Soft Sensors for Pulp Freeness and Outlet Consistency Estimation in the Alkaline Peroxide Mechanical Pulping (APMP) High-Consistency Refining Process

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In the mechanical pulping process, some process state and product quality variables are difficult to measure on-line. In this paper, soft sensors were used to estimate Canadian Standard Freeness (CSF) and outlet consistency (C_{out}) after the high consistency refining stage of the alkaline peroxide mechanical pulping (APMP) process. After the secondary variables for modeling that are readily available processed measurements in pre-treatment and the HC refining stage was selected, models based on the case-based reasoning (CBR) method were developed to estimate CSF and C_{out}. The ability of CBR soft sensors to predict CSF and C_{out} was tested using data collected from an APMP mill, and the results were satisfactory. Additionally, two typical soft sensor methods that back propagation network (BP) algorithms and support vector regression algorithms (SVR) were employed to predict CSF and C_{out} and evaluate the performance of the CBR soft sensor. As a result, the proposed soft sensor demonstrated a better performance than the BP method and can be regarded as of comparable quality to the SVR method.

Keywords: APMP pulping; Soft sensor; Case-based reasoning; Pulp quality

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INTRODUCTION

Alkaline peroxide mechanical pulping (APMP) is a popular form of mechanical pulping. The APMP process is similar to chemi-thermo mechanical pulping (CTMP) and thermo mechanical pulping (TMP) processes, which consist of chip pre-treatment and refining. Because high-consistency (HC) refining is energy intensive in the main line of the APMP process, the HC refining process is usually cascaded with a low consistency (LC) refining process to save energy and maintain pulp properties (Illikainen *et al*. 2007; Andersson *et al*. 2012).

There has been a lot of research conducted to better understand mechanisms of mechanical pulping in the refining process, particularly the effect of operating parameters such as specific energy (SE), refining intensity, and wood qualities on pulp properties (Li *et al*. 2011). Strand and Mokvist (1989a, 1989b) proposed a model adopted from a grinding process based on comminution theory to describe the refining kinetics and predict pulp properties. This method can be used for controllability analysis and optimization of the refining process (Strand *et al*. 1991; Lama *et al*. 2006). Besides producing a set of equations that calculate the residence time of the pulp in the refiner, and hence the refining intensity, the research results of Miles *et al*. (1991a, 1991b) and Stationwala *et al*. (1993) give a direction for determining model variables influencing mechanical pulp properties. Qian and Tessier (1995) proposed a mathematical model to predict the pulp properties based on Miles's theory. Mathematical models that describe the operating variables and process conditions on pulp quality were employed using model-based control and optimization of the refining process (Broderick *et al.* 1996; Strand 1996; Tessier *et al.* 1997; Runkler *et al.* 2003; Tervaskanto *et al.* 2009; Harinath *et al.* 2011).

Optimization and control of pulp quality is based on frequent pulp quality analysis (Sikter *et al.* 2008). The pulp properties analyzer is usually mounted on the latency chest after the LC refining stage. Unfortunately, there is little end-quality feedback, as the long time delay between the HC and LC process stages makes it difficult to control HC refining. HC refining is of great importance and directly contributes to the final pulp quality outcome (Broderick *et al.* 1996). Without real-time relevant measurements, there is no reasonably reliable information that can be used to adjust the settings of the various refining parameters. To overcome this problem, soft sensors need to be developed to generate continuous predictions of key processes and pulp quality properties. Even though on-line sensors are implemented, soft sensors are a necessarily redundant measurement for feedback control purposes (Sikter *et al.* 2008).

A soft sensor is a model that infers and calculates process variables and product qualities that are difficult to measure on-line from readily available process measurements (Kadlec *et al.* 2009). Regarding the estimation of pulp quality characteristics, chip impregnation and refining is a multivariable and nonlinear process (Qian *et al*. 1997), and there is a resulting difficulty in establishing a satisfying mechanism model for pulp property estimation. A data-driven method is a good choice for realizing optimization and control of the refining process *via* modeling (Qian *et al.* 1997; Thibault *et al*. 2003).

Artificial neural networks (ANN) and fuzzy logic models act as soft sensors that enable the operators to control and optimize the refining process (Bard *et al.* 1999; Runkler *et al.* 2003). When studying the impact of refining operations on pulp quality, multivariate analysis (MVA) methods such as principal component analysis (PCA) and partial least squares (PLS) are popular modeling techniques applied to data-driven soft sensors (Broderick *et al*. 1996; Broderick 1997; Harrison *et al.* 2004, 2007). Additionally, the polynomial and neural fuzzy models are often employed in predicting the properties of pulp and paper sheets (Jiménez *et al*. 2007; Ferrer *et al.* 2011; González *et al.* 2011). These properties act as a function of the operating variables. However, both statistical modeling techniques and ANN are computationally complex, and they slow the training process for large scale data sets. Moreover, a wide range pilot trial is required to obtain training and calibrated data, but mill managers and operators are highly reluctant to run the types of experiments needed to determine model coefficients on their machines. Therefore, it is necessary to explore and research a new method for the estimation of pulp properties.

As a relatively new reasoning technique and machine-learning method in artificial intelligence (AI), case-based reasoning (CBR) uses the solutions from similar cases (source cases) to solve a new case (target case) (Yan *et al*. 2015). The method gains knowledge conveniently and with high efficiency and does not require transcendental knowledge and other related information. These models were developed using historical process data, on-line properties, or lab test measurements. Moreover, the computation complexity is only linear with respect to the number of attributes and cases (Zhou and Chai 2014).

This paper adopts CBR to establish a soft-sensing model for the estimation of pulp qualities including Canadian Standard Freeness (CSF) and process variables (outlet consistency, C_{out}).

EXPERIMENTAL

Process Description

The alkaline peroxide mechanical pulping (APMP) process involves at least a single stage of refining. Before the refining process, wood chips are compressed prior to the impregnation with various amounts of sodium hydroxide, hydrogen peroxide, and stabilizers including DTPA, sodium silicate, and magnesium sulfate (Cort and Bohn 1991). In this study, the refining process consisted of two refining stage that were primary refining (high consistency) and secondary refining (low consistency). The pulp property and process state were estimated after the primary stage. The high consistency refining process is shown in Fig. 1.

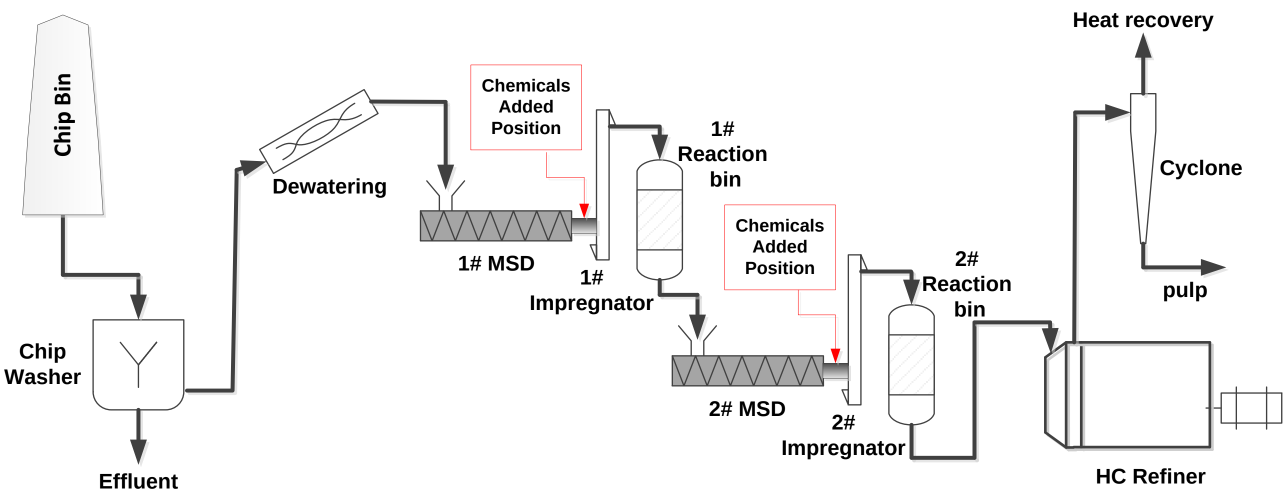

Fig. 1. Flow chart of the high consistency refining process

After washing and screening, dewatered wood chips were conveyed into the first stage model screw device (MSD, is a substitute for impressafiner^{TM}) and compressed to remove some of the water-soluble organic components of the wood (Cort and Bohn 1991). Chemicals were added at the MSD outlet before the compressed chips entered the first stage impregnator, where the pressure was relieved and chips were gently shredded to open up the wood structure, thus allowing for increased penetration of the chemicals. The impregnated chips were kept in a reaction bin for a certain retention time, which was dependent on production rate and the material level of the reaction bin.

The second stage of impregnation was similar to the first stage. The differences between the two impregnation stages were the applied power of MSD (relating to the rotational speed and compression ratio of the screw) and the chemicals applied to the impregnator.

After two pre-treatment stages, chips were moved to the refiner by a screw conveyer. In the high consistency refining stage, chips were defibrated and fibrillated in the refiner, and they were transformed into pulp with the required properties (Law *et al.* 2000). With the exception of chemical flow, the pre-treatment stage and HC refining process on-line variables are given in Table 1.

Table 1. On-line Process Variables and their Tag Name in Pre-Treatment and Primary Stage

Device	Variable	Tag Name	Unit
1# MSD	Power	P_1	kw
	Specific Power	SP_1	Kwh/Ton
1# Reaction Bin	Temperature	T_1	℃
	Material Level	L_1	%
2# MSD	Power	P_2	Kw
	Specific Power	SP_2	Kwh/Ton
2# Reaction Bin	Temperature	T_2	℃
	Material Level	L_2	%
HC Refiner	Production Rate	PR	Adt/Day
	Refiner Room Pressure	P_r	Bar
	Motor Load	ML	MW
	Specific Energy	SE	Kwh/ Adt
	Dilution Water Flow	F	L/Min
	Vibration	V	Mm/S
	Acceleration Of Vibration	V_a	%
	Plate Gap	G	Mm
	Plate Pressure	P_p	Bar

Materials

The wood chips were a blend of eucalyptus (10%, by oven dry weight), acacia (70%), and pine (20%). Chemical formulations and their flow tag names are given in Table 2.

Table 2. Chemicals Applied in the Pre-Treatment and their Tag Name

Chemicals	White Water (Enriched)	NaOH	H_2O_2	DTPA	Stabilizer	Unit
1st Impregnation	f_1		f_3	f_5	f_7	l/min
2nd Impregnation		f_2	f_4	f_6	f_8	

Process Characteristic Analysis

Pre-treatment

The chip size and moisture content are key disturbance variables in the CTMP or TMP HC refining process (Qian and Tessier 1995). However, chip size was more uniform and moisture content was fairly constant during the APMP process because the chips were been pre-treated after two stages impregnation (Cort and Bohn 1991). The results of pre-treatment on two-stage impregnations are shown in Fig. 2.

Accordingly, the performance of the two-stages of MSD and the quantity of applied chemicals are the important variables influencing energy consumption and pulp properties in the HC refining process (Law *et al*. 2000).

Fig. 2. Chips after washing and the first and second stages of impregnation

HC refining

The most used direct control variables in refining are specific energy and refining intensity (Li *et al*. 2011). Specific energy is defined as the motor load divided by the production rate (oven dry wood), and it is adjusted by regulating the refiner plate gap clearance and dilution water flow rates. At some mills, the plate gap clearance is not measured, and plate vibration has to be used instead. Refining intensity, defined as the specific energy applied to a unit mass of fiber per refiner bar impact, is a function of cumulative forces applied to the fiber during its residence time in the refiner (Qian and Tessier 1995). Refining intensity is much more difficult to calculate and measure in an industrial refiner. Different refiner installations result in different system characteristics. For a given plate configuration, increasing the refining intensity could be adjusted by either increasing the rotational speed of the refiner discs or lowering the consistency (Su and Hsieh 1994; Alami *et al.* 1997). However, most industrial installations have a fixed rotational speed, and refining intensity is largely a function of refining consistency.

Refiner plate wear occurs gradually over several hundred hours. As service time increases, the bars on the plate surface are gradually worn down, affecting the process dynamics and the refining efficiency. As this occurs, increased refining pressure is needed to maintain pulp properties. Meanwhile, the vibration of the refiner also increases.

In the HC refining process, the refining outlet consistency (C_{out}) is the key value in determining refined pulp properties (Alami *et al.* 1997). Canadian Standard Freeness (CSF) is typically used to define the quality of refined pulps. Therefore, a case-based reasoning method was proposed for soft sensor modeling of C_{out} and CSF.

Case-Based Reasoning Modeling Method

The quality of pulp depends to a great extent on operating conditions and pre-treatment. In an industrial APMP line, there are different process conditions corresponding to different operation conditions. For a given refiner installation, the same process conditions produce similar pulp with consistent properties. Namely, it is different process conditions that result in different pulp qualities. Therefore, any group consisting of different process conditions and their corresponding pulp qualities could be chosen as a case. If enough cases covered all the possible production site process conditions, one could obtain the pulp qualities from case bases when a group of process conditions occurs. CBR soft-sensor modeling mainly includes case representation, case retrieval, case reuse, case revision, and case retention (Zhou and Chai 2014; Yan *et al*. 2015). The strategy diagram for CBR soft-sensor modeling is shown in Fig. 3.

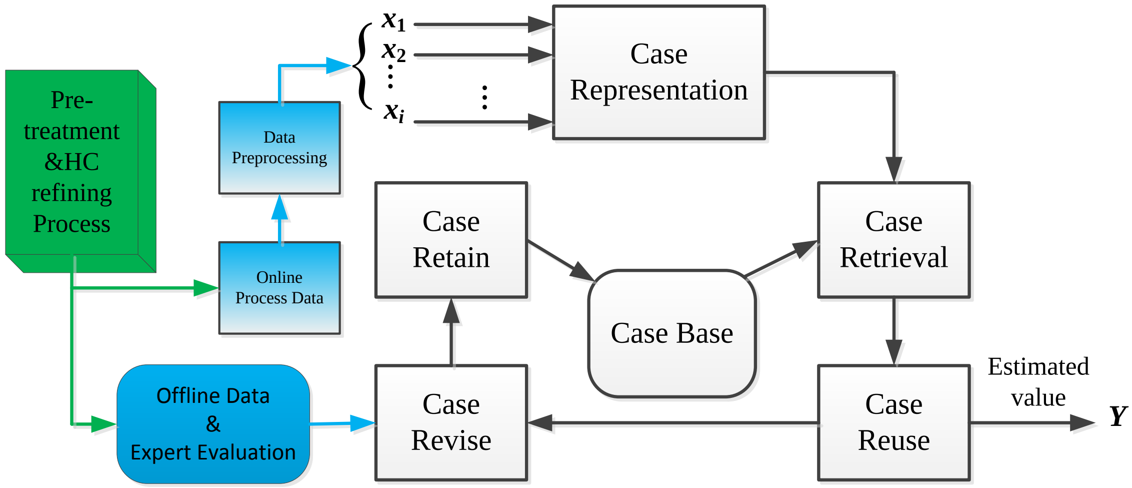

Fig. 3. Strategy diagram of the CBR soft-sensor for pulp quality

Selection of secondary variables and case representation

The first step in making a successful soft-sensor is to properly select secondary variables. These are the key process variables affecting the pulp quality in the pre-treatment and refining stages. Those variables were obtained from process characteristic analysis based on proven study. Statistical analysis, such as MVA and correlation analysis, elucidate the dependency between estimating values (Y) and process variables. Once the secondary variables were selected, the next step was to express the source cases using appropriate methods in order to build a case base, known as case representation.

In a source case, the selected secondary variables $X(x_1, x_2, \ldots, x_i)$ (i=1,2, …, k) were featured values of each case, and solution Y was the pulp quality value. Each source case C_n (n = 1, 2, …, p) could be expressed in the following pair-wise functions:

$$C_n : \langle X_n ; Y_n \rangle, \quad n = 1,\ 2,\ \cdots,\ p \tag{1}$$

$$X_n = \left(x_{1,n},\ x_{2,n}, \cdots,\ x_{i,n} \right),\ i = 1,\ 2,\ \cdots,\ k\ ;\ n = 1,\ 2,\ \cdots,\ p \tag{2}$$

where p is the total number of the cases in the case base, k is the number of the secondary variables, X_n and Y_n denote the secondary variables and the solution (pulp quality), respectively, in the nth cases in the case base, and $x_{i,n}$ denotes the ith feature value of nth cases in the case base.

Case retrieval and case reuse

When the pulp quality of new process conditions needed to be estimated, the new problem selected secondary variables as a new case (C: X without Y) that would be searched to find similar cases, and then obtained the pulp quality (Y) through case reuse.

In order to find similar cases, the similarity (SIM) of the new case ($x_1, x_2, \ldots, x_i$) to each source case in the case base was calculated for comparison.

The variable sim_i is the similarity of ith feature value (x_i) of a new case to ith feature value ($x_{i,n}$) of an nth source case, where the larger the sim_i, the more similar the new case and source case. The value of sim_i was obtained as follows:

$$sim_i = 1 - \frac{\left| x_i - x_{i,n} \right|}{\max\left(x_i,\ x_{i,n} \right)} \tag{3}$$

The similarity (SIM_n) of the new case $C(x_1, x_2, \ldots, x_i)$ to the *n*th source case (C_n) was obtained as follows,

$$SIM_n = \sum_{i=1}^{k} \omega_i \times sim_i \quad \text{n=1, 2, } \cdots\text{, p} \tag{4}$$

where ω_i (i = 1, 2, …, k) is the weight of the *i*th feature value attribute, representing the degree to which the similarity (sim_i) of the feature value could affect the SIM_n results of new and source cases. The constraint condition is

$$\sum_{i=1}^{k} \omega_i = 1 \quad \text{and} \quad \omega_i \geq 0 \tag{5}$$

The *p SIM*es were obtained using Eq. 4 and ranked from smallest to largest. Conventionally, the K-nearest neighbor (K-NN) is employed to determine which cases are similar, wherein K is the number of neighbors and Y_1–Y_K are K case solutions corresponding to the top K similarities (*SIM*). The unknown outcome, *Y*, of a new case can then be obtained by calculating the mean value of the K case solutions according to Eq. 6:

$$Y = \frac{1}{K} \sum_{j=1}^{K} Y_j \tag{6}$$

However, the conventional K–NN method is highly influenced by the value of K. If K is too high, the CBR retrieves too many unrelated cases, which may lead to poor results. In contrast, if K is too small, the CBR may lack sufficient reference cases to make a correct decision. In this paper, the estimated value *Y* was not determined using the constant K cases, and instead the neighbor cases were retrieved if their *SIM* was equal to or greater than a threshold value (SIM_{TV}) (Zhou and Chai 2014). The threshold (SIM_{TV}) is a given value and was determined in the CBR soft sensor process as follows:

$$SIM_{TV} = \begin{cases} SIM_{TV}, & SIM_{\max} \geq SIM_{TV} \\ SIM_{\max}, & SIM_{\max} < SIM_{TV} \end{cases} \tag{7}$$

where $SIM_{\max}$ = Max (SIM_n), n = 1, 2, …, p.

The solution *Y* was used as the final soft-sensor result for the output. The new case solution, *Y*, was obtained as in Eq. 8, where *l* was the number of cases that the *SIM* was equal to or greater than SIM_{TV}, and SIM_j was the j^{th} *SIM*.

$$Y = \begin{cases} \dfrac{\sum_{j=1}^{l} SIM_j \times Y_j}{\sum_{j=1}^{l} SIM_j}, & l = num\ (SIM_n \geq SIM_{TV}),\ \ (SIM_{\max} \geq SIM_{TV}) \\ Y_j, & SIM_j = \text{Max}\ (SIM_n),\ \ (SIM_{\max} < SIM_{TV}) \end{cases} \tag{8}$$

Case revision and case retention

Following the operation mentioned above, the new case *C (X; Y)* was stored (with the new solution *Y*) in the case base if the estimated value was the correct result as evaluated by expert operators, or according to the specification limitation. If the solution was not satisfactory, then the case was dropped, or the correct data was introduced according to offline data confirmed by experts.

Accordingly, a reasoning learning process was completed. When future process data emerges, the pulp quality will be able to be monitored in real time by utilizing the process described above.

Case Base Building

Data collection and preprocessing

On industrial sites, managers and operators generally would be reluctant to run pilot trials to investigate relationships between pulp quality and the selected secondary variables. The CBR soft sensor has fewer requirements for sampling data because the source case base can be obtained from pre-existing data, if the process has been operating for some time. Moreover, case revision and case retention can maintain the case base at an up-to-date state. To build the case base, a large database of operating conditions and their resulting pulp qualities were collected from the DCS database and daily reports without affecting the pulp production, with no modifications to the facility.

Because there are two reaction bins between pre-treatment and HC refining, process lags must be synchronized beforehand. The synchronizing time was obtained by the following equations,

$$\begin{cases} \tau_1 = \dfrac{c_1 \times V_1 \times L_1}{PR} \\ \tau_2 = \dfrac{c_2 \times V_2 \times L_2}{PR} \end{cases} \tag{9}$$

where τ_1 is the time when first stage impregnated chips were conveyed to the second stage impregnation stage; and τ_2 is the time second stage impregnated chips were conveyed to the HC refining stage. The variables c_1 and c_2 are the consistency of chips in bin 1 and bin 2, and V_1 and V_2 are the volume of each bin.

Additional steps include raw data filtering and systematically removing dubious periods of the operation such as a low production rate and aberrant process behavior.

Selection of secondary variables and attributing weight values ω_i

During pre-treatment and refining, some operation variables (such as chemical flows) were regulated using the ratio control method. A number of variables were adjusted following another variable. Some variables resulted in the synchronous change of their corresponding process variables (such as motor load and SE). To a certain extent, these correlative variables shared common information of the pre-treatment and refining process.

Equation 4 shows that both ω_i and sim_i influence the similarity (SIM_n) calculation results between new cases and source cases. Obviously, the different combinations of weights ω_i affected the similarity results, thereby affecting the estimation of the pulp quality. The sim_i is a fixed value calculation when new cases occur. However, if the feature value x_i and x_{i+d} have a high level of association, putting their similarity sim_i and sim_{i+d} into the calculation for SIM_n, the efficiency of case retrieval will be affected.

Preliminary secondary variables were selected based on process characteristic analysis and expert experience after original data preprocessing. The correlation relationship between pulp quality variables and each of the preliminary secondary variables was investigated. Multicollinearity diagnostics were also applied to detect multicollinearity problems with preliminary secondary variables to avoid redundancies.

The correlation coefficient shows the association between two variables *(U, V)*, which can be obtained as follows,

$$r_{uv} = \frac{\sum_{m=1}^{N}(u_m - \bar{u})(v_m - \bar{v})}{\sqrt{\sum_{m=1}^{N}(u_m - \bar{u})^2 (v_m - \bar{v})^2}} \tag{10}$$

where *u-bar* and *v-bar* are the sample mean of *U* and *V*.

The values of the correlation coefficient are always between -1 and +1. A positive correlation coefficient indicates that two variables increase or decrease together; a negative correlation coefficient indicates that as one variable increases, the other decreases. A correlation coefficient of zero indicates that there is no linear relationship between the two variables.

The variance inflation factor (VIF) measures the impact of collinearity among the variables in a regression model and is defined as,

$$VIF_{\mathrm{i}} = \frac{1}{1 - R_i^2} \tag{11}$$

where R_i^2 is the coefficient of determination of the model that includes all variables except the *i*th variable. If $VIF_i \geq 10$ (VIF_i; *i*th variable variance inflation factor) then there is a problem with multicollinearity.

The above algorithm was calculated using MATLAB 2010b (Natick, MA, USA) software. The results included a correlation matrix containing the correlation coefficients of pulp quality variables and preliminary secondary variables. In addition, there was a vector consisting of the VIF of each preliminary secondary variable. Taking both the correlation coefficient and VIF into account, the final secondary variables were selected.

Because the correlation coefficient could partly recognize the dependency between two variables, the attribute weight value in this study, ω_i, was obtained as follows,

$$\omega_i = \frac{\left| r_{yx_i} \right|}{\sum_{i=1}^{k} \left| r_{yx_i} \right|} \tag{12}$$

where r_{yx_i} is the correlation coefficient of the pulp quality of the *i*th selected secondary variable.

The secondary variables for estimation of CSF and C_{out} are listed in Table 3, and the attribute weight values ω_i are listed in Table 4. The threshold value (SIM_{TV}) for both CSF and C_{out} were 0.90.

Table 3. Secondary Variables for Estimation of CSF and C_{out}

X	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	
Variable tag name	SP_1	f_1	SP_2	f_2	PR	SE	p_p	G	f	V	V_a	

The value of ω_i also provided information about how much influence each operation variable had over the pulp quality, and the results listed in Table 4 agreed with the process characteristic analysis.

Table 4. Attribute Weight Values ω_i for Estimation of CSF and C_{out}

ω_i		ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9	ω_{10}	ω_{11}
Y	*CSF*	0.09	0.04	0.05	0.06	0.08	0.19	0.06	0.14	0.18	0.05	0.06
	C_{out}	0.13	0.11	0.12	0.13	0.13	0.01	0.13	0.02	0.11	0.08	0.03

RESULTS AND DISCUSSION

Results

The CBR soft sensor results

In this experiment, 145 groups of typical process data consisting of secondary variables and pulp quality values (CSF and C_{out}) were collected. For case bases, 100 groups were randomly selected, while the rest were selected as the tested data set. Figure 4 shows the results of CBR soft sensors used in CSF estimation. Figure 5 shows the scatter diagram of CBR soft sensors used in CSF estimation. Figure 6 shows the results of CBR soft sensors used in C_{out} estimation. Figure 7 shows the scatter diagram of CBR soft sensors used in C_{out} estimation.

The estimation results provided by CBR soft sensors almost concurred with CSF and C_{out} sample tests. As Figs. 5 and 7 show, the effectiveness of the CBR soft sensor was acceptable.

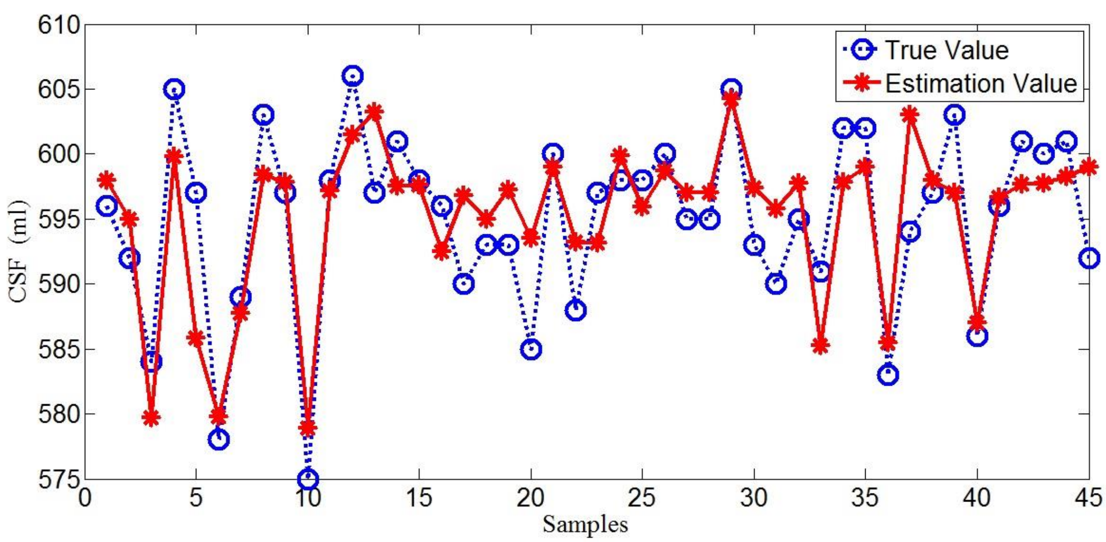

Fig. 4. Results of CBR soft sensor for CSF estimation

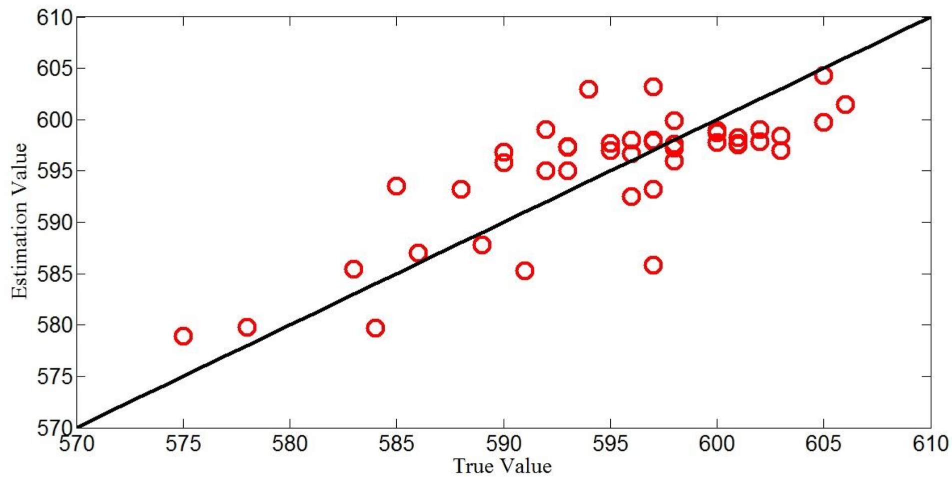

Fig. 5. Scatter diagram of CBR soft for CSF estimation

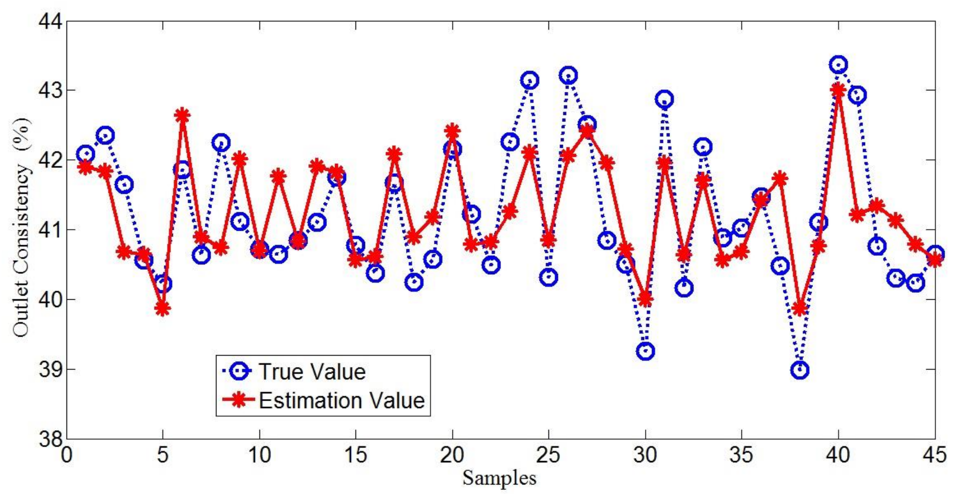

Fig. 6. Results of CBR soft sensor for outlet consistency (C_{out}) estimation

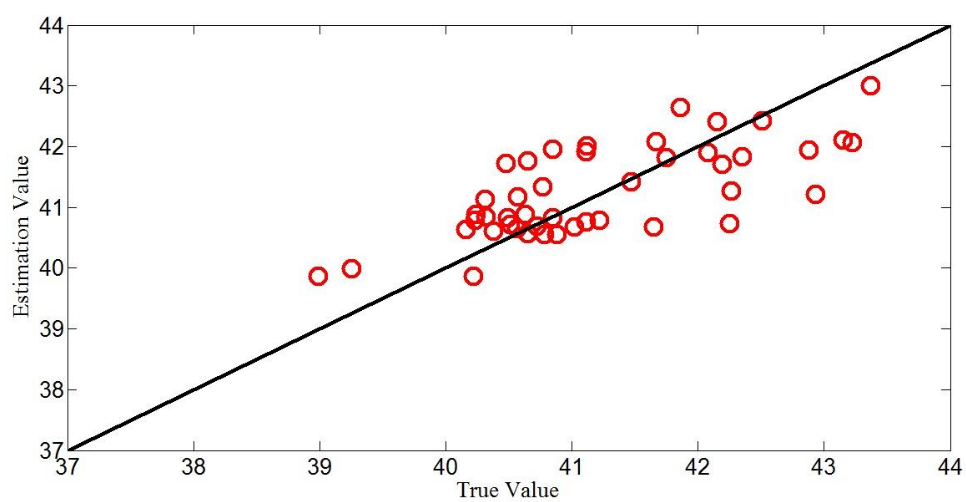

Fig. 7. Scatter diagram of CBR soft sensor for outlet consistency (C_{out}) estimation

Contrast results

To test the performance of the CBR method for the estimation of pulp quality, two typical methods—the back propagation network (BP) algorithm and support vector regression algorithm (SVR)—were used to predict the pulp quality (Kadlec *et al.* 2009). In the BP algorithm, the network structure had three layers. There were 24 hidden layer neurons, and the excitation function was tansig. The other parameters were kept at default settings. In the SVR algorithm, the penalty factor was 1, and the kernel function was the Gaussian radial basis function. The width was 1 for CSF estimation; the penalty factor was 1. The kernel function was the Gaussian radial basis, and the width was 0.0156 for outlet consistency (C_{out}) estimation. All algorithms were designed using MATLAB 2010b.

Figure 8 shows the contrasting results obtained due to the different methods of CSF estimation. Figure 9 shows the contrasting results obtained due to the different methods of C_{out} estimation. The upper half of the figures are the contrasts between estimation results of different methods according to the sample values, and the lower half are the absolute values of the errors between estimation results of different methods and the sample values. The CBR soft sensor is the more accurate method when compared with BP from Fig. 8 and Fig. 9. There was not much difference between CBR and SVR.

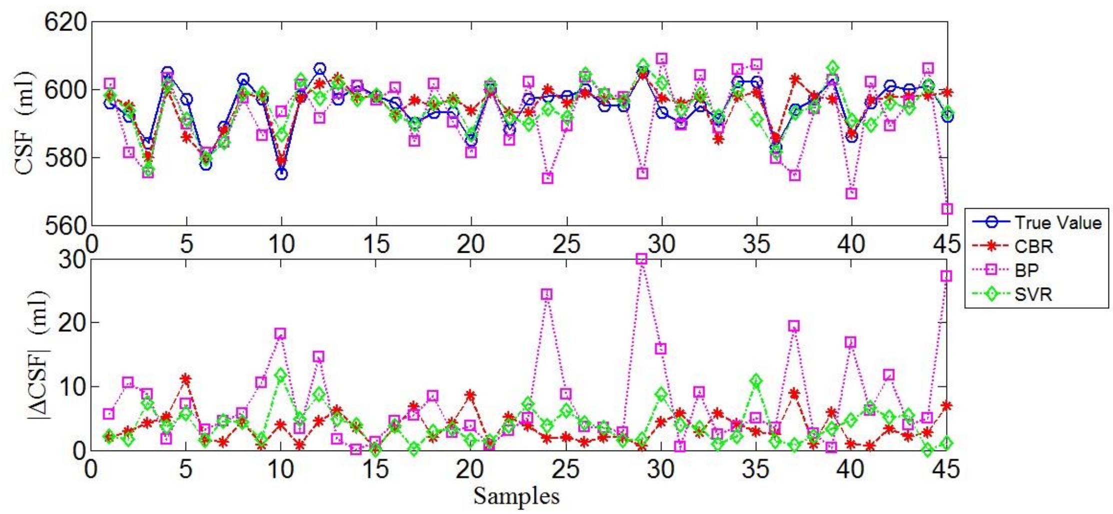

Fig. 8. Contrasting results of different methods for CSF estimation

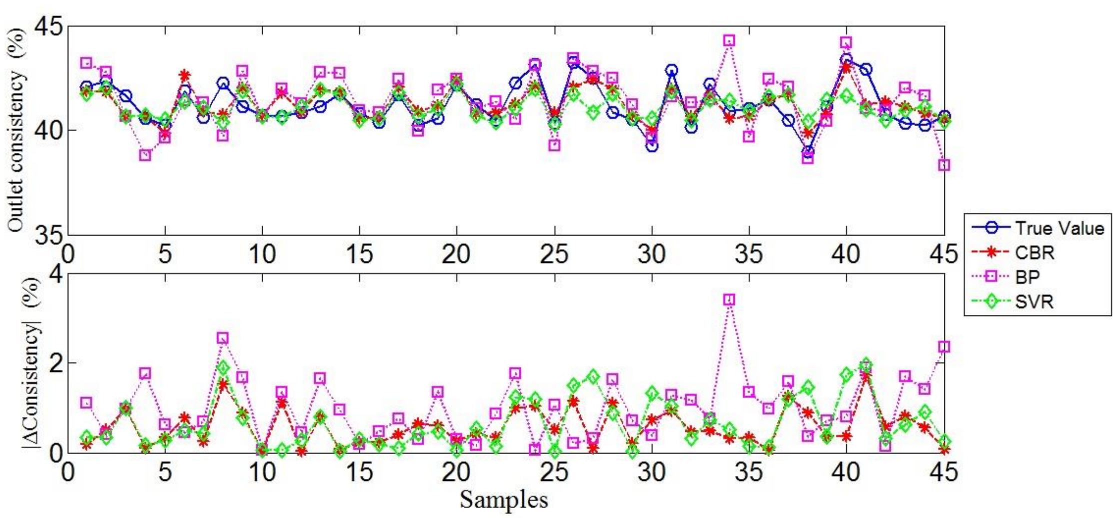

Fig. 9. Contrasting results of different methods for C_{out} estimation

To compare the performance of different methods, the root mean square error (RMSE) was employed to measure the difference between them. The root mean square errors of different methods for estimation of CSF and C_{out} are listed in Table 5. The accuracy of CBR is greater than BP and similar to SVR. The RMSE of each method was obtained as follows,

$$RMSE = \sqrt{\frac{\sum_{m}^{Q}(y_{sample,m} - y_{estimation,m})^2}{Q}} \tag{13}$$

where $y_{sample,m}$ is the mth sample test value, $y_{estimation,m}$ is the mth corresponding value provided by soft sensor, and Q is the number of test samples.

Table 5. Root Mean Square Errors of Different Methods

Method		CBR	BP	SVR
RMSE	***CSF***	4.2934	10.3383	4.7113
	C_{out}	0.7053	1.231	0.8424

CONCLUSIONS

1. In this study, the case-based reasoning (CBR) method was adopted to develop a soft sensor for predicting pulp quality. Soft sensors presented in this paper could estimate the pulp freeness and outlet consistency in the APMP process following the HC refining stage that is normally only available through off-line laboratory tests. Experiments on the historical data of estimating CSF and C_{out} verify the effectiveness of the CBR method, and the estimations provided by soft sensors concurred with freeness sample tests. Additionally, the proposed soft sensor had a better performance than the BP method in this study, and its accuracy is as good as the SVR method.
2. As a kind of intelligent algorithm, CBR does not need too much parameter adjustment during the process of problem solving. When the attribute weight values ω_i were determined, the computation complexity was less than BP and SVR. Thus, the method recommended in this paper has practical application advantages. In addition, the CBR model could also be employed for prediction of other pulp properties such as fiber size distribution, shive content, *etc*.
3. Soft sensors that provide real-time information on freeness and outlet consistency can help reduce energy consumption of the refining process and maintain a uniform quality of pulp. Additional research should be directed towards retaining and maintain the case base when the soft sensor is implemented in the APMP mill to monitor the production process, in order to avoid the long delay introduced by laboratory tests.

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REFERENCES CITED

Alami, R., Boileau, I., Harris, G., Lachaume, J., Karnis, A., Miles, K. B., and Roche, A. (1997). "Impact of refining intensity on energy reduction in commercial refiners: Effect of primary-stage consistency," *TAPPI J.* 80(1), 185-193.

Andersson, S., Sandberg, C., and Engstrand, P. (2012). "The effect of rotor position on pulp properties in a two-zoned low consistency refiner," *Nord. Pulp Pap. Res. J.* 27 (3), 525-530. DOI: 10.3183/npprj-2012-27-03-p525-530

Broderick, G., Paris, J., and Valade, J. L. (1996). "Fiber development in chemimechanical pulp refining," *TAPPI J.* 79(4), 193-201.

Broderick, G., Lanovette, R., and Valade, J. L. (1997). "Optimization refiner operation with statistical modeling," *Can. J. Chem. Eng.* 75(1), 79-87. DOI: 10.1002/cjce.5450750114

Bard, J., Patton, J., and Musavi, M. (1999). "Using RBF neural networks and a fuzzy logic controller to stabilize wood pulp freeness," in: *Proceedings of International Joint Conference on Neural Networks (IJCNN)*, Washington DC, USA, pp. 4247-4252.

Cort, C. J., and Bohn, W. L. (1991). "Alkaline peroxide mechanical pulping of hardwoods," *TAPPI J.* 74(6), 79-84.

Ferrer, A., Rosal, A., Valls, C., Roncero, B., and Rodriquez, A. (2011). "Modeling hydrogen peroxide bleaching of soda pulp from oil-palm empty fruit bunches," *BioResources* 6(2), 1298-1307. DOI: 10.15376/biores.6.2.1298-1307

González, Z., Rosal, A., Requejo, A., and Rodríguez, A. (2011). "Production of pulp and energy using orange tree prunings," *Bioresour. Technol.* 102(18), 9330-9334. DOI: 10.1016/j.biortech.2011.07.088

Harrison, R. P., Leroux, R., and Stuart, P. R. (2004) "Multivariate analysis of refiner operating data from a TMP newsprint mill," *Pulp & Paper Canada* 105(4), 79-82.

Harrison, R. P., Roche, A., and Stuart, P. R. (2007). "Impact of TMP refining line interruptions and reject refiner operations on pulp and paper variability," *TAPPI J.* 6(12), 3-9.

Harinath, E., Biegler, L. T., and Dumont, G. A. (2011). "Control and optimization strategies for thermo-mechanical pulping processes: Nonlinear model predictive control," *J. Process Contr.* 21, 519-528. DOI: 10.1016/j.jprocont.2011.01.009

Illikainen, M., Härkönen, E., Ullmar, M., and Niinimäki, J. (2007). "Power consumption distribution in a TMP refiner: Comparison of the first and second stages," *TAPPI J.* 6(9), 18-23.

Jimenez, L., Angulo, V., Caparros, S., and Ariza, J. (2007). "Comparison of polynomial and neural fuzzy models as applied to the ethanolamine pulping of vine shoots," *Bioresour. Technol.* 98(18), 3440-3448. DOI: 10.1016/j.biortech.2006.11.002

Kadlec, P., Gabrys, B., and Strandt, S. (2009). "Data-driven soft sensors in the process industry," *Comput. Chem. Eng*. 33(4), 795-814.DOI: 10.1016/j.compchemeng.2008.12.012

Law, K. N., Lanouette, R. Y., and Ang, K. C. (2000). "A new approach to mechanical pulping-pretreatment of chips by normal-to-grain compression prior to refining," *TAPPI J*. 83(9), 63-74.

Lama, I., Perrier, M., and Stuart, P. (2006). "Controllability analysis of a TMP-newsprint refining process," *Pulp Pap.-Canada* 107(10), 44-48.

Li, B., Li, H., Zha, Q., Bandekar, R., Alsaggaf, A., and Ni, Y. (2011). "Review: Effects of wood quality and refining process on TMP pulp and paper quality," *BioResources* 6(3), 3569-3584

Miles, K. B., and Karnis, A. (1991a). "The response of mechanical and chemical pulps to refining," *TAPPI J*. 74(1), 157-164.

Miles, K. B., May, W. D., and Karnis, A. (1991b). "Refining intensity, energy consumption, and pulp quality in two-stage chip refining," *TAPPI J*. 74(3), 221-230.

Qian, X., and Tessier, P. (1995) "A mechanistic model for predicting pulp properties from refiner operating conditions," *TAPPI J.* 78 (4), 215-222.

Qian, Y., Liu, H., Zhang, X., and Tessier, P. (1997). "Optimization of a wood chip refining process based on fuzzy relational models," *Comput. Chem. Eng.* 21(10):S1137-S1142. DOI: 10.1016/s0098-1354(97)00202-0

Runkler, T. A., Gerstorfer, E., Schlang, M., Junnemann, E., and Hollatz, J. (2003). "Modelling and optimisation of a refining process for fibre board production," *Control Eng. Pract.* 11, 1229-1241. DOI: 10.1016/s0967-0661(02)00233-2

Strand, B. C., and Mokvist, A. (1989a). "On-line modeling of refiner performance," *Pulp Pap.-Canada* 90 (12), T499-T504.

Strand, B. C., and Mokvist, A. (1989b). "The application of comminution theory to describe refiner performance," *J. Pulp Pap. Sci.* 15 (3): J100-J105.

Strand, W. C., Ferritsius, O., and Mokvist, A. V. (1991). "Use of simulation model in the on-line control and optimization of the refining process," *TAPPI J.* 74(11), 103-108.

Stationwala, M. I., Miles, K. B., and Karnis, A. (1993). "The effect of first-stage refining conditions on pulp properties and energy consumption," *J. Pulp Pap. Sci.* 19(1), J12-J18.

Su, W., and Hsieh J. (1994). "The effect of TMP refining using -an adjustable-speed drive on energy consumption and pulp quality," *TAPPI J.* 77(9), 111-117.

Strand, B. C. (1996). "Model-based control of high-consistency refining," *TAPPI J.* 79(10), 140-146.

Sikter, D., Karlström, A., Sandberg, C., and Engstrand, P. (2008). "Economic perspectives on quality control in TMP refining processes," *Nord. Pulp Pap. Res. J.* 23(3), 305-314. DOI: 10.3183/npprj-2008-23-03-p305-314

Tervaskanto, M., Ikonen, E., and Ahvenlampi, T. (2009). "Refiner quality control in a CTMP plant," *IEEE International Conference on Control and Automation*, Christchurch, New Zealand, pp. 1266-1271. DOI: 10.1109/icca.2009.5410443

Tessier, P., Broderick, G., Desrochers, C., and Bussière, S. (1997). "Industrial implementation of motor load and freeness control of chemimechanical pulp refiners," *TAPPI J.* 80(12), 135-142.

Thibault, J., Taylor, D., Yanofsky, C., Lanouette, R., Fonteix, C., and Zaras, K. (2003). "Multicriteria optimization of a high yield pulping process with rough sets," *Chem. Eng. Sci.* 58, 203-213. DOI: 10.1016/s0009-2509(02)00470-0

Yan, A., Shao, H., and Wang, P. (2015). "A soft-sensing method of dissolved oxygen concentration by group genetic case-based reasoning with integrating group decision making," *Neurocomputing* 169, 422-429. DOI: 10.1016/j.neucom.2014.07.081

Zhou, P., and Chai, T. Y. (2014). "Data-driven soft-sensor modeling for product quality estimation using case-based reasoning and fuzzy-similarity rough sets," *IEEE Trans. Autom. Sci. Eng.* 11(4), 992-1003. DOI: 10.1109/tase.2013.2288279

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