Honorable Members of PUPID,

Well, it is already the third week of May and as I write this I am in Seoul, South Korea where I will be for the rest of the year.

This last September, the ISA Automation Week 2012 was at the Orange County Convention Center in Orlando, Florida. If you couldn’t be there, you can listen to the audio and read the Powerpoint presentations and papers by going to the links on the PUPID website. As they say, it’s the next best thing to being there.

Our division net membership has decreased slightly from 457 to 432 members with 1 new division member since February. The membership has stayed nearly constant since last January. Welcome to the new member!

I am also pleased to be able to include ‘s paper and see the presentation “Recursive Update of a Reduced-Order Dynamic PLS Soft Sensor and its Application to Digester Control” from the ISA Automation Week 2011 Technical conference that was held in Mobile, AL.

I am honored to announce the 2013 ISA PUPID Scholarship Winner, Kayla Louise Young, from Miami of Ohio.

I hope it is an encouragement to you to become more involved with the Division and to enroll more members from the great international pulp & paper community.

Please do not hesitate to contact me at my email brad.carlberg@bsc-engineering.com to discuss how you can help PUPID.

Do feel free to forward the Newsletter to your friends and colleagues who may have an interest in it.
ABSTRACT

Open Loop Method
(Ziegler-Nichols)

The control system is allowed to come to a steady-state condition after the controller is placed on manual. A unit step change next taken on the controller output. The apparent delay time (Td) and the maximum reaction slope (Sm) are measured.

Based upon the following Ziegler and Nichols open loop method equations, the control mode settings are calculated by inserting the proper apparent delay time (Td) and the maximum slope of reaction curve (Sm):

Proportional Controllers

\[ K = \frac{1}{S_m T_d} \]

Proportional Plus Integral Controllers

\[ K = 0.9 \frac{T_i}{S_m T_d} \quad T_i = 3.33 T_d \]

Proportional Plus Integral Controllers

\[ K = 1.2 \frac{T_d}{S_m T_d} \quad T_i = 2 T_d \quad T_D = 0.5 T_d \]

where:

K = Proportional Gain
Ti = Reset Time
Td = Derivative Time
S_m = maximum slope of reaction curve
Td = apparent delay time

---

Calendar of Events

Get a quick overview of the ISA PUPID events for 2013 by going to the Calendar at:

http://www.isa.org/~pupid/2013_PUPID_Calendar.htm

2013 APPITA Conference & Exhibition
May 8 – 10, 2013
Melbourne Park Function Centre,
Melbourne Australia
http://www.appita.com/

2013 Pan Pacific Conference
11/20/2013 to 11/22/2013
Hotel Horison
Bandung, West Java Indonesia
http://www.reptech2013.org/

2013 TAPPI PEERS Conference
09/15/2013 to 09/18/2013
Green Bay, WI USA
http://www.tappipeers.org/

2013 BLRBAC Fall Meeting
10/7/2012 to 10/9/2012
www.blrbac.org

2013 China Paper Technical Conference
09/02/2013 to 09/04/2013
China International Exhibition Center
Beijing
http://www.chinapaperexpo.cn/

2013 ISA FALL LEADERS MEETING
SATURDAY, NOVEMBER 2, 2013 AND
SUNDAY, NOVEMBER 3, 2013

ISA AUTOMATION WEEK 2013
MONDAY, NOVEMBER 4, 2013 THROUGH
THURSDAY, NOVEMBER 7, 2013
NASHVILLE CONVENTION CENTER
NASHVILLE, TN

Come meet your leaders & get involved!

ABTCP 2013-46th Pulp & Paper
International Congress & Exhibition
10/8/2013 to 10/10/2013
Transamerica Expo Center
Sao Paulo, Brasil
http://www.abtcp2013.org.br/ingles/
The Ziegler and Nichols closed loop method in this discussion is referred to as the ultimate method. In this procedure, tune all reset and derivative action out of the controller (TI = TD = 0) leaving only the proportional mode. With the controller on automatic, tune the controller gain for continuous oscillatory cycle following an upset. If the gain is too high, the system will be unstable. If the gain is too low, the system will dampen out.

When the system continues to oscillate on an upset, the gain is noted and referred to as the ultimate gain ($S_u$). Also, the period of time between cycles is noted and referred to as the ultimate period ($P_u$). These values are used in the following Ziegler and Nichols closed loop ultimate method equation for controller tuning:

**Proportional Controllers**

$$K = 0.5S_u$$

**Proportional Plus Integral Controllers**

$$K = 0.45S_u \quad T_i = \frac{P_u}{1.2}$$

**Proportional Plus Integral Controllers**

$$K = 0.6S_u \quad T_i = \frac{P_u}{2} \quad T_d = \frac{P_u}{8}$$

where:

- $K$ = Proportional Gain
- $T_i$ = Reset Time
- $T_d$ = Derivative Time
- $S_u$ = Ultimate gain
- $P_u$ = Ultimate period

*This Tuning Tip was excerpted from “Analog Control Techniques & Tuning (with Ziegler-Nichols)” by Ralph K. Johnson of Bailey*.  
*ISA Members can download this paper FOR FREE from the ISA Pulp & Paper Industry Division website at [http://www.isa.org/~pupid/RKJohnson_Tuning_1990.pdf](http://www.isa.org/~pupid/RKJohnson_Tuning_1990.pdf).*
WELCOME TO THE new ISA Pulp & Paper Industry Division Member since February 2013

Mr. L.C. Shane C. Bernard

HERE’S A REMINDER TO THE ISA Pulp & Paper Industry Division Members who need to renew their membership

Mr. Jed Albao
Ms. Meredith M. Allen
Mr. Fabrizio Bongiorno Arasanz
Mr. Richard Harold Bansley, III
Mr. Chris D. Bassett
Michael J. Beckman
Mr. Ananth Prakash Benedict
Chad Britt
Mr. Lam Ngoc Bui
Mr. Timothy Mark Church
Joel Ray Cotton
Ryan DeHut
Mr. Thomas DePuy
Mr. FELIPE ALVES FERREIRA
Sundari G
Mr. Franklin D. Garcia

Mrs. Alicia Marie Garcia-Tunon
Mr. Harman Gill
Mr. Antonio Tome Guerra, Sr.
Mr. Bryan M. Hodges
Mr. Heikki Isotalo
Mrs. Beverly T. James
Mr. David Jeffries
Andre Luiz Kakehasi
Mrs. Luciane Keller Coutinho
Mr. Aref Lariei
Mr. Eric Larouche
Mr. Paul Gerard Makinen, CCST
Mr. Jorge Cesar Meneli
Mr. Jeffery A. Miller
Mr. James L. Moles
Mr. Timothy F. Murphy

Zachary M. Murphy
Mr. John Russ Nyquist, CCST
Mr. Tyler G. Ous
Mr. Robson Ribas
Willington Pereira Santos
Mr. Mauricio R Rodrigues Silva, Sr.
Mr. Fabio Silveira Silva
Jared D. Smith
Fabricio Souza Torres
Mr. Srinivasan
Mr. Richard E. St James, CAP, CCST
Ms. Yolanda Stewart
Mr. Jeffrey Brannon Swett
Mr. Adam West
Mr. Frank J. Westerlund

DON’T FORGET TO RENEW!
**Who’s Doin’ Anything?:**

Andritz to upgrade recovery boiler and sulfite liquor boiler at Stora Enso Nymölla and Domsjö Fabriker plants in Sweden

GRAZ, Austria, May 15, 2013 (Press Release) - International technology Group ANDRITZ has received orders from Stora Enso Nymölla AG and Domsjö Fabriker AB, Sweden, to modernize a recovery boiler and a sulfite liquor boiler. Due to technology and equipment supplied by ANDRITZ Energy & Environment (AE&E), the capacity of the two boiler plants can be increased by up to 20%. Both start-ups are scheduled for 2013.

For Stora Enso's liquor recovery boiler in Nymölla, which went into operation in 1971, AE&E will supply the plate-type heat exchangers for pre-heating the combustion air in combination with an economizer to pre-heat the feed water. This technical concept is characterized by a long lifetime of the boiler and lower maintenance effort required; thus scheduled plant shutdowns can be reduced to a minimum and the plant's capacity increased significantly. The scope of supply for sulfite liquor boiler no. 9 at Domsjö Fabriker, in operation since 1962, comprises replacement of the super heater and evaporator heating surfaces, as well as partial replacement of the front and rear walls of the liquor boiler. The new AE&E design will improve the fouling behavior of the boiler and enhance efficiency by up to 20%. Due to the very short assembly period of 18 days, the customer will only have a very brief production shutdown.

Mohawk develops notebook paper base for smart phones as it ‘rides’ digital wave [From the web]

ALBANY, NY, May 16, 2013 (Local News) - The newest case for Apple's iPhone comes from the combination of a San Francisco startup and a paper mill in upstate New York.

The base of the newest DODOcase, released Thursday, is 30 pages of notebook paper from Mohawk, a Cohoes paper company that is anything but extinct. An elastic strap holds the iPhone in place. A version for the Samsung Galaxy S3 is coming soon.

It is the latest sign of the full-on digital revolution going on at Mohawk (a paper mill that dropped the words "Fine Papers" from its name last year).

X-Treme Packaging implements Amtech’s Imaginera Software System at corrugated box plant in Calgary, AB

FORT WASHINGTON, PA, May 15, 2013 (Press Release) - Amtech Software president, Cosmo DeNicola, is pleased to announce that X-Treme Packaging, a Calgary, AB based corrugated box plant, has implemented Amtech's Imaginera Software System. Imaginera will help X-Treme Packaging streamline their order entry's saving time for both their customers and themselves.

Comprehensive and flexible, Imaginera keeps your business moving forward, strengthening every area of your operation from financial applications to plan management and customer service. Amtech keeps its customers ahead of the marketplace with new releases and modules that take into account global trends and the evolving mobile technology landscape.

Amtech Software is the box industry's leading supplier of software solutions. Amtech Software has been installed in over 850 box plants of all shapes and sizes. Over 35,000 box plant employees use Amtech Software every day.
WHO’S DOIN’ ANYTHING?: (CONTINUED)

Port Hawkesbury Paper seeks to diversify product base, looks at bioeconomy, sugar technology [From the web]

PORT HAWKESBURY, NS, May 17, 2013 (Local News) - Just as groups in the Strait area are looking for ways to diversify its economy, the region’s largest employer is looking to diversify the products it manufactures.

Since restarting the former NewPage paper mill in Point Tupper in October, Port Hawkesbury Paper has been looking to expand its product line.

The year-long closure of the mill following its former owning filing for bankruptcy protection prompted some soul-searching among local municipal, business and development officials about the need to further diversify the region’s economy. While the mill did reopen after obtaining financial assistance from the province and a negotiated power rate structure, only one of the mill’s two paper machines has been restarted and it employs about half as many people as it did prior to shutdown.

Bellmer to rebuild dryer section of PM 5 at Erfurt & Sohn’s mill in Germany

SCHELBRONN, Germany, May 15, 2013 (Press Release) -

There is quite some analogy between the world’s leading manufacturer of ingrain wallpapers Erfurt & Sohn, established in 1827, and Gebr. Bellmer, established in 1842: Erfurt & Sohn as well as Bellmer are family-owned companies whose quality products “made in Germany” have an excellent international reputation. Both our companies had good reason to celebrate in 2012: Erfurt & Sohn celebrated its 185th and Bellmer its 170th anniversary.

Their long-term business relationship was refreshed and continued earlier this year when Erfurt & Sohn awarded Bellmer the order for the rebuild of their dryer section (pre/ and post dryer section) of PM 5.

Target of the rebuild was on the one hand the improvement of quality and on the other hand the increase of the machine speed.

The scope of supply includes parts of the dry wire system, 8 automatic dry wire tensioners, parts for the paper web guiding system and 70 dry wire guide rolls which will be manufactured in the new Bellmer Works 3 featuring a working area of 5,000 sqm. Since end of 2012, the up-to-date roll division has been located there.

Rolls, the core of paper machines, can there be produced even faster and more cost-efficient. Also frame parts for the dryer section will be provided by Bellmer. Furthermore, Bellmer has assumed the tasks of disassembling and remounting the pre/ and post dryer section. Startup and training of the customer’s personnel form also part of the order.

Holmen and investment fund Eurofideme 2 to build SEK 650 million wind farm at Norrtälje, Sweden

STOCKHOLM, May 17, 2013 (Press Release) - Together with investment fund Eurofideme 2, Holmen has decided to build a wind farm in the municipality of Norrtälje in a jointly-owned company. The annual production is an estimated 165 GWh and the wind farm is planned to commence operation in autumn 2014.
WHO’S DOIN’ ANYTHING?: (CONTINUED)

Eurofideme 2, a renewable energy infrastructure fund of Mirova*, has acquired half the shares in the company that Holmen founded to run wind power production on its own land in the municipality of Norrtälje near Hallsta Paper Mill. The decision now marks the start of installation of 17 wind turbines with an installed power capacity of a total 51 MW and an expected annual production of 165 GWh. An environmental permit has already been obtained. According to the plan, the turbines will be taken into operation in autumn 2014.

"This project will exploit Holmen’s excellent opportunities to produce wind power on its own land,” says Holmen’s President and CEO Magnus Hall. “It is also an important element in our focus on renewable energy, set to increase our self-sufficiency in electricity.”

"It is a great opportunity for Eurofideme 2 to be co-investing in this project of national interest for wind in the Stockholm County with a high quality partner like Holmen” commented Raphael Lance, Director of Eurofideme 2.

The cost of constructing the wind farm is an estimated SEK 650 million and will be financed by a bank loan to the jointly-owned company plus capital from shareholders Holmen and Eurofideme 2. Holmen’s investment will largely be met by income from the sale of shares in the company, and the transaction will therefore not have any noticeable effect on Holmen’s cash flow. The transaction will affect Holmen Energi’s operating profit in the second quarter by approximately SEK 100 million.

* Eurofideme 2, a fund managed by Mirova Environment and Infrastructure and part of Mirova, the Responsible Investment division of Natixis Asset Management, is investing through its wholly-owned subsidiary Wotan SA.
RECURSIVE UPDATE OF A REDUCED-ORDER DYNAMIC PLS SOFT SENSOR AND ITS APPLICATION TO DIGESTER CONTROL
BY
HECTOR J. GALICIA\textsuperscript{1} Q. PETER HE\textsuperscript{2} JIN WANG\textsuperscript{1}
\textsuperscript{1}DEPARTMENT OF CHEMICAL ENGINEERING, AUBURN UNIVERSITY, AUBURN, AL 36849
\textsuperscript{2}DEPARTMENT OF CHEMICAL ENGINEERING, TUSKEGEE UNIVERSITY, TUSKEGEE, AL 36088

PRESENTED AT ISA AUTOMATION WEEK 2011 IN MOBILE, AL
Recursive Update of a Reduced-Order Dynamic PLS Soft Sensor and its Application to Digester Control

Hector J. Galicia\textsuperscript{1}, Q. Peter He\textsuperscript{2}, Jin Wang\textsuperscript{1}
\textsuperscript{1}Department of Chemical Engineering, Auburn University, Auburn, AL 36849
\textsuperscript{2}Department of Chemical Engineering, Tuskegee University, Tuskegee, AL 36088

Keywords: Dynamic PLS, soft sensor, recursive update algorithm, data scaling, digester control.

ABSTRACT

Kraft pulping is the most commonly used chemical pulping process which usually utilizes a continuous Kamyr digester. Control of a continuous Kamyr digester is quite challenging, and one of the main reasons is that the primary product quality variable (i.e. Kappa number) is not measured on-line. To tackle this challenge, we have developed a reduced-order dynamic PLS soft sensor (RO-DPLS) to predict the Kappa number. The RO-DPLS soft sensor provides superior prediction performance compared to the traditional DPLS soft sensor which is demonstrated by both simulated and industrial case studies. However, industrial processes often experience time-varying changes and the performance of the off-line developed soft sensor often deteriorates over time. In this work, the previously developed RO-DPLS soft sensor is extended to its on-line adaptive version. Specifically, we examine four recursive PLS algorithms as well as the corresponding data scaling approaches. One simulated case study and two industrial case studies are used as benchmarks to compare the performance of the different algorithms. In addition, the findings on the properties of different recursive algorithms are discussed in order to provide some useful insights for practitioners. Finally, a simulated case study of wood type change (i.e. the raw material switch from soft wood to hard wood) is used to demonstrate the effectiveness of the recursive RO-DPLS soft sensor applied for feedback control.
1. INTRODUCTION

In many industrial processes such as distillation and pulping processes, the primary product variables are not measured on line or not measured frequently but are required for feedback control. For example, for high yield Kamyr digesters, the product quality variable Kappa number, can only be measured in a laboratory and is usually measured once per hour with half an hour to one hour measurement delay. To address this challenge, many data-driven soft sensors have been developed and implemented in process industry. Due to the growing popularity, demonstrated usefulness, and huge potential, soft sensor development has attracted many research interests in the past two decades. Among different approaches, the most popular modeling techniques applied to data-driven soft sensor are principal component analysis (PCA), partial least squares (PLS), artificial neural networks (ANN) and support vector machine (SVM). Kadlec et al. [1-2] provide a comprehensive review on the characteristics of the data generated from industrial processes, and different data-driven soft sensor modeling techniques. A more systematic and thorough discussion on the design procedures of soft sensor and their applications for solving industrial problems can be found in [3]. Among different datadriven soft sensor approaches, the dynamic partial least squares (DPLS) soft sensor approach has been applied to many industrial processes due to its simplicity and available adaptive versions. In our previous work [4], a theoretical analysis on the DPLS soft sensor modeling approach is provided. Additionally, it is proved that for a LTI system, the DPLS soft sensor is a dynamic estimator that can adequately capture process dynamics provided that enough lagged variables are used to build the model. Moreover, to address some limitations of the traditional DPLS soft sensor when applied to processes with large transport delays, a reduced-order DPLS (RO-DPLS) soft sensor approach is developed. Case studies of both simulated and industrial Kamyr digester demonstrate the improved performance from RO-DPLS soft sensor compared to the traditional DPLS soft sensor.

Industrial processes often experience time-varying changes, such as variations in process input material, process fouling and catalytic decaying. As a result, the performance of the off-line developed soft sensor often deteriorates. In these circumstances, it is desirable to update the soft sensor model with new process data to reflect the process changes. Various adaptation techniques have been published to update the DPLS soft sensor on-line. Helland et al. (1992) [5] introduce a recursive PLS regression algorithm which updates the model based on new data without increasing the size of data matrices. Qin (1998) [6] further proposes a block-wise RPLS, as well as a moving window and forgetting factor adaptation schemes. Dayal and MacGregor [7] propose a computationally efficient recursive PLS version by using the kernel algorithm (Lindgren, Geladi and Wold, 2005) [8] for the PLS computation rather than the NIPALS method [9]. In this work, the previously proposed RO-DPLS soft sensor is extended to its on-line adaptive version to track process changes and to focus on addressing several practical issues. Different model update approaches have been examined, as well as the corresponding data scaling methods. Various simulated cases studies, as well as two data sets collected from an industrial Kamyr digester run by MeadWestvaco Corp. are used to compare different methods. The rest of the paper is organized as following: Sections 2 and 3 review different adaptive PLS algorithms and data scaling approaches. Section 4 presents several case studies that are used to compare the different model updating and data scaling methods described in previous sections. The final Section 5 presents conclusions of this work.

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2. PLS MODEL UPDATE ALGORITHMS

In this section, we briefly review the PLS algorithm and its four recursive model update approaches, namely regular recursive PLS (RPLS), block-wise RPLS (BRPLS), moving window block-wise RPLS (MW-BRPLS), and forgetting factor block-wise RPLS (FF-BRPLS).

2.1 PLS REGRESSION

In this subsection, the traditional batch PLS algorithm is discussed as it is the foundation of different recursive algorithms. \( \mathbf{X} \in \mathbb{R}^{n \times m} \) and \( \mathbf{Y} \in \mathbb{R}^{n \times p} \) are used to denote the input and output data matrices, where \( n \) is the number of samples, \( m \) is the number of independent variables, and \( p \) is the number of dependent variables. Assume \( \mathbf{X} \) and \( \mathbf{Y} \) are linearly related by:

\[
\mathbf{Y} = \mathbf{X} \mathbf{C} + \mathbf{V}
\]  

(1)

where \( \mathbf{C} \) is the coefficient matrix and \( \mathbf{V} \) is the noise matrix with appropriate dimensions. The PLS regression method derives the linear model by first decomposing data matrices \( \mathbf{X} \) and \( \mathbf{Y} \) into bilinear terms.

\[
\mathbf{X} = \mathbf{T} \mathbf{P}^T + \mathbf{E}
\]  

(2)

\[
\mathbf{Y} = \mathbf{U} \mathbf{Q}^T + \mathbf{F}
\]  

(3)

where \( \mathbf{T} \in \mathbb{R}^{n \times d} \) and \( \mathbf{U} \in \mathbb{R}^{n \times d} \) are the score matrices of \( \mathbf{X} \) and \( \mathbf{Y} \) respectively, and \( d \) denotes the number of retained latent variables. Matrix \( \mathbf{P} \in \mathbb{R}^{m \times d} \) and \( \mathbf{Q} \in \mathbb{R}^{p \times d} \) are known as the loading matrices. Matrices \( \mathbf{E} \) and \( \mathbf{F} \) are the corresponding residual matrices. The scores of \( \mathbf{X} \) and \( \mathbf{Y} \) are related with a linear model:

\[
\mathbf{U} = \mathbf{T} \mathbf{B} + \mathbf{R}
\]  

(4)

where \( \mathbf{B} \in \mathbb{R}^{d \times d} \) is a diagonal matrix of inner model coefficients that is obtained by minimizing the residual \( \mathbf{R} \). Consequently, the estimates of \( \mathbf{\hat{Y}} \) of \( \mathbf{Y} \) are:

\[
\mathbf{\hat{Y}} = \mathbf{T} \mathbf{B} \mathbf{Q}^T + \mathbf{F}
\]  

(5)

For convenience, the following notation is used to represent the modeling procedure that obtains the PLS model \( \{\mathbf{T}, \mathbf{P}, \mathbf{U}, \mathbf{Q}, \mathbf{B}\} \) from the pair of data matrices \( \{\mathbf{X}, \mathbf{Y}\} \).

\[
\{\mathbf{X}, \mathbf{Y}\} \xrightarrow{\text{PLS}} \{\mathbf{T}, \mathbf{P}, \mathbf{U}, \mathbf{Q}, \mathbf{B}\}
\]  

(6)
2.2 RECURSIVE PLS

The recursive PLS was originally published by Helland in [5], which suffers from numerical instability for rank deficient data. This issue was later addressed by Qin in [6]. In this work, Qin’s approach is implemented to update the PLS model when new data becomes available. In the RPLS approach, instead of using old data and new data to rebuild the PLS model, the PLS model derived from the old data is augmented with the new data to obtain an updated PLS model. Here \((X, Y)\) and \((X_1, Y_1)\) are used to denote the old and new data, respectively. In [6], it is shown that performing PLS on a data pair \(\begin{bmatrix} X^T & X_1^T \end{bmatrix}^T, \begin{bmatrix} Y^T & Y_1^T \end{bmatrix}^T\), results in the same regression model as performing PLS on the data pair \(\begin{bmatrix} P & X \end{bmatrix}^T, \begin{bmatrix} Q & Y \end{bmatrix}^T\), provided that the residual matrix \(E\) of \(X\) is essentially zero. In typical PLS applications, the number of samples of the old data set \(n\) is greater than the retained latent variables \(a\), which makes the regular RPLS a much more efficient way of updating the PLS model.

2.3 BLOCK-WISE RPLS

To further improve the computation efficiency, Qin [6] also presents the block-wise RPLS, where a PLS sub-model is first built using the new data pair \((X_1, Y_1)\); then the sub-model is combined with the existing model to derive the updated PLS model, i.e., \((X_1, Y_1) \rightarrow \{T_1, P_1, U_1, Q_1, B_1\}\). It is shown in [6] that performing PLS on the data pair \(\begin{bmatrix} X^T & X_1^T \end{bmatrix}^T, \begin{bmatrix} Y^T & Y_1^T \end{bmatrix}^T\) results in the same regression model as performing PLS on the data pair \(\begin{bmatrix} P & P_1 \end{bmatrix}^T, \begin{bmatrix} Q & Q_1 \end{bmatrix}^T\), provided that the residual matrices of \(X\) and \(X_1\) are essentially zero; i.e., \(E = 0\) and \(E_1 = 0\).

2.4 BLOCK-WISE RPLS MOVING WINDOW APPROACH

To adequately adapt process changes, it is desirable to exclude older data by incorporating a moving window approach. Given \((X_1, Y_1) \rightarrow \{T_1, P_1, U_1, Q_1, B_1\}\) [6], the MW-BRPLS simply performs PLS regression on the following pair of matrices \(\begin{bmatrix} P \ P_{l-1} \ldots \ P_{l-w+1} \end{bmatrix}^T, \begin{bmatrix} Q_{l-1}B_{l-1} \ldots \ Q_{l-w+1}B_{l-w+1} \end{bmatrix}^T\). When the new data pair \((X_{l+1}, Y_{l+1})\) becomes available, a PLS sub-model is first derived; i.e., \((X_{l+1}, Y_{l+1}) \rightarrow \{T_{l+1}, P_{l+1}, U_{l+1}, Q_{l+1}, B_{l+1}\}\), then \(P_{l+1}\) and \(Q_{l+1}B_{l+1}\) are augmented into the first column of the previous matrix and the last column is dropped out. The window size \(w\) controls how fast the old data are excluded from the model. A narrow window makes the model adapt faster to new data.

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2.5 BLOCK-WISE RPLS FORGETTING FACTOR APPROACH

An alternative approach for on-line adaptation is to use a forgetting factor. Following [6], the PLS model at step $i$ is obtained by performing PLS on the following data pair $([P_i \lambda P_{i-1}]^T, [QB \lambda Q_k B_k]^T)$, where subscript $ic$ denote the combined model obtained at step $i-1$, and $\lambda$ is the corresponding forgetting factor. A $\lambda$ close to zero forgets old data faster.

3. DATA PREPROCESSING

In the PLS algorithm, the data pair $(X, Y)$ is usually scaled to zero mean and unit variance, so that different variables will influence the regression model to the same extent. Because processes are time varying, the means and variances of the process variables usually change over time, correspondingly the means and variances should be updated as well. This paper focuses on three online data scaling methods that accompany with the different model update approaches.

I. Recursive scaling and centering (RSC): For each variable

$$\bar{x}_t = \frac{n-1}{n} \bar{x}_{t-1} + \frac{1}{n} x_t$$

(7)

$$\sigma^2_t = \frac{n-2}{n-1} \sigma^2_{t-1} + \frac{1}{n-1} (x_t - \bar{x}_t)^2$$

(8)

where $n$ is the total number of data points and $t$ is the current time stamp. Note that $n$ keeps increasing as more data becomes available, and the influence of the new data points diminishes with increased $n$.

II. Moving window scaling and centering (MWSC): For each variable

$$\bar{x}_t = \frac{w-1}{w} \bar{x}_{t-1} + \frac{1}{w} x_t$$

(9)

$$\sigma^2_t = \frac{w-2}{w-1} \sigma^2_{t-1} + \frac{1}{w-1} (x_t - \bar{x}_t)^2$$

(10)

where $w$ is the window width which stays constant. Therefore, the effect of the new samples will not increase as more data becomes available.

III. Forgetting factor scaling and centering (FFSC): For each variable

$$\bar{x}_t = \alpha \bar{x}_{t-1} + (1-\alpha) x_t$$

(11)

$$\sigma^2_t = \alpha \sigma^2_{t-1} + (1-\alpha) (x_t - \bar{x}_t)^2$$

(12)
4. COMPARISON OF DIFFERENT UPDATING APPROACHES

In this section, the previously developed RO-DPLS soft sensor [4] is extended to its recursive version. The different recursive PLS algorithms and data scaling methods that are reviewed in the previous two sections are applied. One simulated case study and two industrial case studies of a single vessel Kamyr digester are used to compare the performance of different recursive PLS approaches and the corresponding scaling methods.

In case study I, the Purdue model [10] is implemented to simulate a high yield Kamyr digester. An open loop simulation with secondary variables (e.g. liquor measurements) and primary variable (i.e. Kappa number) sampled every 6 minutes is performed. Integrated white noise disturbances are introduced to white liquor compositions, and five wood compositions at the inlet. Measurement noise is added to unmeasured disturbances, primary and secondary variables as described in [4]. Two simulated data sets of 3000 samples and 2500 samples are used for training and testing, respectively. The RO-DPLS soft sensor is set up as in [4]. For case studies II and III, two industrial data sets are used. The data sets were collected from a high yield Kamyr digester at a pulp mill located in Mahrt, Alabama run by MeadWestvaco Corp from 2006 and 2010, respectively. For case study II, 1100 samples and 420 samples from the first data set are used for training and testing, respectively. For case study III, 1100 samples from the data collected in 2006 are used for training, and 420 samples from the data set collected in 2010 are used for testing. The RO-DPLS soft sensor settings for the industrial case are the same as reported in [4]. Clearly, case study III presents a significantly more challenging problem as training and testing data are collected so far away in time.

4.1 RO-DPLS MODEL UPDATE AND PERFORMANCE COMPARISON

Every recursive update algorithm has certain tuning parameters associated with it. Consequently, extensive experiments have been done to test different settings of each algorithm. For the ease of illustration, a few representative cases are selected to report including the optimal one. The specific settings for different update algorithms are listed in Table 1.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Update frequency/Setting</th>
<th>Scaling method</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPLS</td>
<td>10, 50, 100 samples</td>
<td>RSC</td>
</tr>
<tr>
<td>BRPLS</td>
<td>50, 100, 200 samples</td>
<td>RSC</td>
</tr>
<tr>
<td>MW-BRPLS</td>
<td>2, 3, 4 blocks of 50 samples</td>
<td>MWSC</td>
</tr>
<tr>
<td>FF-BRPLS</td>
<td>FF 0.2, 0.5, 0.8 with blocks of 50</td>
<td>FFSC</td>
</tr>
</tbody>
</table>

To assess the performance of the different model update algorithms, the mean squared prediction error (MSPE) is utilized.
\[
\text{MSPE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2
\]  

(13)

Where \(y_i\) and \(\hat{y}_i\) are the measured and predicted Kappa numbers at the digester exit. To eliminate the effect of outliers on different recursive update algorithms, off-line outlier detection has been performed to remove outliers from the industrial data sets. Consequently, a fair comparison of different recursive update algorithms together with the corresponding data scaling method is obtained. Results of the comparison are summarized in Table 2-Table 5.

Table 2: Performance of regular RPLS

<table>
<thead>
<tr>
<th>Index</th>
<th>Update frequency</th>
<th>Case I</th>
<th>Case II</th>
<th>Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSPE</td>
<td>10 samples</td>
<td>0.0660</td>
<td>16.8925</td>
<td>20.8786</td>
</tr>
<tr>
<td></td>
<td>50 samples</td>
<td>0.0777</td>
<td>15.8383</td>
<td>24.2623</td>
</tr>
<tr>
<td></td>
<td>100 samples</td>
<td>0.0780</td>
<td>16.3479</td>
<td>24.1189</td>
</tr>
</tbody>
</table>

Table 3: Performance of BRPLS

<table>
<thead>
<tr>
<th>Index</th>
<th>Update frequency</th>
<th>Case I</th>
<th>Case II</th>
<th>Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSPE</td>
<td>50 samples</td>
<td>0.1202</td>
<td>14.6378</td>
<td>123.6080</td>
</tr>
<tr>
<td></td>
<td>100 samples</td>
<td>0.1071</td>
<td>15.4846</td>
<td>36.0571</td>
</tr>
<tr>
<td></td>
<td>200 samples</td>
<td>0.1117</td>
<td>15.5604</td>
<td>48.8755</td>
</tr>
</tbody>
</table>

Table 4: Performance of MW-BRPLS

<table>
<thead>
<tr>
<th>Index</th>
<th>Update frequency</th>
<th>Case I</th>
<th>Case II</th>
<th>Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSPE</td>
<td>50 samples</td>
<td>0.0863</td>
<td>17.6212</td>
<td>30.2221</td>
</tr>
<tr>
<td></td>
<td>100 samples</td>
<td>0.1023</td>
<td>18.0705</td>
<td>27.9673</td>
</tr>
<tr>
<td></td>
<td>150 samples</td>
<td>0.1291</td>
<td>16.4916</td>
<td>35.3683</td>
</tr>
</tbody>
</table>

Table 5: Performance of FF-BRPLS

<table>
<thead>
<tr>
<th>Index</th>
<th>Update frequency</th>
<th>Case I</th>
<th>Case II</th>
<th>Case III</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSPE</td>
<td>50 samples (ff=0.2)</td>
<td>0.0782</td>
<td>17.9399</td>
<td>21.7646</td>
</tr>
<tr>
<td></td>
<td>50 samples (ff=0.5)</td>
<td>0.1006</td>
<td>15.5128</td>
<td>26.8180</td>
</tr>
<tr>
<td></td>
<td>50 samples (ff=0.8)</td>
<td>0.1030</td>
<td>15.5256</td>
<td>41.6904</td>
</tr>
</tbody>
</table>

The performance data indicates that among all four RPLS algorithms, the regular RPLS algorithm performs the best, not only in terms of the MSPE, but also in the fact that is the least sensitive to the size of the updating block. In contrast, the block-wise RPLS performs the worst. Specifically, for the challenging case study III, the prediction performance is quite sensitive to the size of the updating data block. However, if it has been proved that both regular RPLS and BRPLS are equivalent to the batch PLS, one may ask why their performance differs from each other significantly in these case studies. The answer is that the condition for the equivalency to hold, i.e., the PLS model for the historical data

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and the PLS sub-model for the new data has to capture the variability in \(X\) and \(X_1\) blocks completely, which is generally not satisfied for industrial data. When the size of the new data block is too small, the PLS sub-model may not adequately capture the variability of the new process condition, as the variability in the residual space of the PLS sub-model is completely discarded. On the other hand, if the size of the new data block is too big, the delay associated with data accumulation may deteriorate the soft sensor performance. Therefore, for the cases where the process is not sampled highly frequently, RPLS is a more reliable choice compared to BRPLS.

One way to interpret the RPLS algorithm is that \(P^T\) and \(BQ^T\) can be viewed as the representative samples for the historical data \(X\) and \(Y\), as they are the set of orthogonal bases that span the principal subspace of data block \(X\) and \(Y\), respectively. Similarly, for BRPLS, \(P^T_1\) and \(B_1Q^T_1\) can be viewed as the representative samples for the new data block. When RPLS and BRPLS are implemented, the number of latent variables is often determined by cross-validation, and is usually much smaller than the number of samples in the data sets. Therefore, part of the information contained in the original data will be missing if we use \(P^T\) and \(BQ^T\) to replace the data block. By choosing the new data block carefully, the PLS sub-model can adequately capture the variability in the new data. However, this may be very difficult to achieve when there are sudden changes in the process, as shown in Figure 1(b) for case study III.

![Figure 1: Performance of model update algorithms for case study III](image)

- a) RPLS, b) BRPLS, c) MW-BRPLS, d) FF-BRPLS
The performance of the two modified versions of BRPLS comes in between RPLS and BRPLS, with FF-BRPLS (with small forgetting factor) performs similarly to RPLS in terms of MSPE. However, it is clear that FF-BRPLS is slightly biased as shown in Figure 1(d). In addition, FF-BRPLS has more tuning parameters (forgetting factor, size of data block etc.) compared to the RPLS algorithm which only requires to provide the number of samples of the new data block. Therefore, in the rest of the paper the regular RPLS is selected to implement the recursive version of the RO-DPLS soft sensor.

Finally, it has been recognized that data scaling affects the soft sensor performance, especially when there exists operation point changes. One disadvantage associated with the commonly used data scaling method, i.e., Equation (7) and (8), is that when \( n \) (i.e., the number of samples) is very large, the mean and variance will no longer change, as the weighting assigned to the new data will become negligible. To address these limitations, we propose a modified scaling method in Equations (7) and (8) replacing \( n \) by \( N \), where \( N \) is a fixed value. In this way, weightings are assigned to the previous data and the new data. This approach makes more sense for the RPLS algorithm, because when updating the PLs model, the weight assigned to the new data is also fixed. To illustrate the effect of fixed \( N \), a simulation is performed where different \( N \) is used to scale the data. Figure 2 shows the MSPE for the three case studies. Clearly, depending on the characteristics of the process, there is a certain range of \( N \) that optimizes the soft sensor performance.

![Graphs](image)

Figure 2: Effect of scaling in MSPE with fixed \( N \). a) Case I, b) Case II, c) Case III.

### 4.2 APPLICATION OF THE RECURSIVE RO-DPLS SOFT SENSOR TO DIGESTER CONTROL

In this section, the recursive version of the RO-DPLS soft sensor is applied to control a simulated Kamyr digester. Two control scenarios are compared; one with the Kappa number measurement feedback and the other with the soft sensor predicted Kappa number feedback. In this case study, a very challenging control problem is considered, namely rejecting the disturbance of wood type change. To make the simulation more realistic, integrated white noise disturbance is added to the wood composition during the entire simulation. It should be pointed out that wood type change (from softwood to hardwood and vice versa) is a major disturbance in pulping process, which usually results in off-spec product during the transition [11].

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4.2.1 SIMULATION SETUP

The extended Purdue model [10] is implemented to simulate the Kamyr digester. The simulation starts with softwood as feeding material, then 6 hours after the process has reached steady state for soft wood feeding, the wood type change (i.e., step disturbance) is introduced and switch to hardwood feeding. The secondary variables are sampled every 6 minutes, and the primary variable is sampled every 30 minutes plus 30 minutes measurement delay. For soft sensor update, the regular RPLS algorithm is implemented and updated periodically every 10 samples (i.e. every 5 hours).

4.2.2 SIMULATION SETUP AND PERFORMANCE EVALUATION

In [12], the transfer function model for the Kamyr digester is identified through step response. The transfer function uses a second order plus time delay (SOPTD) to approximate the dynamics between the input (lower heater temperature) and the output (pulp Kappa number), i.e.,

\[
G(s) = \frac{K_p e^{-(\theta_p + \theta_m)s}}{\tau^2 s^2 + 2\zeta \tau s + 1}
\]

with \(K_p = -2.4\), \(\tau = 34.7\) min., and \(\zeta = 0.78\). Here \(\theta_p\) represents the transport delay associated with the pulping process and \(\theta_m\) is used to denote the measurement delay associated with Kappa number. Based on the identified SOPTD model, the PID controller settings are determined by following internal model control (IMC) tuning relationships. For closed-loop cases, the closed-loop time constant \(\tau_c = \theta_p + \theta_m\), which is a relative conservative setting. For Kappa number measurement feedback, the overall delay time \(\theta = \theta_p + \theta_m\) = 142.3 min., and the feedback frequency is every 30 minutes. For soft sensor estimated Kappa number feedback, because the soft sensor predicts the future Kappa number [4] with future horizon \(\theta_f = 42\) min., the overall delay \(\theta = \theta_p - \theta_f = 70.3\) min. The same tuning rule is applied to both control scenarios. The corresponding PID controller tuning parameters are listed in Table 6.

<table>
<thead>
<tr>
<th>Case</th>
<th>Feedback scheme</th>
<th>(K_c)</th>
<th>(\tau_0) (min)</th>
<th>(\tau_d) (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL-1</td>
<td>Measurement feedback</td>
<td>-0.0796</td>
<td>54.21</td>
<td>22.27</td>
</tr>
<tr>
<td>CL-2</td>
<td>Soft sensor feedback</td>
<td>-0.114</td>
<td>54.21</td>
<td>22.27</td>
</tr>
</tbody>
</table>

The performance of the recursive soft sensor is evaluated first, and then the closed-loop performances for the two PID controllers are compared. Figure 3(a) plots the open-loop Kappa number measurement response to a wood type change and wood composition disturbance together with the soft sensor prediction with model recursive update. It is clear that by updating the soft sensor model, the soft sensor can track the variation of Kappa number after this type of major disturbance occurs. Figure 3(b) illustrates the closed-loop performance for the two control scenarios. By comparing both responses, it is evident that by feeding back the predicted future Kappa number, the closed-loop performance can be significantly improved by reducing settling time considerably. This improvement is mainly due to the
significant reduced overall process delay (i.e., from $\theta$ to $\theta - \theta_i$) which allows a much more aggressive controller. In addition, the improvement is caused due to the more frequent feedback which is also enabled by the soft sensor.

![Figure 3: Kappa number response of different scenarios. (a) Open loop response to a wood type change disturbance. (b) Comparison of closed loop responses to a wood type change disturbance.](image)

5. CONCLUSIONS

In this paper, four different algorithms for updating the RO-DPLS soft sensor model are investigated. Among those, the block-wise algorithms are found to be quite sensitive to the size of the updating block. This is a consequence of two possibilities. When the size of the new data block is too small, the PLS sub-model may not adequately capture the variability of the new process condition, as the variability in the residual space of the PLS sub-model is completely discarded. On the other hand, if the size of the new data block is too big, the delay associated with data accumulation may deteriorate the soft sensor performance. Therefore, for the cases where the process is not sampled highly frequently, RPLS is a more reliable choice compared to BRPLS.

Additionally, we proposed a modified scaling method in Equations (7) and (8) to overcome the disadvantage of the commonly used data scaling method, i.e., giving negligible weight to new data as $n$ becomes large. This is achieved by replacing $n$ by $N$, where $N$ is a fixed value. In this way, weightings are assigned to the previous data and the new data. Simulation results for the three case studies indicate that there exists a range of $N$ that optimizes the soft sensor performance.

Finally, the performance of the recursive version of the RO-DPLS soft sensor is demonstrated using a challenging case of a simulated high yield Kamyr digester, i.e., the transition between different types of raw material. Simulation results indicate that not only the soft sensor with recursive update is able to capture the process dynamics, but the closed-loop performance can be significantly improved by reducing the settling time considerably. The improvement is mainly due to the overall reduction of
process delay time, which allows a more aggressive controller, and the more frequent feedback that is enabled by the soft sensor.

REFERENCES


Recursive Update of a Reduced-Order Dynamic PLS Soft Sensor and Its Application to Digester Control

Hector Galicia\(^1\), Q. Peter He\(^2\), Jin Wang\(^1\)

\(^1\)Department of Chemical Engineering, Auburn University
\(^2\)Department of Chemical Engineering, Tuskegee University
Dr. Q. Peter He received his BS degree in chemical engineering from Tsinghua University, Beijing, China, in 1996 and MS and PhD degrees in chemical engineering in 2002 and 2005 from the University of Texas, Austin. He is currently an associate professor at Tuskegee University. His research interests are in the general areas of process modeling, monitoring, optimization and control, with special interests in the modeling and optimization, fault detection and classification of batch processes such as semiconductor manufacturing and pharmaceutical processes. He is also interested in biological system modeling and disease diagnosis. He has had over 3 years of experience in semiconductor and chemical industries.
Outline

- Background
- Previous results
  - RO-DPLS static soft sensor
- Recursive model update schemes
- Application of recursive RO-DPLS soft sensor to digester control
- Conclusion and discussion
Background

- In many industrial processes, the primary product variables that are required for feedback control are either not measured online or not measured frequently.
- To address this challenge, many soft sensors approaches have been developed and implemented in process industry.
- Compared to model-based soft sensors such as Kalman filter and Luenberger observer, the data-driven soft sensors are easy to develop and implement online.
- Among different data-driven approaches, PLS is one of the most commonly applied approaches in industry applications.
Our previous work[1]

• We provided the first theoretical analysis on the dynamic PLS soft sensor modeling approach, proved that it is a dynamic state estimator for LTI system, and derived the conditions to ensure the soft sensor will capture the dynamics of the process adequately.

• We proposed a reduced-order DPLS (RO-DPLS) soft sensor approach to address the limitations of the traditional DPLS soft sensor when applied to processes with large transport delays such as continuous digester.

Continuous Kamyr Digester

• **Control challenges**
  - Long residence time.
  - Kappa number is not measurable in real time.
  - Biological feedstock varies stochastically.
  - Complex nonlinear dynamic behavior.

• **Primary control goal**
  - Reduce the variability of Kappa number.

• **Secondary control goal**
  - Reduce the energy cost and white liquor usage.
Comparison of the static RO-DPLS soft sensor with regular DPLS soft sensor

DPLS

RO-DPLS

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Recursive soft sensor update

- Industrial processes often experience time-varying changes.
  - Variations in process input material.
  - Process fouling and catalytic decaying are some examples.
- It is desirable to update the soft sensor model with the new process data to reflect the process changes.
- In this work, we extend the previously developed RO-DPLS soft sensor to its adaptive version.
  - The properties of four model update schemes and the corresponding data scaling methods are investigated through simulated and industrial case studies of Kamyr digesters.
  - Our findings are expected to provide useful information and some guidance to practitioners.
## PLS model update schemes

- Model update schemes have different characteristics and associated tuning parameters.

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recursive PLS (RPLS)</td>
<td>$X = \begin{bmatrix} P^T \ X_1 \end{bmatrix}$, $Y = \begin{bmatrix} BQ^T \ Y_1 \end{bmatrix}$</td>
</tr>
<tr>
<td>Block RPLS (BRPLS)</td>
<td>$X = \begin{bmatrix} P^T \ P_1^T \end{bmatrix}$, $Y = \begin{bmatrix} BQ^T \ B_1Q_1^T \end{bmatrix}$</td>
</tr>
<tr>
<td>Block-Moving Window (MW-BRPLS)</td>
<td>$X = \begin{bmatrix} P_s^T \ P_{s-1}^T \ \vdots \ P_{s-w+1}^T \end{bmatrix}$, $Y = \begin{bmatrix} B_s Q_s^T \ B_{s-1} Q_{s-1}^T \ \vdots \ B_{s-w+1} Q_{s-w+1}^T \end{bmatrix}$</td>
</tr>
<tr>
<td>Block-forgetting factor (FF-BRPLS)</td>
<td>$X = \begin{bmatrix} P_s^T \ \lambda P_{sc}^T \end{bmatrix}$, $Y = \begin{bmatrix} B_s Q_s^T \ \lambda B_{sc} Q_{sc}^T \end{bmatrix}$</td>
</tr>
</tbody>
</table>

Where:
- $P$: loading matrix for $X$
- $Q$: Loading matrix for $Y$
- $s$: block of data
- $sc$: Combined model
- $w$: Window size
- $\lambda$: Forgetting factor
Data preprocessing

- For off-line model building, the data preprocessing is usually an iterative process.
- The linear relationship between $X$ and $Y$ extracted from the process data can be easily distorted by measurement noise, the presence of outliers, and/or autocorrelated measurements.
- For online applications:
  - It is generally impossible to repeat the data preprocessing steps with plant expert inputs as in off-line model building.
- Outliers have been manually removed from the industrial data sets before soft sensor building.
  - This issue is being addressed in a separate work.
On line data scaling

- In PLS, the data pair \( \{X,Y\} \) is usually scaled to zero mean and unit variance.
  - Variables influence the regression model to the same extent.
- Means and variances of the process variables usually change over time.
  - Means and variances of regressor variables should be updated as well.
- Three different data scaling methods
  - Recursive scaling and centering (RSC)
    \[
    \bar{x}_n = \frac{n-1}{n} \bar{x}_{n-1} + \frac{1}{n} x_n \\
    \sigma^2_n = \frac{n-2}{n-1} \sigma^2_{n-1} + \frac{1}{n-1} (x_n - \bar{x}_n)^2 + (\bar{x}_n - \bar{x}_{n-1})^2
    \]
  - Moving window scaling (MWSC)
    \[
    \bar{x}_n = \frac{w-1}{w} \bar{x}_{n-1} + \frac{1}{w} x_n \\
    \sigma^2_n = \frac{w-2}{w-1} \sigma^2_{n-1} + \frac{1}{w-1} (x_n - \bar{x}_n)^2
    \]
  - Forgetting factor scaling (FFSC)
    \[
    \bar{x}_n = \alpha \bar{x}_{n-1} + (1 - \alpha) x_n \\
    \sigma^2_n = \alpha \sigma^2_{n-1} + (1 - \alpha) (x_n - \bar{x}_n)^2
    \]
Description of data sets and case studies

• Simulated case study.
  – Extended Purdue model, 300 hrs data for training and 250 hrs data for testing.
  – Open loop simulation with secondary variables (e.g. liquor measurements) and primary variable (i.e. Kappa number) sampled every 6 minutes.

• Two industrial data sets collected in 2006 (data set I) and 2010 (data set II) from a Kamyr digester at MWV.
  – **Industrial case study I**: training and testing both from data set I.
  – **Industrial case study II**: training data from data set I and testing data from data set II.
    – Significantly more challenging problem as training and testing data sets are collected about 4 years apart.
Model update performance comparison

- To eliminate the effect of outliers on different RO-DPLS model update schemes, off-line outlier detection is performed to remove outliers from the industrial data sets.
- To assess the performance of different model update schemes, we use the following two indices (mean squared error and mean error), plus visual examination.

\[ MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \]

\[ ME = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i) \]
The effect of model update frequency: Simulated case study

(a) MSE vs. Model update interval (No. of samples)

(b) Error vs. Model update interval (No. of samples)

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The effect of model update frequency: Simulated case study

- The RO-DPLS soft sensor performs better when the model is updated more frequently, which is true for all update schemes.
- This is mainly due to the strong time-varying characteristics of the process.
- MSE may not a reliable indicator for soft sensor performance, which is illustrated by the comparison of soft sensor performance with RPLS and FF-RPLS update scheme.
The effect of model update frequency: Industrial case study I & II

Industrial Case I

Industrial Case II

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The effect of model update frequency: Industrial case studies

- The results of RO-DPLS with different model updating schemes are mixed: there is no single method that consistently outperforms others for different update intervals.
- This is probably due to the fact that in the industrial data sets the measurement noises are not necessarily white; in addition, there are limited testing samples in both data sets.
The effect of model update frequency: Industrial case study I
The effect of model update frequency: Industrial case study I

- When the RO-DPLS soft sensor is updated more frequently, it tracks the process variation better, though it may have a slightly higher MSE.
- When the soft sensor is updated less frequently, the model tends to ignore the large process variations and stays closer to the mean of the primary variable.
- These are true for all updating schemes, most clearly demonstrated by RPLS; therefore, ME is a better performance indicator than MSE in this specific industrial case study.
The effect of model update frequency:
Industrial case study II

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The effect of model update frequency: Industrial case study II

- Compared to industrial case study I, the soft sensor performance are noticeably worse, because the initial soft sensor model is no longer good.
- Again, ME is a better indicator of the soft sensor prediction performance, and RPLS with frequent update provides the best performance.
- Because the information contained in the new measurement is quite different from the initial model, the soft sensor performs better if the new data are used directly to update the model.
The effect of the number of PLS component retained for prediction

- The number of PLS component retained for prediction has a big impact on prediction performance.
- The performance of the RO-DPLS soft sensor with five different component selection methods are compared:
  - Number of component is determined through leave-one-out cross-validation (LOO-CV);
  - Number of component is determined through block cross-validation (B-CV);
  - Number of component is fixed at 2;
  - Number of component is fixed at 3;
  - Number of component is fixed at 4;
- Results on RPLS is presented here, the results on other model update schemes are similar.
The effect of the number of PLS components retained for prediction: Simulated case study

- The two cross-validation approaches perform better than fixed component approaches.
- However, around the optimal updating frequency, there is not much difference among different approaches.
Histograms of the number of components determined through cross-validation

(a) B-CV for model update every 10 samples;
(b) BCV for model update every 100 samples;
(c) LOO-CV for model update every 10 samples;
(d) LOO-CV for model update every 100 samples

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The effect of the number of PLS component retained for prediction

- Although cross-validation method is usually recommended to determine the number of components for model prediction, we found that when the soft sensor model is updated frequently, it would be better to fix the number of components.
- When the number of samples for model update is small, the results from the cross-validation method may be overly sensitive to process disturbances.
  - Dramatic changes in the number of selected components negatively affect prediction performance.
Application of the recursive RO-DPLS soft sensor to digester control

- The extended Purdue model is implemented to simulate the continuous Kamyrd digester.
  - Integrated white noise disturbance is added to the wood composition during the entire simulation.
  - Secondary variables are measured every 6 minutes and the primary variable is sampled every 30 minutes plus 30 minutes measurement delay.
- A SOPTD transfer function model is identified through step response to approximate the dynamics between the input (lower heater temperature) and the output (pulp Kappa number).
- **Control problem**: Reject the disturbance after a wood type change.
Open loop response

- The recursive RO-DPLS soft sensor can capture the process dynamics after a major type of disturbance occurs.
Control scenarios

- For feedback control
  - A PID controller is implemented.
  - The PID controller settings are determined by following internal model control (IMC) tuning relationships.
  - To make the comparison consistent, the same closed-loop time constant is used to tune the two controllers.
  - The closed-loop time constant used is a relatively conservative one.
- Two control scenarios are compared.
  - Kappa number measurement feedback.
  - Soft sensor predicted Kappa number feedback.

<table>
<thead>
<tr>
<th>Case</th>
<th>Feedback scheme</th>
<th>$K_c$</th>
<th>$\tau_i$(min)</th>
<th>$\tau_d$(min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CL-1</td>
<td>Measurement feedback</td>
<td>-0.0796</td>
<td>54.21</td>
<td>22.27</td>
</tr>
<tr>
<td>CL-2</td>
<td>Soft sensor feedback</td>
<td>-0.114</td>
<td>54.21</td>
<td>22.27</td>
</tr>
</tbody>
</table>
Closed-loop comparison

- The closed-loop performance can be significantly improved by feeding back the predicted future Kappa number.
  - Significant reduction of overall process delay time.
  - More frequent feedback enable by the soft sensor.
Conclusions

- Four model update schemes are examined, namely PRLS, BRPLS, MW-BPLS and FF-BRPLS, together with their corresponding data scaling methods.
- For processes that experience constant changes and various disturbances such as digester process, RPLS model update scheme generally performs the best with frequent update.
- For frequent model update, it is preferred to use the data directly for update, instead of using the sub-model extracted from the data for soft sensor update.
- When the number of samples for model update is small, it would be better to fix the number of PLS components for prediction, instead of using cross-validation to determine the number of components.
Acknowledgements

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• We thank Dr. Russell Hodges at R.E. Hodges, LLC and Mr. Charles Hodge at MeadWestvaco Corporation for providing the data and digester process knowledge.
2013 ISA PUPID SCHOLARSHIPS
MEET KAYLA LOUISE YOUNG

The ISA Pulp & Paper Industry Division is pleased to award a $2000 scholarship to a college student pursuing a career in pulp & paper. This year, the winner is another “top-notch” student with an impressive scholastic record as well as extracurricular activities and having demonstrated a significant interest in the pulp and paper industry. The winner is Kayla L. Young. Kayla sent in her completed application form from the PUPID website, an official transcript from her university, three letters of recommendation from persons familiar with her character, and answered three questions describing his interest in the pulp and paper industry, her educational accomplishments, her school activities and her leadership roles. You can read a little bit about her in the rest of this article.

Kayla L. Young, a 21-year old junior majoring in Chemical Engineering with a concentration in Paper Science at Miami University in Oxford, Ohio, hails from Maineville, Ohio, where she graduated from Kings High School, in nearby Kings Island, where she was a cheerleader for 12 years and a dancer for 7 years and competed in bowling for 5 years and was able to attend the Pepsi Youth Bowling Championships.

Kayla is the daughter of Mike, who works for Mane Inc. and Tina, who works for Macy’s Credit and Customer Service Inc. and has two younger brothers, Eric, 17, and Jason, 15.

Kayla will graduate in May 2014 and currently has a GPA of 2.34. Kayla is still searching for a summer internship this summer (she was offered a non-paying internship), so maybe some of you readers can help her. Kayla says long term she would like to work for Procter and Gamble in Research and Development or to work for Georgia Pacific as a Process Engineer or in Research and Development. While studying at Miami of Ohio, she has been a member of Miami Student TAPPI and plans to tryout for the Miami Shakerettes for the upcoming year.

For fun, Kayla enjoys hanging out with friends and family, shopping, bowling, dancing, and playing video games.

(The picture was taken at the 2013 Miami University PSE Foundation Banquet where Pat Dixon, ISA Pulp & Paper Industry Division Education Chair, awarded Kayla the 2013 scholarship.)
LETTERS TO THE EDITOR

Send your comments on this newsletter to me at brad.carlberg@bsc-engineering.com or post a message to the ISA PUPID Technical Discussion Forum List Serve & “get something started”!

You can reach the site at http://www.isa-online.org/cgi-bin/wa.exe?A0=PUPID or by going to the PUPID or the main ISA websites and looking for the “ISA Technical Divisions”
LINKS TO RELATED WEBSITES

ISA PULP & PAPER WEBSITE
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QUICKIES

ISA PULP & PAPER TECHNICAL DISCUSSION FORUM

Anybody (not necessarily an ISA or PUPID member) can subscribe to the PUPID Pulp & Paper Technical Discussion Forum. To subscribe, go to the PUPID homepage at http://www.isa.org/~pupid/, select "Pulp & Paper Technical Discussion Forum" in the pick box, click "Go", and enter you email address and a password.

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Any ISA member can register for a free email address and online mailbox. If you set it up, your ISA email address will be yourname@member.ISA.org. To register, go to http://www.isa.org/membership/benefits/, and follow the registration instructions.

ISA PUPID CALENDAR

Get a quick overview of ISA PUPID events for 2002 by going to the Calendar at:
http://www.isa.org/~pupid/2002_PUPID_Calendar.htm
World Corners

Canada Corner
Nothing from anyone there this time!

Central & South American Corner
Nothing from anyone there this time!

Far East Corner
Nothing from anyone there this time!

From the Land of the Midnight Sun
Nothing from anyone there this time!

European Corner
Nothing from anyone there this time!
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Brad S. Carlberg, P.E.
Hyundai Engineering & Construction
brad.carlberg@bsc-engineering.com

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Dixon Process Automation Services, Inc.
PatJ Dixon@DPAS-INC.com

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Paul Burnett
(203) 482-3553
paulburnett@att.net

Advisor
Richard E. Britton, P.E.
Retired – International Paper
richardbritton1@comcast.net
(251) 342-0998

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vacant

Advisor
Larry E. Wells, P.E.
CCSA, LLC
ccsallc@bellsouth.net

Assistant Newsletter Editor
Frank Wilson
Pacific Lumber Company
fwilson@palco.com
(707) 764-4210

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ISAPulp & Paper Industry Division
P.O. Box 12277
Research Triangle Park, NC 27709

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