regression by Kernels

Examples:

<table>
<thead>
<tr>
<th>Kernel Type</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>$&lt;x_i, x_j&gt;$</td>
</tr>
<tr>
<td>Polynomial</td>
<td>$(&lt;x_i, x_j&gt;+c)^p$</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>$\tanh(c+\gamma &lt;x_i, x_j&gt;)$</td>
</tr>
<tr>
<td>Radial Basis function/Gaussian kernel</td>
<td>$exp(-\gamma</td>
</tr>
</tbody>
</table>

Choosing a Kernel depends on application
Nonlinear System Identification: Case studies

- MI Soft Sensor
What is a Soft Sensor?

Analytical
Quality variable measured every few hours

Expensive
High Maintenance Cost

Inferential
Quality variables measured every few seconds or minutes

Online Analyzer

Product samples

Lab Analysis

Process

Process measurements

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))
Application to MI data from EVA polymerization plant

- Empirical Soft sensor previously implemented

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

- 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
Nonlinear System Identification: Case studies

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: $C=100, \epsilon=0.3, \gamma=1e-6$

Extruder Schematic

Basic system components:
- Gas and Polymer
- Excess Gas
- Vacuum Degas
- Ti 02
- Water Housing
- Plate
- Dryer and Hopper
- Pelletiser
- Screen Pack
- Screw Pack
- Head Range
- In-Line Extruder
- Pi 03
- Pi 04
- Pi 05
- Pi 06
- Ti 03
- Screen Pack
- Head Range
- Screw Pack
- Pelletiser
- Online Analyzer

SVR Soft Sensor

Bias updating (>30 mins)?

NSERC-Matrikon-Suncor-iCORE IRC Seminar; 3 December 2007
MI data from EVA polymerization unit (AT Plastics, Edmonton)

~ 10 grades
Challenge: Single Model!
Comparing the two models (without bias update):

SVR based softsensor

MSE = 2896.6891

NLS based softsensor

MSE = 2494.8906
Comparing 2 hrs-bias values of the two models

SVR based softsensor

NLS based softsensor

MSE=2896.6891

MSE=2494.8906
Nonlinear System Identification: Case studies

MI Soft Sensor (contd..)

- Comparing 2 hrs-bias values of the two models

**SVR based softsensor**

- **MSE=2896.6891**

**NLS based softsensor**

- **MSE=2494.8906**

Higher bias fluctuation within grades
Comparing the two models (with 2hrs bias update):

SVR based soft sensor

MSE = 67.6935

Lower MSE
(~ 4-fold better)

NLS based soft sensor

MSE = 225.4973

NSERC-Matrikon-Suncor-iCORE IRC Seminar; 3 December 2007
Comparing the two models (with 2hrs bias update):

- SVR based soft sensor
  - MSE = 67.6935

- MI based soft sensor
  - MSE = 225.4973

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

**SVR based soft sensor**

Better predictions

**NLS based soft sensor**

Higher variance in the predictions (undesirable for control)
pH neutralization process
- Highly Nonlinear dynamic system
- Inputs: Acid, Base flow rates
- Output: pH of mixture

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

- Assume Nonlinear ARX structure (NARX)

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

- 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
Validation results:

**SVR-NARX model** with heuristically selected parameters \((n_a=1, n_b=[3, 5], d=[3, 3])\)

- **MSE** = 0.82511
- **\(R^2\)** = 72.6015%

**Wavenet-NARX model** (MATLAB SYSID Toolbox) with best fit parameters \((n_a=1, n_b=[2, 5], d=[1, 2])\)

- **MSE** = 1.6504
- **\(R^2\)** = 61.2502%
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
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