

On the diagnosis of a fouling condition in a kraft recovery boiler: combining process knowledge and data-based insights

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ABSTRACT: Fouling is still a major challenge for the operation of kraft recovery boilers. This problem is caused by accumulation of ash deposits on the surfaces of heat exchangers in the upper part of the boiler over time. The first consequence is the reduction of steam production due to loss of heat transfer and, finally, the shutdown of the boiler due to clogging.

The present work investigated the operational condition of a modern kraft boiler under a critical fouling condition. This boiler had even faced a manual cleaning due to a clogging event. This analysis combined process knowledge, plant team experience, and a data-driven approach, given the complexity of the process. In this sense, historical data covering this critical period of operation were collected. After a cleaning procedure, they were used to obtain a predictive neural network model for the flue gas pressure drop in the boiler bank, which is an indirect measure of ash deposit accumulation. Once validated, it was used for sensitivity analysis, with the aim of quantifying the effects of the model inputs.

Five variables out of eighteen accounted for nearly 60% of the total effect on pressure drop. Namely, primary air temperature (21.6% of the total effect) and flow rate (11.1%), black liquor flow rate (9.9%) and temperature (8.4%), and white liquor sulfidity (8.6%). The analysis of these results mainly suggested an excess of carryover, which composes the ash deposits. Recommended actions to mitigate the fouling condition involved adjustments to the primary air system before the more drastic solution of reducing the boiler load.

Application: This article shows the synergy in combining process knowledge and data-driven insights to better understand complex phenomena such as the fouling problem in kraft recovery boilers. The resulting more targeted information helps reduce diagnostic and decision-making time, leading to more efficient operational actions.

Fouling still represents a major operational challenge in kraft recovery boilers. This problem results from the accumulation of ash deposits on the surfaces of the heat exchangers in the upper section of the boiler over time. These deposits increase the resistance to heat transfer between the hot flue gas and fresh water, impacting the generation of high-pressure steam. In addition, they can also lead to unstable operation, reduced boiler load, tube surface corrosion, higher maintenance costs, and even clogging of flue gas channels, which can result in unplanned boiler shutdown. The commonly adopted cleaning strategy for fouling control is the use of a sootblowing system, whose effect may be limited as the boiler campaign progresses. Even with an improved boiler design and air system, modern kraft recovery boilers also face the problem of fouling, mainly in boiler banks [1].

The composition and properties of the ash deposits on the tube surfaces of kraft recovery boilers derive from several mechanisms. Most of the ash is formed by small particles called fume. They originate from the reactions of vaporized alkali metals from the burning of the black liquor and from the reduction reactions in the char bed with main-

ly sulfur, chlorine, and carbon. The sodium and potassium release increases with increasing furnace temperature, which is a positive function of boiler load and air system temperature. Another mechanism is provided by the carryover of relatively larger particles. They refer to the burned and unburned black liquor particles entrained by the furnace gases. It is generally low in modern kraft recovery boilers, mainly due to the improved air system, but may increase depending on black liquor firing conditions and air system operation. There is also the carryover of char bed fragments, which increases with higher temperatures. Intermediate size particles, between fume and carryover particles, also originate from the black liquor and the char bed. The ash deposits can then be composed of fume, carryover, and intermediate size particles. There are also several mechanisms related to ash deposition on the heat transfer surfaces; namely, inertial and turbulent impaction for larger particles, thermophoresis for smaller particles, and condensation of alkali metal vapors. Flue gas components can also react with existing ash deposits, and different concentrations can affect flue gas mass transfer to surfaces. The deposits are subjected to the sintering process,

from which they become relatively hard. The rate at which this occurs increases with temperature, which can limit the effectiveness of the sootblowing system. The dynamics of fume and carryover formation and therefore the amount, composition, and behavior of the ash deposits depend on several operational factors such as pulping conditions, black liquor properties, and boiler furnace conditions. Regarding the latter, for example, the primary air level is related to controlling the sulfur reduction reactions that occur on the surface of the char bed and to maintain its shape, while the secondary air level is related to the liquor burning process. More information can be found in [1-3] and references therein.

The fouling phenomenon in kraft recovery boilers has been investigated for decades to understand its mechanisms and develop predictive tools for it. It continues to be an active source of study, as evidenced by recent works. Pérez and Vakkilainen [4] compared turbulence models and two-dimensional (2D) and three-dimensional (3D) meshes for unsteady CFD ash deposition models. The authors reported that the three-dimensional approach may be required for better accuracy when dealing with fine particle deposition. Pérez, Vakkilainen, and Hyppänen [5] presented a CFD particle rebound-stick model to predict ash deposition in a boiler bank. Particles of different sizes were analyzed, and the authors found that they had a different arrival rate, sticking efficiency, deposition rate, and deposition distribution. In another work [6], the same authors used a CFD model with a stick-rebound mechanistic approach and dynamic meshes to predict the growth of ash deposits in a boiler bank. The authors analyzed two particle diameters. They reported that the smaller one showed round, uniform deposits, while the larger one showed more irregular distribution with some high local peaks. The same authors [7] also proposed a CFD model with dynamic mesh to predict the shape of the deposits. Different tube arrangements of a boiler bank were analyzed. They observed that larger transversal spacings appear to have less effect on deposition and therefore heat transfer. Jukola, Kytälä, and McKeough [8] used a CFD model to predict sodium release during black liquor burning. The authors reported more realistic results regarding the spatial distribution of the sodium release in the furnace, which is necessary for a better understanding of fume formation and its consequences. Leppänen et al. [9] presented a CFD model for the formation of fine fume particles and their deposition in kraft recovery boilers. The authors pointed out its accuracy with real measurements, mainly for particle composition. Leppänen et al. [10] showed a CFD model to simulate alkali metal chemistry and fume particle formation in a kraft boiler. The results were partially validated with field measurements. The authors reported that it provides information on fume composition, chlorine, and potassium enrichment factors, as well as particle mass concentration at different locations in the boiler.

Fouling is a very complex phenomenon involving thermodynamics, fluid mechanics, and particle sticking and rebound mechanisms, to name a few. For example, computational fluid dynamics (CFD) modeling for ash deposition generally adopts a 2D geometry; however, in some cases, a 3D approach may be required [4]. Furthermore, parameters such as ash particle arrival rate, sticking efficiency, and deposition rate are not directly available [6]. Also, variability in raw material and chemical components affects fouling formation and behavior in biomass boilers. For kraft boilers, these characteristics are related to wood species, pulping conditions, black liquor properties, and firing conditions, and more specifically, to sulfur, potassium, and chlorine contents in the liquor [1-3]. This complexity makes it difficult to use a purely mathematical description for fouling control applications, which has also led to the use of the data-based approach. For example, Versteeg and Tran [11] applied principal component analysis (PCA) for fouling monitoring. Operational data from three kraft boilers were used. PCA was used to identify key operational variables that contributed to fouling and plugging. The authors reported that this multivariate statistical technique can be used to visualize changes in boiler fouling conditions over short and long periods. Almeida and Park [12] used the hidden Markov model (HMM) approach to monitor the accumulation of ash deposits in a heat transfer section of a kraft boiler. The data refer to the pressure drop of the flue gas along the series of heat exchangers up to the electrostatic precipitator. The authors reported that this signal processing technique was able to provide the current state of the boiler in relation to the fouling condition. The accumulation of ash deposits is a function of boiler design and operation, which means it varies from boiler to boiler. In this sense, data-driven modeling can help describe fouling behavior, as it captures information directly from operational data.

The present work investigates the operational condition of a real kraft recovery boiler in an advanced fouling scenario. A manual cleaning has already been carried out on this boiler due to a clogging event. The focus is on the boiler bank, which is most critical for fouling in modern kraft boilers [1]. The ash deposits in this case are a mixture of fume and carryover particles. The study combined the process- and data-driven approaches. This type of hybrid analysis is becoming increasingly mandatory in complex systems, such as the case in question. On the one hand, partial knowledge of the process can limit obtaining pure mathematical models, and on the other hand, large amounts of available data can help generate practical insights into process conditions. Such a combination results in relatively accurate models without completely losing explainability, as in the case of pure black-box modeling. There is a multitude of techniques based on data from the areas of multivariate statistics and artificial intelligence. None of them are the one-size-fits-all solution to all kinds of problems. Given the ability of nonlinear input-output mapping and robustness

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to noisy data, as is the case of industrial measurements, the neural network modeling was adopted in this work. This artificial intelligence technique has proven to deal satisfactorily with process data over the past two decades. After identifying a characteristic model of the current condition of the boiler, a sensitivity analysis was performed. This type of study is useful for pointing out the model inputs with the greatest influence on a response of interest [13]. This is done by quantifying the effect of each of them. Such an analysis can contribute to the diagnosis of the problem by suggesting more targeted actions. The model output in this work was the flue gas pressure drop across the boiler bank, which is commonly used as an indirect measure of ash deposit accumulation [1]. The results obtained were compared with the classical linear regression analysis.

Sensitivity analysis is usually performed based on a characteristic model of normal operating conditions. The model of this work is related to the boiler fouling condition, and thus this study provided the variables most correlated with this critical situation. On the one hand, this result can be used to verify whether the selected subset of variables is as expected, as this analysis can also generate new insights into the condition of the process. On the other hand, the possibility of quantifying the effects of such variables is useful to obtain the strength of the correlations. All this information together can help the plant team diagnose the boiler fouling condition.

METHODOLOGY

Figure 1 depicts the methodology adopted in this work. Each step is described below.

Data preprocessing

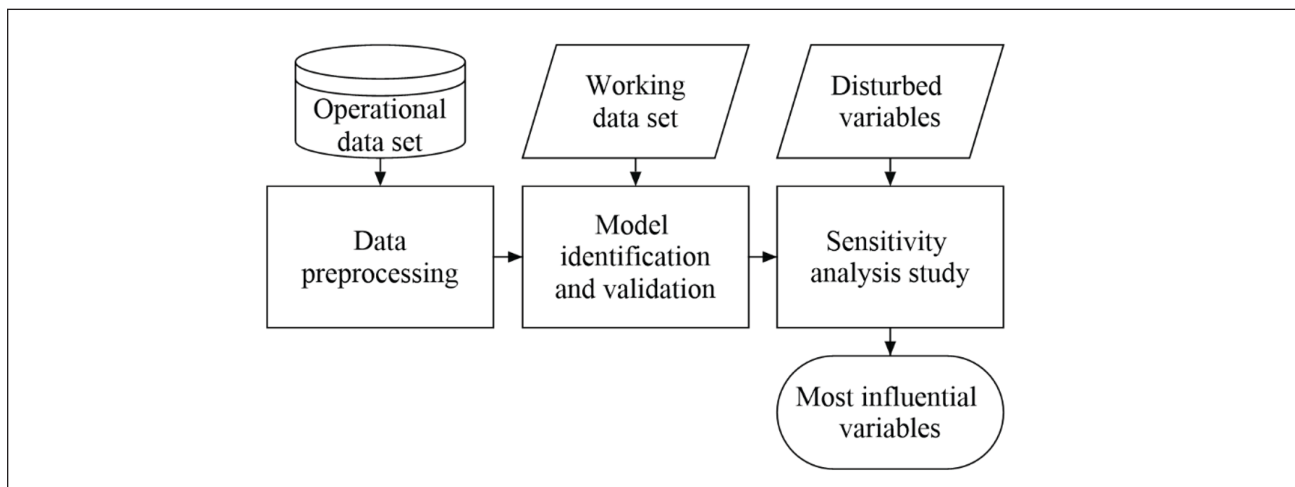
This initial step is essential to become familiar with the data collected at the mill. It concerns the identification of patterns, trends, discrepancies, and operational dynamics. This is usually done visually using plots. As more than a hundred variables were provided by the mill in this work, it was nec-

essary to select a subset of them. This task was based on prior visual analysis and knowledge of the process, considering the fouling phenomenon and the pressure drop of the flue gas in the boiler bank as the response variable. Next, data cleaning was performed to remove missing values, erroneous registers, and anomalous data. Instead of the sample mean ($\bar{x}$) and standard deviation (s), the Hampel filter [14] with median ($\tilde{x}$) and median absolute deviation (MAD) statistics was adopted to remove anomalous data. These statistics are less sensitive to extreme and non-normal data, reducing the chance of misclassifying outliers. This filter is applied to each variable separately. In the end, all samples with at least one variable value identified as an outlier were disregarded. The working data set, generated as a result of all the previous tasks, was used as input information for the identification of the neural network model.

Neural network model identification and validation

The objective in this step is to obtain a predictive model for the flue gas pressure drop across the boiler bank of the kraft boiler. The choice for using neural networks (NN) is due to their nonlinear input-output mapping capability and robustness to noisy data, inherent to process measurements [15]. The commonly used multi-layer perceptron (MLP) architecture was adopted, with a single hidden layer using the hyperbolic tangent and the output layer using the identity function. The flow of information in this case is as follows. Briefly, the values of the input variables are initially weighted and combined before being fed to the elementary processing units that make up the hidden layer. These units are responsible for the nonlinear mapping. After a second weighting and combination process, the output layer provides the final estimate for the response variable; in this case, the pressure drop of the flue gas.

The previously obtained working data set was randomly divided into two subsets. Namely, a training subset, containing 75% of the samples, used to parameterize the model,



1. Methodology steps.

and a test subset, with the remaining samples, used to verify its generalization capacity in relation to the process knowledge acquired during its training. The training phase is carried out in a supervised manner; that is, the values of the response variable are available. This process is iteratively performed until the error between model estimates and target values is satisfactory. The target values in this case refer to the flue gas pressure drop in the boiler bank. One issue to be defined is the number of elementary units in the hidden layer. This is usually done empirically through a 10-fold cross-validation procedure. The idea is to minimize the overfitting problem that can occur when the model loses its ability to generalize due to overtraining. This procedure provides average correlation coefficients as a function of the number of hidden units, which was varied from 1 to 30 in this work. This coefficient measures the degree of association between mill values and model estimates for the response variable. The closer to one, the better. The selected model is the one with the number of hidden units that presents the highest average value. This model is then re-identified using all samples from the training subset, which is useful due to the larger amount of data for parameterization. The generalization ability of this resulting model is evaluated using the test subset. This veri-

fication is usually based on residual analysis, where the residual is the difference between mill values and model estimates for the response variable. The results obtained were compared with classical linear regression analysis [16]. A reliable model is essential for a sensitivity analysis study.

Sensitivity analysis study

This step used the previous model to find the input variables with the greatest effect on the flue gas pressure drop in the boiler bank. A common sensitivity analysis procedure [13] in MLP neural networks is based on their connection weights [17], where the knowledge extracted from the data is stored during training. Another, adopted in the present work, directly perturbs the input signals, one at a time, and observes the respective changes in the model response to calculate the mean squared error (*MSE*) [18]. This result is then compared with a reference *MSE* value obtained from the perturbation-free outputs.

RESULTS AND DISCUSSION

Data preprocessing

The historical data provided by the pulp mill comprised approximately sixteen months of operation, from June 1, 2017, to October 10, 2018. They refer to the critical period

Disturbed Variable (<i>i</i>)	<i>MSE_i</i>	<i>Dev^{a,b}</i>
White liquor sulfidity, %	1.04e-02	8.6%
Black liquor dry solids, %	5.86e-03	3.6%
Black liquor flow rate, L/s	1.16e-02	9.9%
Black liquor temperature, °C	1.02e-02	8.4%
Black liquor pressure (average), kPa	3.42e-03	0.9%
Primary air flow rate, Nm ³ /s	1.27e-02	11.1%
Primary air temperature, °C	2.22e-02	21.6%
Primary air pressure (average), kPa	3.84e-03	1.4%
Secondary air flow rate, Nm ³ /s	7.64e-03	5.6%
Secondary air temperature, °C	6.03e-03	3.8%
Secondary air pressure (average), kPa	2.87e-03	0.3%
DNCG secondary air flow rate, Nm ³ /s	7.68e-03	5.6%
DNCG secondary air temperature, °C	8.03e-03	6.0%
DNCG secondary air pressure (average), kPa	3.64e-03	1.2%
Tertiary air flow rate, Nm ³ /s	6.04e-03	3.8%
Tertiary air temperature, °C	9.00e-03	7.1%
Temperature at secondary air level (average), °C	2.96e-03	0.4%
Tertiary air pressure (average), kPa	3.31e-03	0.8%
MSE = mean squared error; DNCG = diluted noncondensable gases. ^a Perturbation-free model: MSE reference value ($MSE_{Ref} = 2.59 \cdot 10^{-3} \text{ (kPa)}^2$) ^b $Dev(\%) = [(MSE_i - MSE_{Ref}) / \sum_{i=1}^{18} (MSE_i - MSE_{Ref})] \cdot 100$		

1. Sensitivity analysis results, given the neural network (NN) model.

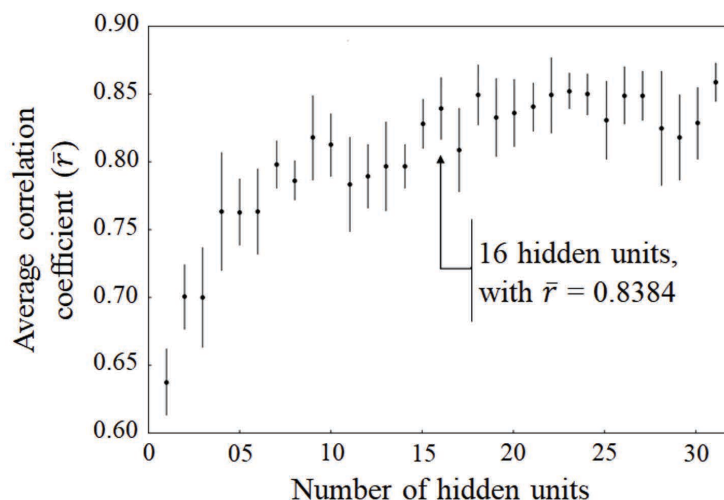
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of fouling in the boiler. Sampling was carried out using hourly averages, totaling 11,905 records per variable. A considerably high number of 123 variables was available, which most of the time is not suitable for data-driven applications and particularly for sensitivity analysis studies.

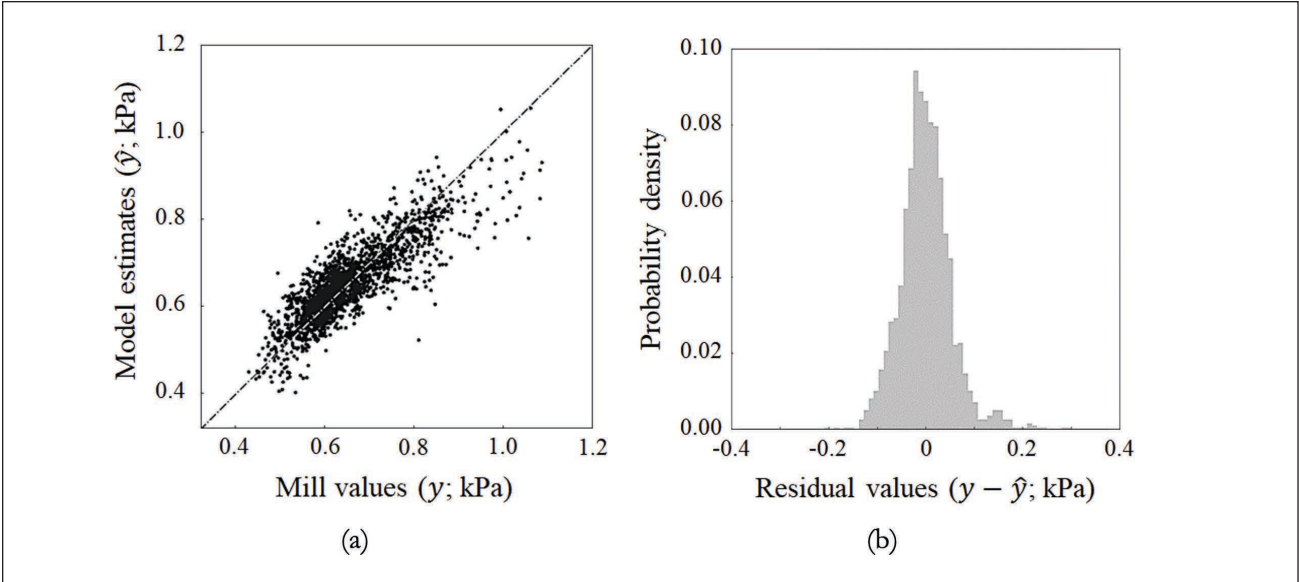
To reduce the dimensionality of the problem, a selection of variables based on process knowledge was carried out together with the plant team. An initial analysis showed six groups of variables, namely, black liquor, air system, flue gas outlets, feed water, generated steam, and ash composition. We chose to work with the variables belonging to the black liquor and air system groups as model input. The reason is that they are closely related to the causes of the fouling phenomenon in kraft recovery boilers [1-3]. Both groups refer to the lower furnace, where a stable operating condition is essential to mitigate fouling in the upper part of the boiler. The resulting subset of 18 variables used as model inputs is shown in **Table I** (first column). It is known that black liquor sulfidity is influenced by the operating conditions of pulping and washing. However, only the white liquor sulfidity was available online and was therefore adopted as input to the model. It is also known that black liquor chemistry affects fouling behavior. For instance, high levels of chlorine and potassium can lower the ash melting temperature, increasing fouling [2]. However, that kind of information was not available with reasonable frequency. Starting from the idea of describing the general behavior of the boiler, average values were considered in the case of multiple measurements of the same variable. An example is given by the pressure of the black liquor measured on the boiler walls. Regarding data cleaning, 613 samples with missing values or erroneous registers and 3,490 samples identified as outliers by the Hampel filter were disregarded. The resulting working data set used as input to the model consisted of 7,802 samples.

Neural network model identification and validation

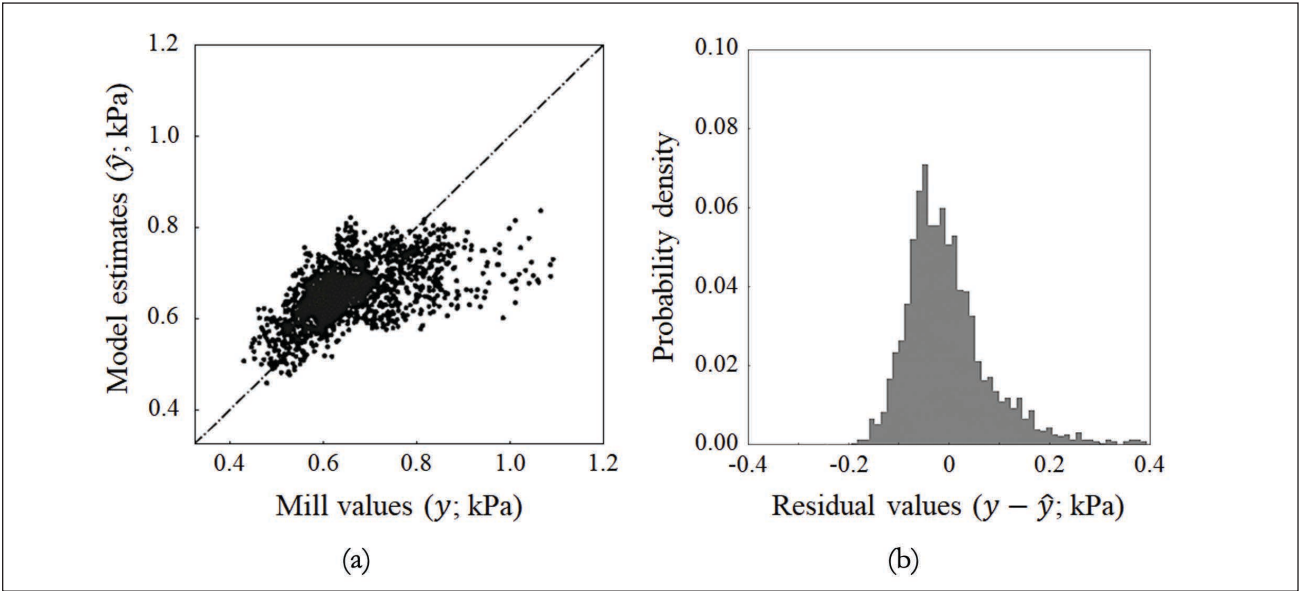
The objective was to obtain a predictive neural network (NN) model relating the eighteen input variables that were associated with the black liquor and air system to the flue gas pressure drop in the boiler bank of the kraft boiler. The training and test subsets comprised 5,850 (75% of 7,802) and 1,952 (25%) samples, respectively. **Figure 2** shows the result of the 10-fold cross-validation procedure using the training data, with the average correlation coefficients ($\bar{r}$) as a function of the number of hidden elements. Vertical bars correspond to ± 1 standard deviation. It can be seen that $\bar{r}$ increases, as desired, until it stabilizes from approximately fifteen hidden units. Based on the principle of parsimony, the simplest satisfactory model should be chosen. In this sense, the NN model with sixteen hidden elements was selected, whose $\bar{r}$ is equal to 0.8384. This model was then re-identified using all the training data. **Figure 3** shows the result when using it with the test data. The parity relation in Fig. 3a compares the model outputs ($\hat{y}$; on the y-axis) with the mill-collected values (y ; on the x-axis) for the flue gas pressure drop across the boiler bank. The correlation coefficient between them is considerably high, equal to 0.853. In Fig. 3b, the histogram of the residuals ($y - \hat{y}$) shows an approximately normal distribution, with a mean value close to zero, as desired. A slight underestimation ($y > \hat{y}$) can be observed in this plot (residuals around 0.2 kPa) for very extreme values of flue gas pressure drop (above approximately 0.9 kPa, as can be seen in Fig. 3a), probably due to the relatively small amount of data on this boiler condition. Thus, the flue gas pressure drop in the boiler bank was satisfactorily described by the neural network model using sixteen hidden units. These results were compared to the classic multiple linear regression (MLR) model. **Figure 4** shows a significantly lower correlation



2. Cross validation results: average correlation coefficient ($\bar{r}$) as a function of the number of hidden units in the neural network model.



3. Neural network model results over the test data set: (a) parity relation between plant values (y) and model estimates ($\hat{y}$), and (b) residuals ($y - \hat{y}$) distribution.



4. Multiple linear regression model results over the test data set: (a) parity relation between plant values (y) and model estimates ($\hat{y}$), and (b) residuals ($y - \hat{y}$) distribution.

coefficient of 0.567 (in Fig. 4a) and a considerable right-skewed distribution for the residuals, characterizing underestimation (in Fig. 4b). These larger residuals correspond to the mill values of the flue gas pressure drop above approximately 0.7 kPa, being more severe from approximately 0.9 kPa (as can be seen in Fig. 4a). Overestimation ($y < \hat{y}$) can also be observed, with the peak of the residual distribution to the left of the desired zero value (more precisely, between -0.1 and zero). These negative residual values extend over the usual range of flue gas pressure drops between 0.5 and 0.7 kPa (as can be seen in Fig. 4a by the skewed distribution of points along the reference line).

Table II presents a quantitative comparison between the two models. This analysis corroborates the use of a nonlinear modeling provided by neural networks in this work, given the complexity of the fouling phenomena.

Sensitivity analysis study

A predictive model can be used for many purposes. In the present work, a sensitivity analysis study was carried out. Our idea was to find the input variables with the greatest effect on the flue gas pressure drop in the boiler bank, given the boiler fouling condition, quantifying such effects. When applied to the original training data, the previous NN

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Statistic	MLR Model	NN Model (16 hidden units)
Pearson correlation coefficient (r)	0.567	0.853
Mean of the error, kPa	-3.17e-03	-0.427e-03
Standard deviation of the error, kPa	0.0839	0.0533
Maximum error (in absolute), kPa	0.393	0.300
Minimum error (in absolute), kPa	1.65e-05	1.91e-05
Mean absolute error (MAE), kPa	0.0629	0.0396

II. Comparison between the neural network (NN) model and the multiple linear regression (MLR) model regarding the prediction of flue gas pressure drop along the boiler bank using the test data set.

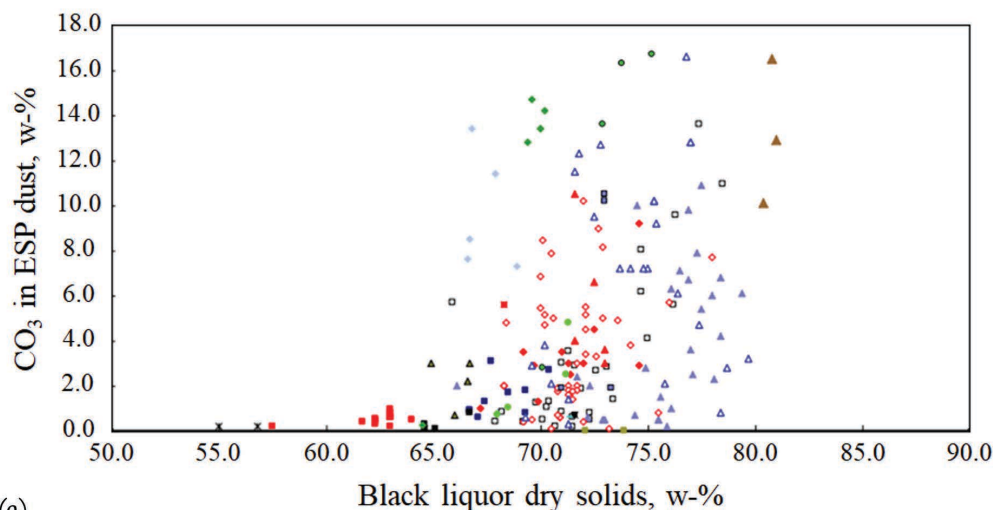
model resulted in a coefficient of determination (R^2_{Ref}) of 0.769 and a mean squared error (MSE_{Ref}) of $2.59 \cdot 10^{-3}$ (kPa)². These values served as a reference (Ref), as they were obtained in a perturbation-free condition. Table I (second and third columns) shows the results when perturbing each model input variable, as previously described. For example, given the perturbation in white liquor sulfidity, $MSE = 1.04 \cdot 10^{-2}$ (kPa)² and its relative effect on flue gas pressure drop in the boiler bank is equal to 8.6%. The formula used for this calculation is shown at the bottom of Table I. The greatest effects are associated with primary air and black liquor (highlighted in italics). Namely, primary air temperature (21.6%) and flow rate (11.1%); black liquor flow rate (9.9%) and temperature (8.4%); and white liquor sulfidity (8.6%). These five variables, out of the eighteen model inputs initially selected, account for almost 60% of the total effect on flue gas pressure drop, given the fouling condition of the boiler.

First, it can be noted that the variables most correlated with the pressure drop of the flue gas in the boiler bank are related to the fouling problem; this subset corroborates the critical condition of the boiler. These correlations might not be as significant; for example, in the case of a local problem with the passage of the flue gas due to a malfunction of the sootblowing system. This qualitative analysis based on available knowledge about the process also serves to validate the results. However, it is important to bear in mind that this type of analysis can lead to new insights, which can contribute to improving the knowledge about the process. Furthermore, the quantitative result provided by the sensitivity analysis is also useful as a clue in diagnosing the problem. The influence of each variable on boiler fouling is described separately below. However, given the interaction between them, it is also important to keep in mind that the cause of a fouling problem should consider the overall operating scenario.

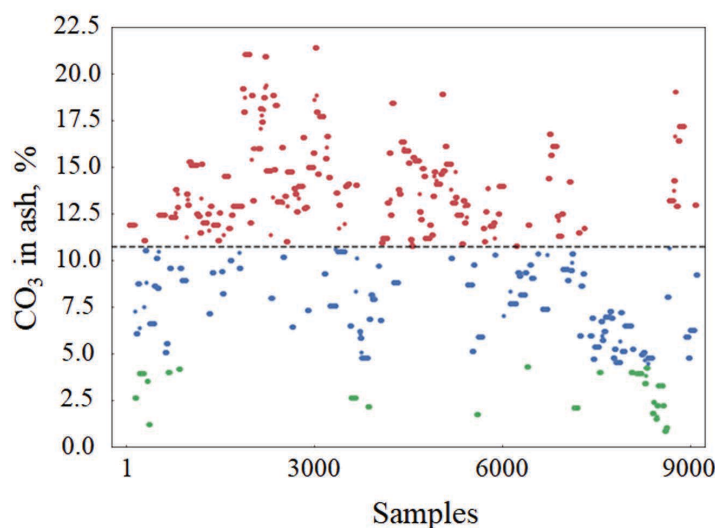
The primary air level plays a key role in the dynamics of fume and carryover formation. For example, high air temperatures increase the volatilization of alkali metals and

other species, and large air flows increase carryover [1,2]. This relationship is decisive for the amount and composition of the ash deposits, and consequently, their behavior. Thus, *primary air flow rate and temperature* are critical for fouling control, which may explain their relatively larger effects, mainly for temperature (21.6%). Together, both parameters accounted for 32.7% (21.6%+11.1%) of the total effect on the flue gas pressure drop in the boiler bank.

It is known that the lower furnace temperature is closely related to the characteristics of the ash deposits. One way to estimate this temperature is by the level of carbonate (CO_3) in the ash. **Figure 5a** shows the positive correlation between measurements of carbonate content, collected in dust samples from the electrostatic precipitator (ESP) in several kraft boilers, with the load of dry solids. It is also known that the high content of dry solids increases the lower furnace temperature. Thus, the higher the carbonate content in the ashes, the higher the lower furnace temperature. This is explained by the excess sodium released at higher temperatures that forms carbonate in the ashes. Higher lower furnace temperatures, which depend considerably on the *flow rate and temperature of the black liquor*, favor the formation of fume and carryover. Fume particles in the flue gas increase due to increased vaporization of sodium compounds from the char bed and the release of sodium from the liquor pyrolysis. For the second, higher liquor burning load and boiler furnace temperature favor particle carryover, especially in the case of relatively smaller liquor droplets. Higher air flows aggravate both situations by increasing the velocity of the flue gases in the lower furnace. Higher concentrations of carbonate can also contribute to lowering the ash melting temperature. More information related to carbonate can be found in [1-3]. The flow rate and temperature of the black liquor were responsible for 18.3% (9.9%+8.4%) of the total effect on the flue gas pressure drop in the boiler bank. Figure 5b shows the result of laboratory analyses of the CO_3 content in dust samples collected in the electrostatic precipitator of the boiler under analysis in this work. Done three times a day



□ A • B ▲ C ◊ D ■ E ▲ F ▲ G • H ■ I • J ■ K ▲ L • M ■ N □ O ■ P × Q — X • Y ■ Z ▲ W



● $\text{CO}_3 < 4.5$ ● $4.5 \leq \text{CO}_3 < 10.7$ ● $\text{CO}_3 \geq 10.7$ --- Average CO_3 (10.7)

5. Carbonate (CO_3) content in ash deposits in the electrostatic precipitator (ESP): (a) as a function of dry solids for 21 different kraft recovery boilers [1], and (b) in the kraft recovery boiler of the present study for several dust samples (source: pulp mill data).

on average, it corresponds to the fouling condition period. A considerable number of CO_3 content values between 10% and 15% are observed, with extreme values around 20%. The average value is equal to 10.7%. Given that the usual range is $4.5\% \pm 3\%$ (based on pulp mill data), this analysis suggests a considerably high boiler temperature. This result is in agreement with that obtained through the sensitivity analysis in relation to the flow rate and temperature of the black liquor. The combination of process and data-driven analysis is very beneficial given the overall complexity of industrial operations.

The effect of the *sulfidity in the white liquor* (8.6%) on

flue gas pressure drop should be analyzed carefully. Its relationship with the sulfidity of the black liquor is not straightforward and depends on the operating conditions of pulping, washing, and evaporation of the mill [19-21]. It is known that higher levels of sulfur in the boiler can increase the formation of ash deposits due, for example, to a considerable decrease in the ash melting temperature [1,22]. The range of the sulfidity of the white liquor in the hardwood-based mill of the present case study was between 27.5% and 36% (based on pulp mill data) during the fouling condition period.

These results showed a significantly greater effect of the

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primary air temperature and considerable effects of the black liquor flow rate and temperature. Furthermore, laboratory analysis showed substantial carbonate content in the ash. This scenario indicates a relatively much higher temperature in the lower furnace of the boiler, which favors the formation of fume and carryover. Considering the operation of the boiler at high load, as desired, one recommendation concerns the reduction of the primary air temperature. The effect of the primary airflow was also significant, suggesting excess carryover. In this sense, another recommendation refers to checking the pressure and velocity of the primary air level along the boiler walls. These recommendations contribute to decreasing the flow rate and temperature of the furnace gases, which, in turn, decreases the carryover rate. The resulting lower temperature and pressure for the flue gas contribute to attenuating the formation and strength of the ash deposits. Naturally, the effect of any change must be carefully considered before taking any action. For example, airflow adjustments depend on boiler load. Other possible actions that may take longer to implement refer to changes in the properties of the black liquor and in the sootblowing system. An example of the former might be the reduction of sulfidity, upon further analysis. For the second, it may refer to a more efficient local sootblowing strategy, focusing on more critical regions of the boiler bank. Combined actions can lead to greater effects in practice. A drastic action with greater economic impact, often taken in severe fouling conditions, concerns the reduction of boiler load. In this sense, a sensitivity analysis study can point out possible intermediate actions that contribute to prolonging the functioning of the boiler throughout its campaign.

CONCLUSIONS

The boiler in the present work was facing a critical fouling condition. Fouling negatively affects steam production, tube surface corrosion, maintenance costs, and even unplanned boiler shutdown. This was the case with this boiler, where manual cleaning was carried out due to a clogging event. Modern kraft recovery boilers can still have this problem, particularly on the boiler bank.

This work aimed to better understand the current operating condition of the boiler. Given the complexity of the fouling phenomenon, a data-based approach was used. For this, the pulp mill provided data on the functioning of the boiler during this period. After identifying and validating a predictive neural network model for the flue gas pressure drop across the boiler bank, a sensitivity analysis study was carried out. The objective was to find the variables with the greatest effect on the pressure drop given the fouling scenario. This quantitative analysis pointed to a subset of 5 of the 18 variables initially selected by the plant team. Namely, primary air temperature and flow rate, black liquor flow rate and temperature, and white liquor sulfidity. Analysis of this result, along with laboratory analyses that showed

high levels of carbonate in the boiler's ESP dust, indicated a very high temperature in its lower furnace, with possible excess carryover. The recommended actions were towards adjustments, mainly in the primary air parameters, before proceeding with the more drastic action of reducing the boiler load.

Better understanding of the complex relationships between boiler operating variables and the fouling problem is beneficial for taking more targeted actions. Sensitivity analysis can reduce the time spent on diagnosis and decision making, contributing to more efficient operational actions. An important issue concerns the primary selection of variables to be used as model inputs. In this sense, other variables with an impact on the fouling problem can be considered; for example, the sulfidity and the levels of sodium, chlorine, and potassium in the black liquor. The combination of process knowledge, plant team experience, and data-driven insights can lead to a better understanding of the fouling problem in kraft recovery boilers. **TJ**

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LITERATURE CITED

1. Vakkilainen, E.K., *Kraft Recovery Boilers: Principles and Practice*, Suomen Soodakattilayhdistys r.y., Helsinki, 2005.
2. Tran, H., "Fouling of tube surfaces in kraft recovery boilers," *Int. Recovery Boiler Conf.*, Finnish Recovery Boiler Committee, Helsinki, 2004.
3. Adams, T.N., Ed., *Kraft Recovery Boilers*, TAPPI Press, Atlanta, 1997.
4. Pérez, M.G. and Vakkilainen, E.A., *Fuel* 237: 806(2019). <https://doi.org/10.1016/j.fuel.2018.10.066>.
5. Pérez, M.G., Vakkilainen, E., and Hyppänen, T., *Fuel* 181: 408(2016). <https://doi.org/10.1016/j.fuel.2016.05.004>.
6. Pérez, M.G., Vakkilainen, E., and Hyppänen, T., *Fuel* 185: 872(2016). <https://doi.org/10.1016/j.fuel.2016.08.045>.
7. Pérez, M.G., Vakkilainen, E., and Hyppänen, T., *Fuel* 158: 139(2015). <https://doi.org/10.1016/j.fuel.2015.04.074>.
8. Jukola, P., Kytälä, J., and McKeough, P., "Predicting sodium release in recovery boilers in conjunction with CFD furnace modeling," *Int. Recovery Boiler Conf.*, Finnish Recovery Boiler Committee, Helsinki, 2014.
9. Leppänen, A., Tran, H., Taipale, R., et al., *Fuel* 129: 45(2014). <https://doi.org/10.1016/j.fuel.2014.03.046>.
10. Leppänen, A., Välimäki, E., Oksanen, A., et al., *TAPPI J.* 12(3): 25(2013). <https://doi.org/10.32964/TJ12.3.25>.
11. Versteeg, P. and Tran, H., *TAPPI J.* 8(11): 22(2009).

12. Almeida, G.M. and Park, S.W., *Comput.-Aided Chem. Eng.* 27: 1467(2009). [https://doi.org/10.1016/S1570-7946\(09\)70635-2](https://doi.org/10.1016/S1570-7946(09)70635-2).
13. Saltelli, A., Chan, K., and Scott, E.M., *Sensitivity Analysis*, Wiley, New York, 2009.
14. Davies, L. and Gather, U., *J. Am. Stat. Assn.* 88(423): 782(1993). <https://doi.org/10.1080/01621459.1993.10476339>.
15. Haykin, S., *Neural Networks and Learning Machines*, 3rd edn., Pearson, Hoboken, NJ, USA, 2009.
16. Montgomery, D.C., Peck, E.A., and Vining, G.G., *Introduction to Linear Regression Analysis*, 5th edn., Wiley, New York, 2012.
17. Alkmim, A.R., Almeida, G.M., Carvalho, D.M., et al., *Environment Technol.* 41(19): 2424(2019). <https://doi.org/10.1080/09593330.2019.1567609>.
18. Almeida, G.M., Cardoso, M., Rena, D.C., et al., *Int. J. Comput. Intell. Appl.* 9(1): 69(2010). <https://doi.org/10.1142/S146902681000277X>.
19. Gomes, R.M. and da Silva Júnior, F.G., *BioResources* 15(2): 3945(2020). <https://doi.org/10.15376/biores.15.2.3945-3961>.
20. Andersson, P.A., "Dynamic Na/S balance of a kraft pulp mill: Modeling and simulation of a kraft pulp mill using WinGEMS," M.S. thesis, Karlstad University, Karlstad, Sweden, 2014.

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21. Alabi, S.B., "Development and implementation of an online kraft black liquor viscosity soft sensor," Ph.D. dissertation, University of Canterbury, Christchurch, New Zealand, 2010.
22. Salmenoja, K., "Superheater corrosion in modern recovery boilers," *Int. Recovery Boiler Conf.*, Finnish Recovery Boiler Committee, Helsinki, 2004.

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In this work, we start from an already known critical challenge of fouling in a kraft boiler. The objective was to find the operational variables in the boiler with the greatest effect on this fouling condition.

Given the complexity of kraft boiler operation and the fouling phenomenon, a data analysis approach based on neural networks was adopted in this study. The obtained and validated model was used in a sensitivity analysis study. Given the non-explicit nature of neural networks, the process knowledge and experience of the plant team were critical in analyzing the results.

The most difficult aspect of this study was preparation of a working dataset from raw mill data, which was done through data preprocessing. It was particularly interesting to discover the possibility of isolating the most influential process variables in the fouling problem.

The synergy between process knowledge, plant time experience, and data-driven insights should be encouraged in pulp mills with the aim of increasing operations knowledge and reducing decision-making time, especially in the current era of high availability of data and digital transformation. The next step in this research would be to investigate causal inference (i.e., in addition to correlation between variables).

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