Froth Pipeline Water Content Estimation and Control

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Abstract: This paper presents a successful application of soft sensor based control for froth pipeline water content in oil sands industry. Water content is a key process quality variable for inter-site froth transportation through pipeline, which should be controlled within a specific range by adding hot processing water into the pipeline to maintain a reliable operating condition. A dynamic soft sensor incorporated with on-line bias update is developed to estimate the water content in real-time. Based on the soft sensor, a control strategy is consequently implemented to control the froth pipeline water content. Significant improvement of water content control is obtained from the successful application to a froth pipeline, which demonstrates the effectiveness, reliability and advantage of the soft sensor and control proposed.

Keywords: Soft sensor, Estimation, Bias compensation, Inferential control

1. INTRODUCTION

Athabasca oil sands in northern Alberta of Canada, as a source of oil for a diverse range of products, are mixtures of quartz, clay, water, bitumen and accessory minerals. The bitumen is extracted from the oil sands raw material prior to being upgraded to synthetic oil. However, extraction operation is quite unique, not all the physical and chemical mechanisms are fully understood (Kresta, 1997). Among many extraction processing steps, bitumen froth transportation is one of the most important units. Syncrude Canada Ltd., one of the world's largest oil sands companies mainly operating in surface mining, extraction, upgrading and utility facilities (Dougan & McDowell, 1997), strives for innovative ways of froth transportation to maximize bitumen recovery rate and reduce unit cost. One of the major challenges to achieve a reliable and efficient froth transportation is the lack of reliable and accurate key process measurements at a high frequency for control in real-time. Syncrude has been addressing this challenge by utilizing available technology intended for other applications where possible; adapting available technology where feasible; and developing novel technology where necessary (Espejo, 2011).

Soft sensors, also known as inferential estimators, can help in addressing the challenge due to lack of reliable and accurate measurements in real-time, which makes use of readily available process variables to build an inferential model that provides estimates of difficult-to-measure process variables. Soft sensor technology has developed rapidly in the

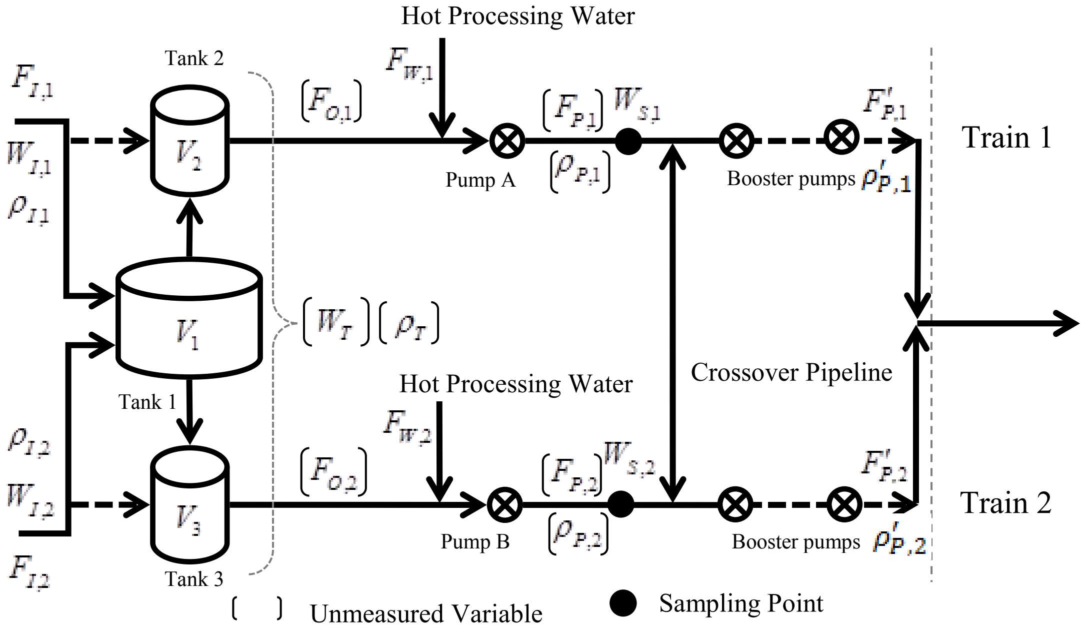


Fig. 1. Process flow diagram

last two decades (Fortuna, Graziani, Rizzo, & Xibilia, 2007), and has been investigated in many process industries (Khatibisepehr & Huang, 2008; Kadlec, Gabrys, & Strandt, 2009).

Model building is a key step in soft sensor development, which is the core of a soft sensor and establishes the connection between available process variables and the quality variable to be estimated. Generally, there are two well-known kinds of approaches to build soft sensor models according to how a priori knowledge is incorporated into the modelling, which are first-principle approaches (Friedman, Neto, & Porfirio, 2002; Yu, 2012), and data-driven approaches (Xie, et al., 2013; Shang, Yang, Huang, & Lyu, 2014). A first-principle model is based on good understanding of the fundamental principles within the target process; thus it has good extrapolating property and is well applicable for control purposes (Khatibisepehr, Huang, & Khare, 2013). However, every modelling technique inevitably has limitations due to their own mechanism and diverse behaviours of industrial processes. If there is no good model maintenance, the reliability and accuracy of soft sensor model output will decrease (Kadlec & Gabrys, 2008). Therefore, output calibration technique is favoured in field because it is simple with low cost but gets relatively good performance (Ni, Wang, Chen, Ng, & Tan, 2012).

In order to provide a key process variable for control and achieve reliable froth transportation, in our previous work, a data-driven soft sensor was developed to estimate the pipeline froth water content (Shao, Xu, Huang, & Espejo, 2012). However, during the practical application on Syncrude site, it has been aware of that the data-driven soft sensor requires a lot of maintenance efforts and cannot cover all the operation situations, which could not meet the expected control performance, especially during the process transition when froth run through the crossover pipe. To address these issues, in this work, a soft sensor is developed based on a dynamic model by using dynamic mass balance for each train. Meanwhile, to ensure the reliability and accuracy of the soft sensors, a simple but effective and practical soft sensor bias update approach is proposed. Given the reliable and accurate froth water content estimation, a soft sensor based inferential control strategy is proposed to control the froth water content. Successful implementation results of the soft sensor and inferential control are provided and discussed.

2. PROCESS DESCRIPTION AND PROBLEM FORMULATION

2.1. Process Overview

Syncrude inter-site froth pipeline consists of two independent trains, Train 1 and Train 2, to transport froth through one pipeline from one site to the other site for further processing. A simplified schematic diagram of the process is shown in Fig. 1 with the process variables of interest, where the variables in a pair of brackets are unmeasured and the others are obtained through on-line measurement or lab analysis at different sampling rates as listed in Table 1. The froth pipeline is fed from 3 connected froth tanks, Tank 1, Tank 2 and Tank 3, which contain processed froth from upstream. The froth pipeline is fed by two primary pumps, Pump A for Train 1 and Pump B for Train 2, and then discharged by two sets of booster pumps. The pumps are controlled to maintain the levels in the tanks and the flow rates in the froth pipeline to meet the downstream requirement. Before the booster pumps, there is a crossover pipeline so that the froth can still be transported through the pipeline even if one set of the booster pumps are not in service. Two trains are merged prior to being shipped away through only one pipeline.

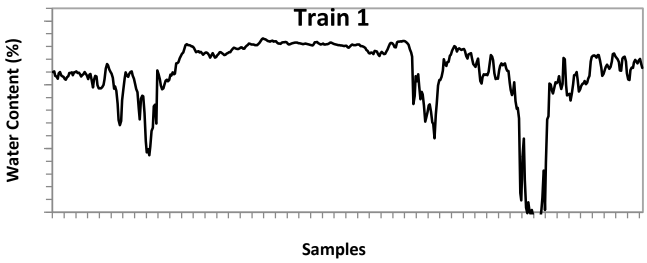
Table 1. Process variables

Symbol	Description	Unit
$F_{I,1}$	Tank 2 inlet froth flow rate	m^3/h
$F_{I,2}$	Tank 3 inlet froth flow rate	m^3/h
V_1	Tank 1 froth volume	m^3
V_2	Tank 2 froth volume	m^3
V_3	Tank 3 froth volume	m^3
$F_{W,1}$	Addition hot water to Train 1	m^3/h
$\rho'_{P,1}$	Train 1 diluted froth density	t/m^3
$F_{W,2}$	Addition hot water to Train 2	m^3/h
$\rho'_{P,2}$	Train 2 diluted froth density	t/m^3
$F'_{P,1}$	Train 1 diluted froth flow rate	m^3/h
$F'_{P,2}$	Train 2 diluted froth flow rate	m^3/h
$W_{I,1}$	Tank 2 inlet froth water%	weight%
$W_{I,2}$	Tank 3 inlet froth water%	weight%
$\rho_{I,1}$	Tank 2 inlet froth density	t/m^3
$\rho_{I,2}$	Tank 3 inlet froth density	t/m^3
$W_{S,1}$	Train 1 froth pipeline water content lab data	weight%
$W_{S,2}$	Train 2 froth pipeline water content lab data	weight%
ρ_T	Density of the froth in the 3 tanks	t/m3
W_T	Water content of the froth in the 3 tanks	%
$F_{O,1}$	Flow rate of the froth from tanks to Train 1	m^3/h
$F_{O,2}$	Flow rate of the froth from tanks to Train 2	m^3/h
$F_{P,1}$	Flow rate of the diluted froth to Train 1	m^3/h
$F_{P,2}$	Flow rate of the diluted froth to Train 2	m^3/h

To maintain froth transport in the pipeline, hot processing water is added to dilute the froth. If the froth water content is within a specified range, the froth can be directly fed to a following process for froth treatment. However, historical data shows that for quite a large fraction of time the water content exceeded the upper bound of the desired range so that the froth had to be reprocessed, which could lead to bitumen loss. Conversely, if the froth water content is lower than the lower bound of the range, the pipeline could be plugged, which results in production time loss. Obviously, good control of the froth water content by manipulating the hot processing water addition is very critical indeed for the industry, as it can improve froth pipeline operation reliability, lower bitumen loss, as well as reduce froth quality variations. To achieve the optimal control of the froth water content, the first and foremost issue is to obtain real-time, reliable, accurate and consistent water content information.

2.2. Existing Froth Water Content Measurements

To measure the water content of the froth for each train, two on-line analysers were installed, one for each train, to monitor in real-time the water content of the froth discharged by primary pumps at the locations indicated in Fig. 1 as “Sampling Point”. However, the variation of the oil sands composition and the nature of multi-phase processing conditions create a harsh environment for in-line instruments, which leads to reliability issues on these two analysers as observed from historical data shown in Fig. 2.



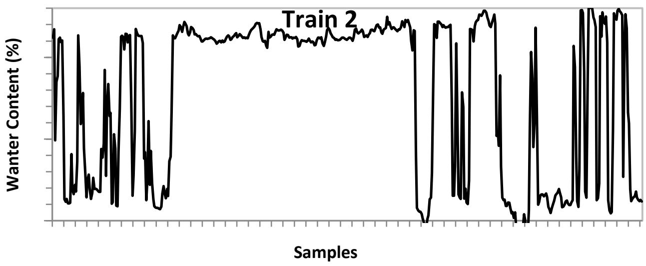


Fig. 2. On-line analyser readings for water contents

It can be seen that both on-line analysers are not reliable and the readings even drop to negative values from time to time, which could cause severe upsets if they are applied for froth water content control.

Due to the importance of the froth water content information, lab analysis, usually called lab data, is available hourly for each train. However, the analysis procedure is carried out off-line, and usually takes one hour to complete. Therefore, lab data is not suitable for control purposes, though it is considered as the most trustful and accurate information for operations most of time.

Due to the limitations of the existing measurements mentioned above, soft sensors are developed to provide more reliable and fast-rate real-time froth water content for the froth water content control.

3. SOFT SENSOR MODEL DEVELOPMENT

Due to the crossover pipeline and different start/stop operating mode of the pumps, the process model is discrete. Therefore, building a first-principle model should be the best choice for the soft sensor development. As a result, the water content soft sensors are developed based on dynamic mass balance analysis. To achieve this, the whole process is separated into three parts, which are discussed in this section.

3.1. Tanks Dynamic Mass Balance

Since the water content and density of the froth in the tanks are not measured, the product of these two variables $\langle W_T \cdot \rho_T \rangle$ is considered as the system state to be estimated.

The water mass balance of the froth coming into, going out of and residing in the tanks from time T to $T + \Delta t$ is

$$\begin{aligned} &\langle W_T \cdot \rho_T \rangle_{T+\Delta t} \cdot \left(V_{1,T+\Delta t} + V_{2,T+\Delta t} + V_{3,T+\Delta t}\right) \\ &= \begin{pmatrix} W_{I,1,T+\Delta t} \cdot \rho_{I,1,T+\Delta t} \cdot F_{I,1,T+\Delta t} \\ +W_{I,2,T+\Delta t} \cdot \rho_{I,2,T+\Delta t} \cdot F_{I,2,T+\Delta t} \end{pmatrix} \cdot \Delta t \\ &-\langle W_T \cdot \rho_T \rangle_T \cdot \left(F_{O,1,T+\Delta t} + F_{O,2,T+\Delta t}\right) \cdot \Delta t \\ &+\langle W_T \cdot \rho_T \rangle_T \cdot \left(V_{1,T} + V_{2,T} + V_{3,T}\right) \end{aligned} \tag{1}$$

where,

$$\begin{aligned} &\left(V_{1,T+\Delta t} + V_{2,T+\Delta t} + V_{3,T+\Delta t}\right) \\ &= \begin{pmatrix} F_{I,1,T+\Delta t} \\ +F_{I,2,T+\Delta t} \end{pmatrix} \cdot \Delta t + \left(V_{1,T} + V_{2,T} + V_{3,T}\right) - \begin{pmatrix} F_{O,1,T+\Delta t} \\ +F_{O,2,T+\Delta t} \end{pmatrix} \cdot \Delta t \end{aligned} \tag{2}$$

Assuming,

$$\langle W_T \cdot \rho_T \rangle_{T+\Delta t} = \langle W_T \cdot \rho_T \rangle_T + \Delta \langle W_T \cdot \rho_T \rangle_{T+\Delta t} \tag{3}$$

and substituting (2) and (3) into (1), it can be obtained that,

$$\begin{aligned} &\Delta \langle W_T \cdot \rho_T \rangle_{T+\Delta t} \\ &= \frac{\begin{pmatrix} \left(W_{I,1,T+\Delta t} \cdot \rho_{I,1,T+\Delta t} - \langle W_T \cdot \rho_T \rangle_T\right) \cdot F_{I,1,T+\Delta t} \\ +\left(W_{I,2,T+\Delta t} \cdot \rho_{I,2,T+\Delta t} - \langle W_T \cdot \rho_T \rangle_T\right) \cdot F_{I,2,T+\Delta t} \end{pmatrix}}{V_{1,T+\Delta t} + V_{2,T+\Delta t} + V_{3,T+\Delta t}} \cdot \Delta t \end{aligned} \tag{4}$$

According to (3) and (4), the system state $\langle W_T \cdot \rho_T \rangle$ can be obtained recursively, with K as time index for the corresponding discrete system with a sampling time of Δt as,

$$\begin{aligned} &\langle W_T \cdot \rho_T \rangle_{K+1} \\ &= \langle W_T \cdot \rho_T \rangle_K + \Delta \langle W_T \cdot \rho_T \rangle_{K+1} \\ &= \langle W_T \cdot \rho_T \rangle_K + \frac{\begin{pmatrix} \left(W_{I,1,K+1} \cdot \rho_{I,1,K+1} - \langle W_T \cdot \rho_T \rangle_K\right) \cdot F_{I,1,K+1} \\ +\left(W_{I,2,K+1} \cdot \rho_{I,2,K+1} - \langle W_T \cdot \rho_T \rangle_K\right) \cdot F_{I,2,K+1} \end{pmatrix}}{V_{1,K+1} + V_{2,K+1} + V_{3,K+1}} \cdot \Delta t \end{aligned} \tag{5}$$

3.2. Pipeline Dynamic Mass Balance

Taking Train 1 as an example, the water mass balance of the froth diluted in the pipeline of Train 1 at time $T + \Delta t$ is,

$$\begin{aligned} &W_{S,1,T+\Delta t} \cdot \rho_{P,1,T+\Delta t} \cdot F_{P,1,T+\Delta t} \\ &= \langle W_T \cdot \rho_T \rangle_{T+\Delta t} \cdot F_{O,1,T+\Delta t} + 100\% \cdot 1 \cdot F_{W,1,T+\Delta t} \end{aligned} \tag{6}$$

Then the real-time recursively estimated water content of the froth in the pipeline of Train 1 with sampling time of Δt is

$$W_{S,1,K+1} = \frac{\langle W_T \cdot \rho_T \rangle_{K+1} \cdot F_{O,1,K+1} + 100\% \cdot 1 \cdot F_{W,1,K+1}}{\rho_{P,1,K+1} \cdot F_{P,1,K+1}} \tag{7}$$

The similar result can be obtained for Train 2.

The unknown variables $F_{O,1,K+1}$ and $F_{P,1,K+1}$ in (6) obey the equation based on volume balance as

$$F_{O,1,K+1} = F_{P,1,K+1} - F_{W,1,K+1} \quad (8)$$

By substituting (8) into (7), the froth water content can be estimated as

$$W_{S,1,K+1} = \frac{\langle W_T \cdot \rho_T \rangle_{K+1}}{\rho_{P,1,K+1}} + \frac{(100\% - \langle W_T \cdot \rho_T \rangle_{K+1})}{\rho_{P,1,K+1} \cdot F_{P,1,K+1}} \cdot F_{W,1,K+1} \quad (9)$$

However, the unknown variables $\rho_{P,1,K+1}$ and $F_{P,1,K+1}$ in (9) cannot be directly calculated because of the cross over pipeline between the two trains, which leads to several different operating modes of the froth pipeline, and is discussed in the following section.

3.3. Pipeline crossover mode and mass balance

Taking Train 1 as an example, the different pipeline cross over operating modes and the corresponding calculation of $\rho_{P,1,K+1}$ and $F_{P,1,K+1}$ are introduced below, and the same result can be applied to Train 2.

Mode 1: All pumps in both of the trains are in operation

$$F_{P,1,K+1} = F'_{P,1,K+1}, \ \rho_{P,1,K+1} = \rho'_{P,1,K+1} \quad (10)$$

Mode 2: All pumps in Train 1 are in operation

$$F_{P,1,K+1} = F'_{P,1,K+1}, \ \rho_{P,1,K+1} = \rho'_{P,1,K+1} \quad (11)$$

Mode 3: Froth from Train 1 is bypassed to Train 2

$$F_{P,1,K+1} = F'_{P,2,K+1}, \ \rho_{P,1,K+1} = \rho'_{P,2,K+1} \quad (12)$$

Mode 4: Froth from Train 1 and Train 2 is transported only through Train 1 booster pumps

$$F_{P,1,K+1} = \frac{F'_{P,1,K+1}}{2}, \ \rho_{P,1,K+1} = \rho'_{P,1,K+1} \quad (13)$$

Mode 5: Froth from Train 1 and Train 2 is transported only through Train 3 booster pumps

$$F_{P,1,K+1} = \frac{F'_{P,2,K+1}}{2}, \ \rho_{P,1,K+1} = \rho'_{P,2,K+1} \quad (14)$$

The mode of the crossover can be identified by detecting the run statuses of Pump A and Pump B, and the flow rates $F'_{P,1,K+1}$ and $F'_{P,2,K+1}$. For example, if Pump A is running, Pump B is running, meanwhile, $F'_{P,1,K+1} > 0$, and $F'_{P,2,K+1} > 0$, then the process is being operated in Mode 1.

Substituting the corresponding equation (10) – (14) into (9) and according to the crossover mode, the froth water content can be recursively estimated, finally.

4. SOFT SENSOR MODEL VALIDATION

To evaluate the soft sensor model performance, the soft sensor model is implemented into a Distributed Control System (DCS) at the Syncrude site to provide an on-line estimate of the froth water content. Fig. 3 and Fig. 4 show the estimation results of the soft sensor models compared with the lab data. From the results, we can see that, by using the developed first-principle dynamic model, the soft sensor is able to provide reliable and reasonable water content estimation. However, Fig. 3 indicates that there is still an obvious bias between the lab data and the soft sensor model for Train 1, which may be introduced by gross errors of the field instruments. Therefore, further adjustment is necessary to reduce the effect of the bias.

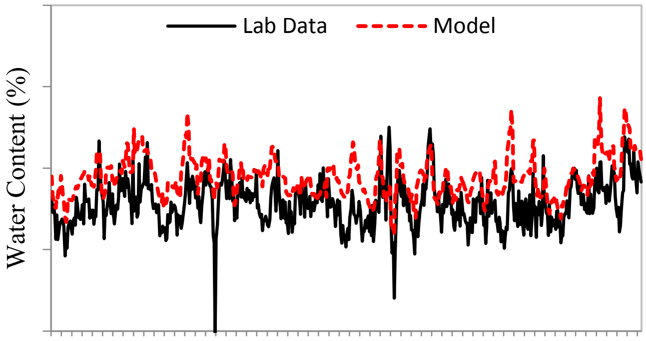


Fig. 3. Train 1 soft sensor model validation result

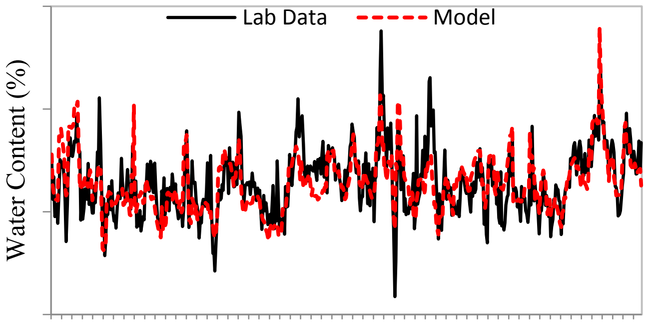


Fig. 4. Train 2 soft sensor model validation result

5. SOFT SENSOR BIAS UPDATE

To further improve the soft sensor performance, critical information obtained from lab data is included in the soft sensor. Due to the DCS computational restriction, a simple bias update strategy is used to correct soft sensor model prediction, where a Proportional-Integral (PI) controller type of algorithm is used for updating the bias between soft sensor output and the lab data. The sampling rate of the lab data is not a constant, which is around 1.5 hour and there is always an uncertain time delay about 1 hour for the lab data. Fig. 5 shows the diagram of soft sensor output bias update strategy.

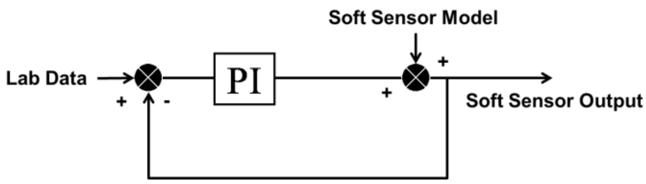


Fig. 5. Soft Sensor Output Bias Update Strategy

From Fig. 5, it can be seen that, every time a lab data is available, an updated bias is added to the soft sensor model through a PI controller, in order to compensate the bias between lab data and soft sensor model. Therefore, the soft sensor model predicts the water content in fast rate but the bias is updated in a rather slow rate. Furthermore, this PI control strategy can guarantee that soft sensor output would follow the lab data asymptotically so that the soft sensor output will not persistently deviate from the actual process variable. Meanwhile, the gain of the PI controller to update bias is adjustable, which can be tuned to achieve a superior performance for soft sensor based closed-loop control.

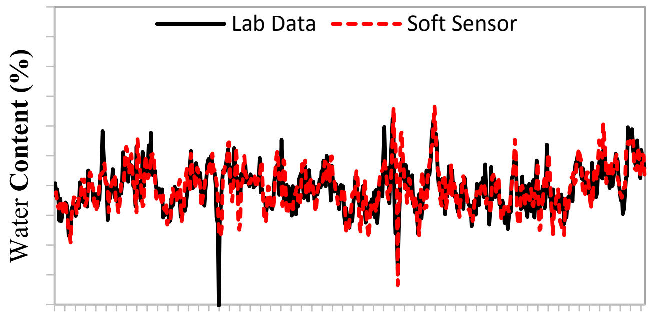
The performance of the soft sensors with the bias update strategy at the same time as indicated in Fig. 3 and Fig. 4 is shown in Fig. 6 and Fig. 7, respectively. In this way, the performance of the soft sensor with bias update can be directly compared with that of the soft sensor model without bias update.

Table 2 shows the performance evaluation in terms of mean absolute error (MAE), standard deviation (STD), and root mean square error (RMSE) for the soft sensor models and soft sensors with bias update.

Table 2. Soft Sensor Performance Result

	Method	MAE	STD	RMSE
Train 1	Model	1.723	1.166	3.955
	Bias Update	0.914	1.190	1.416
Train 2	Model	0.952	1.210	1.463
	Bias Update	0.896	1.158	1.340

From Fig. 6 and Fig. 7, as well as Table 2, it can be clearly seen that the performance of the soft sensor for Train 1 has been significantly improved with the bias update strategy.



Samples: Aug 2013
Fig. 6. Train 1 soft sensor with bias update result

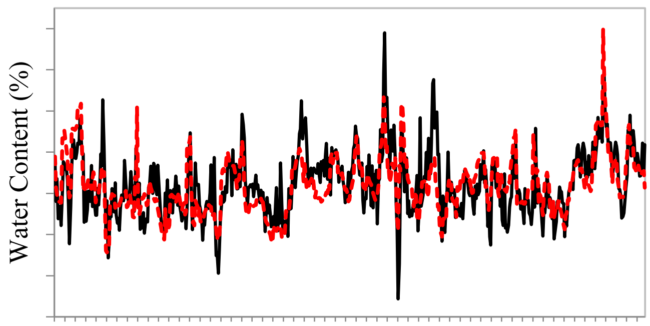


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Fig. 7. Train 2 soft sensor with bias update result

However, the improvement of the soft sensor for Train 2 is not very significant. Even so, the soft sensors with bias update are able to provide more accurate estimates than the models, particularly for the slow trend of variation in the water content.

6. SOFT SENSOR BASED CONTROL

To take full advantage of the developed soft sensor, an inferential cascade control strategy is proposed in this work to control the froth water content. Froth water content estimate from the soft sensor output is applied as the feedback process variable (PV) for the primary controller, hot process water addition is chosen as PV for the secondary controller, which is also the manipulated variable to control the froth water content. The inferential cascade control strategy is designed as shown in Fig. 8.

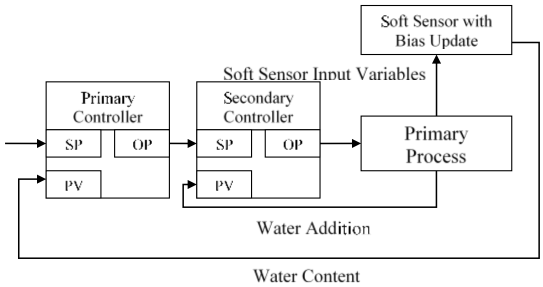

Fig. 8. Soft Sensor Based Feedback Cascade Control Structure

In the implementation, proportional-integral (PI) type

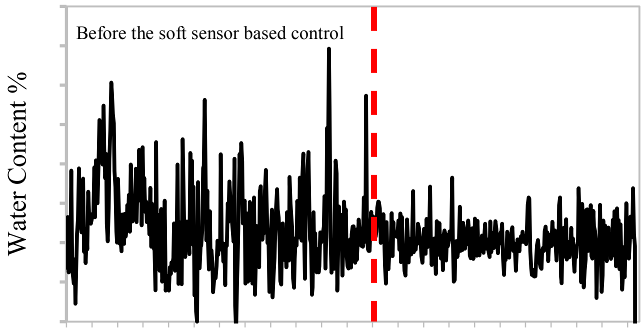

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Fig. 9. Soft sensor based control result of Train 1

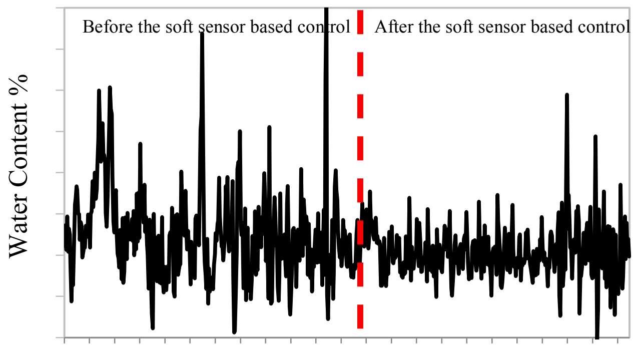

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Fig. 10. Soft sensor based control result of Train 2

controllers were used for both primary and secondary control loops with sampling rate of 1 minute and 1 second, respectively. Furthermore, in order to improve stability, a gap option was practically configured for the primary controller to achieve range control philosophy. The soft sensor and the control strategy were implemented in DCS, and operators can adjust the primary controller set point (SP) to control the froth water content. The results in the actual process are given in Fig. 9 and Fig. 10 to show the control performance improvement before and after the proposed soft sensor based control implementation for Train 1 and Train 2 respectively.

From Fig. 9 and Fig. 10, significant control performance improvements can be seen immediately after the froth water contents were controlled by the proposed control strategy based on the soft sensors.

After the soft sensors were applied for froth pipeline water content control, they have been running continuously and smoothly with satisfactory performance. The current control performance is compared with historical control performance of year 2012. The comparison result is shown in Table 3.

Table 3. Froth Water Content Control Performance Comparison

		Without Control (%)	Soft Sensor based Control (%)
Train 1	Average	28.943	28.021
	STD	2.268	1.191
Train 2	Average	28.612	28.029
	STD	2.529	1.589
Combined	Average	28.798	28.015
	STD	2.253	1.190

From the comparison results, it can be seen that with the soft sensor based closed-loop control, the froth water contents get closer to the desired value than they were before having the inferential control. Meanwhile, the froth water content standard deviation dropped to almost a half of the value they were before the inferential control. These results have demonstrated that the operational performance, reliability and stability have been significantly improved after the new soft sensor based inferential control was put on-line.

7. CONCLUSIONS

Two first-principle model based soft sensors have been developed and implemented for froth pipeline water content monitoring and control at Syncrude. Process operation data continuously show that the developed soft sensors are reliable and provide improved water content estimate; as a result automatic froth pipeline water content control based on the soft sensor readings is implemented on both trains. The control performance shows that the automatic froth pipeline water content control based on the soft sensors, can improve froth line operation reliability, lower bitumen loss in the downstream process, and reduce froth quality variations. Independent benefit analysis shows that a very significant economic benefit per year has been achieved with the soft sensors and associated control strategy.

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