Operating parameters affecting the thermal performance of biomass boilers

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ABSTRACT: Operating data of a bubbling fluidized bed (BFB) boiler and three stoker grate (SG) biomass boilers from different pulp mills were analyzed over a 2-year period. The results show that in all cases, the thermal performance decreases markedly from 5.5 to 4 lb steam/lb dry biomass as the feedstock moisture content increases from 40% to 60%. The BFB boiler had better thermal performance, although it operated in a higher moisture content range compared with the SG boilers. Multivariate analysis was also performed on one of the SG boilers to determine operating parameters that affect thermal performance. The results show that furnace temperature, oil flow rate, and induced draft fan current positively correlate with thermal performance, while the feedstock moisture content, total air flow, and excess oxygen (O_2) negatively correlate with thermal performance. This implies that when making modifications to improve thermal performance, it is important to take into account correlations among various parameters. In some cases, one positively correlated parameter might cause an increase in a negatively correlated parameter. The net effect might be a decrease in thermal performance.

Application: Mills can find the most suitable way to optimize boiler operation with minimal process upsets.

Biomass (hog fuel) boilers in kraft pulp mills in Canada and the United States typically provide about one third of the mill's energy requirement. Hog fuel, which is a mixture of wood waste, bark, and biomass-based rejects from different parts of the pulping process, is burned in the biomass boiler and the heat of combustion is used to produce superheated steam [1]. The most common types of boilers are fixed bed boilers or stoker grates (SG) and bubbling fluidized bed (BFB) boilers. In SG boilers, the feedstock is fed onto the bottom grate where burning takes place. In BFB boilers, the biomass is delivered onto a hot fluidized sand bed. The biomass is vaporized in lean conditions and burns above the bed where air is introduced. BFB boilers are typically more versatile than SG boilers, operate with a wider range of fuel qualities, and are well suited for burning high moisture fuels. SG boilers, on the other hand, are susceptible to process upsets caused by small changes in fuel characteristics.

The variability of biomass boiler feedstock makes maintaining constant steam generation a challenge. The hog fuel quality, in terms of wood species, shape, size, and moisture content (MC), changes constantly as different wood waste sources are mixed. If the biomass feedstock is stored outside and exposed to rain or snow, MC can reach 70%. A portion of the heat content of the biomass might also be lost because of exposure to long durations of sunshine or biological decay. Depending on dry calorific value of the fuel, the biomass might reach an as-fired net calorific value of zero at high moisture and require auxiliary fuel firing.

The constant change in fuel quality and therefore steam production rate can make quantifying boiler performance difficult. For this reason, thermal performance (TP) values are typically used to provide an overall estimate for the quality of combustion and boiler operation. TP is a measure of how much steam with the required temperature and pressure, or enthalpy, is produced per unit mass of dry biomass. TP values are greatly influenced by boiler design and operation, as well as feedstock quality and consistency.

To optimize the TP of any boiler, first the interaction of the operating parameters needs to be studied. In this work, a systematic investigation was performed on three SG boilers and one BFB boiler to better understand the interaction and interconnectivity of operating parameters and their effect on TP. This paper first discusses the relationship of TP and feedstock MC, and then presents a statistical model for one of the SG boilers to determine the most influential operating parameters using multivariate analysis (MVA).

METHODOLOGY

Two years of daily average operating data were collected from three SG boilers and one BFB boiler. **Table I** lists the average operating data used in this study for each mill. To quantify biomass boiler operation, TP values were calculated using Eq. (1):

$$TP = \frac{F_{steam,T,P}}{F_{biomass,dry}} \tag{1}$$

where $F_{steam,T,P}$ is the flow rate of steam produced from burning biomass at the required superheated temperature and pressure, $F_{biomass,dry}$ is the feed flow rate of dry biomass, and TP is a dimensionless value. Theoretical TP values were calculated from an energy and material balance. The data collected for each biomass boiler were used to calculate TP values.

Multivariate analysis was used to study the interaction of mill A hourly average operating parameters and to find the most influential ones. Multivariate analysis is an effective statistical method to summarize data tables with many variables by creating several new variables containing most of the information [2]. These new latent variables are then used for problem solving and display (i.e., classification, relationships, control charts, and more). The new variables, called the scores, denoted by t, are created as weighted linear combinations of the original variables and each observation has a t value.

Multivariate analysis has been used by our research group to analyze factors affecting ring formation in lime kilns [3], multi-effect evaporator performance [4], recovery boiler fouling and plugging [5], and recovery boiler smelt spout failures [6]. The main challenge associated with MVA and working with a large number of data is dealing with data dimensionality, multicollinearity, noise, and missing data. Principal component analysis (PCA) and orthogonal partial least squares analysis (OPLS) methods are suitable for handling this challenge [7].

In this study, a commercially available software package SIMCA 14 (Umetrics; Umeå, Sweden) was used to construct an MVA model from mill A operating data. The program uses PCA and OPLS for MVA and to summarize the information in the observations as t scores, which are the new latent variables. The group of points in a K dimensional space, where K is the number of variables, is approximated by a hyperplane and the points are projected on that plane [2].

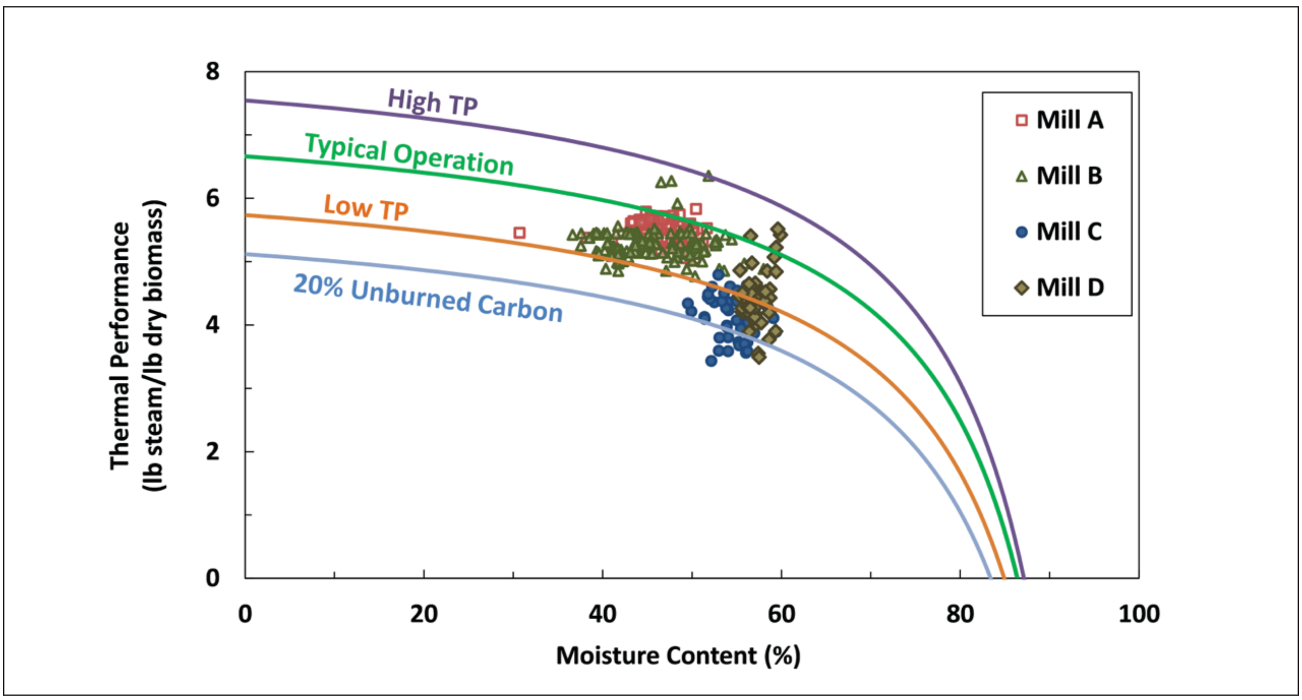
RESULTS AND DISCUSSION

Effect of moisture content on thermal performance

In this study, 2 years of daily average operating data from four biomass boilers at different pulp mills were analyzed, and the results are shown in **Fig. 1**. The boilers at mills A, B, and C are fixed bed, SG-type boilers and the boiler at mill D is a BFB boiler. The MC values for each boiler were either from batch oven-dried values provided by the mill or back calculated from other operating parameters.

To compare steam flow from different boilers with different fuel characteristics, combustion air conditions, and steam enthalpies, all steam flow values are normalized to the steam condition at 820°F and 900 psig. The data points shown on Fig. 1 are instances of normal operation. The steam flow rate, biomass flow rate, total air flow rate, and furnace temperature value ranges are average ± 1 standard deviation. The theoretical TP values were divided into high TP, typical operation, and low TP and calculated from energy and material balance. **Table II** summarizes the parameters used to calculate the theoretical values in Fig. 1.

As shown in Fig. 1, the TP decreases with increasing MC and becomes zero as the MC exceeds 85%. Comparing the calculated values with actual values obtained from each mill, it is evident that the SG boilers were operated at an average feedstock MC of 50%, ranging from 40% to 55%, and the BFB boiler was operated at higher moisture content, 55% to 60%. In both types of boilers, the maximum operable MC (55%–60%) was much lower than the theoretical maximum value (85%), even with auxiliary fuel firing. This was presumably because of the decrease in furnace temperature and the in-



1. Thermal performance (TP) versus moisture content.

Parameter	Mill A	Mill B	Mill C	Mill D
Boiler Type	**Stoker Grate**			**Bubbling Fluidized Bed**
Biomass feed rate, tons/h	29	30	62	50
Moisture content, %	38	40	58	56
Air flow rate, kpph	461	307	587	356
Undergrate air flow rate, kpph	177	170	159	176
Inlet air temperature, °F	192	293	349	219
Natural gas flow rate, scfm	30	124	124	-
Fuel oil flow rate, kpph	2.2	-	-	11.2
Flue gas temperature, °F	416	341	355	329
Excess O_2, %	7.7	5.5	7.3	5
Steam flow rate, kpph	214	266	285	182
Steam temperature, °F	820	827	738	871
Steam pressure, psig	900	915	652	1,178
Steam enthalpy, 1000 Btu/h	301	374	391	259

I. Operating data average values.

Parameter	Low Thermal Performance	Typical Operation	High Thermal Performance
Excess air, %	40	30	10
Radiation and unaccounted heat losses, %	10	5	0
Feedwater temperature, °F	250	300	350

II. Parameters for calculating theoretical thermal performance (TP) values.

crease in water vapor content in the combustion gas as a result of increased moisture content of biomass feedstock. These conditions might have resulted in unburned carbon in the fly ash or bottom ash or prevented some volatiles from burning [8]. Both unburned carbon and volatile loss mean that not all of the heat content of the feedstock is used. To demonstrate this adverse effect, a value of 20% is assumed for unburned carbon and TP values are calculated and shown in Fig. 1.

The results shown in Fig. 1 are representative of normal operation only; however, during biomass boiler operation, it is rare for all operating parameters to be at average conditions. It is also evident that TP is influenced by many different factors, not just MC. To address these challenges and investigate the simultaneous change of all parameters and their effects on TP, MVA was carried out to statistically study the simultaneous change of all the independent operating variables and to quantify the interaction and effect they have on several key dependent variables.

Multivariate analysis

Hourly average operating data from mill A were used in this study to build a statistical model. **Table III** lists main model parameters and their abbreviations. For MVA, an OPLS model was built, where TP and excess oxygen (O_2) were set as output or Y variables and all other process inputs, including moisture content, were set as X variables. The model uses all X variables to explain and predict the changes in Y variables.

Figure 2 shows the score scatter plot for the OPLS model built from mill A operating data from a total of 1400 data points. Each data point on the scatter plot represents one instance for all variables, in this case average hourly values for all operating parameters. The ellipse represents a 95% confidence interval (CI) of the data and the origin of the graph represents the average value across all variables. The further away a point is from the origin (shown by X), the greater it deviates from the average. Points clustered together on the scatter plot on each quadrant have similar collective characteristics and can be connected back to specific operating con-

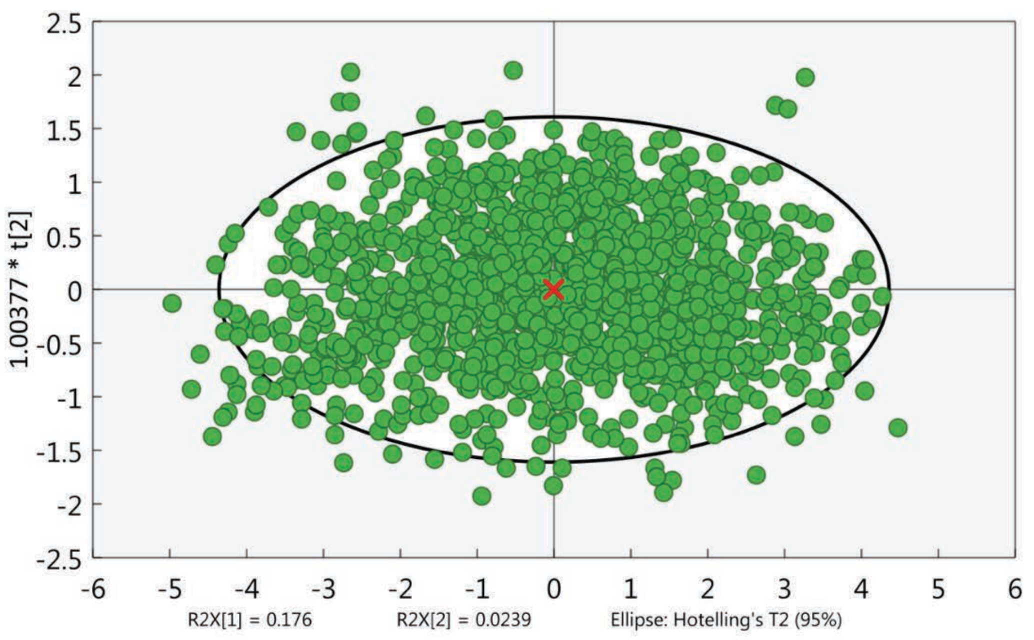
Abbreviation	Parameter
ArchAirFlw	Arch air flow rate
BarkAirFlw	Bark air flow rate
BurnerAirFlw	Gas burner air flow rate
DeAirT	Deaerator temperature
ExcessO2	Outlet excess O_2
GasFlow	Gas flow rate
IDFanCurr	Induced draft fan current
IDFanT	Induced draft fan outlet temperature
InAirT	Inlet air temperature
LowerFurnT	Lower furnace (bed) temperature
MC	Feed moisture content
OilFlow	Oil flow rate
TotalAirFlw	Total air flow rate
TP	Thermal performance
UGAirFlw	Undergrate air flow rate
WindboxAir	Windbox air flow rate
WindsweptAirFlw	Windswept spout air flow rate

III. Model parameters.

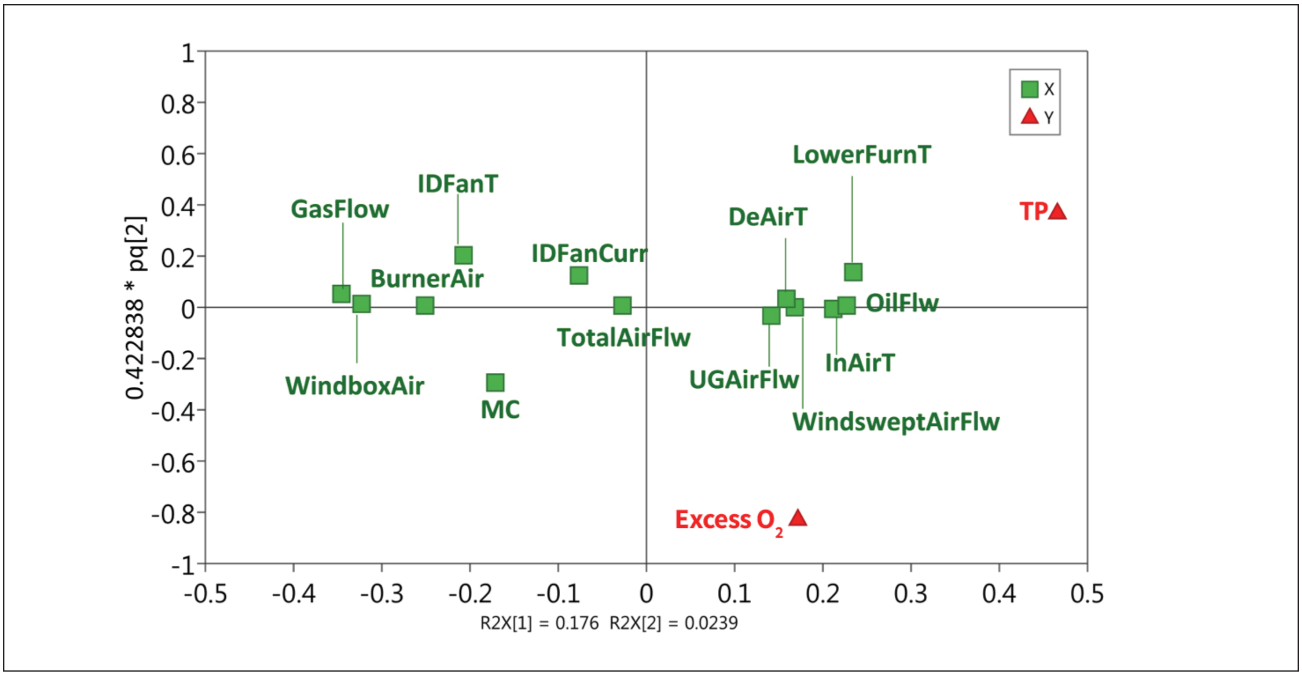
ditions [7]. It is clear from Fig. 2 that most of the data points fit within the 95% CI, meaning that the model explains the data well. On the other hand, the spread of the data points on the scatter plot demonstrates there are many instances where operating parameters are far from average.

The loading plot shows which variables are influential and how they are correlated. Variables placed further away from the origin are more influential in the model and variables grouped together in the loading plot are directly correlated with one another. **Figure 3** shows the loading scatter plot for the mill A model. Note the two Y variables in this model, TP and excess O_2, are situated in opposite quadrants. This means they have a negative correlation (i.e., TP is high when excess O_2 is low). Excess O_2 is sometimes used as an indicator for combustion quality. If this value suddenly increases, it means there is either more air than fuel at that moment, if the combustion quality is the same, or if the air/fuel ratio is the same, it means the combustion quality is poor; both cases lead to lower heat flux in the furnace area. This translates to less steam produced, which would decrease the TP value as well. To understand the correlation between any operating parameters, their locations in Fig. 3 can be used; if they are found in the same quadrants, they have a positive correlation and if they are situated in opposite quadrants, they are negatively correlated.

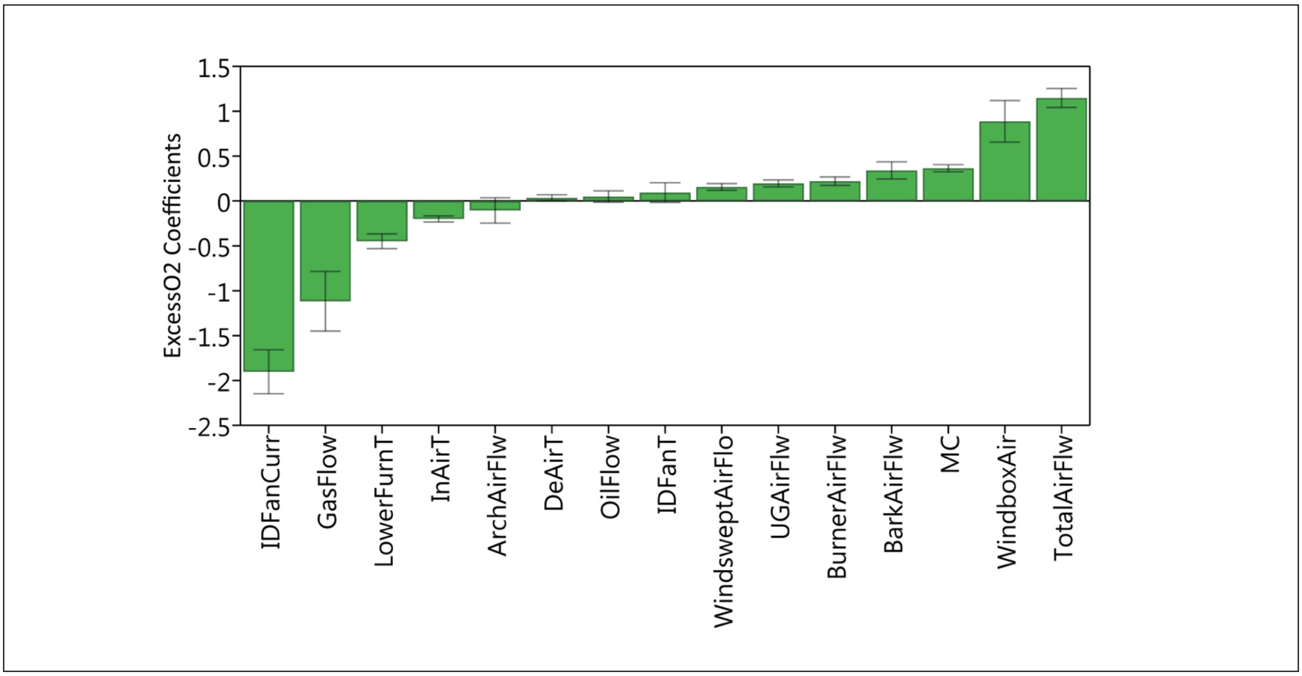
To determine the effect of each X variable on the Y variables separately, a coefficient plot is used where the contribution of each X variable on the corresponding Y variable is determined by a positive or negative coefficient. **Figure 4** shows the coefficient plot for excess O_2 from the OPLS model built for mill A operating data. Induced draft (ID) fan current, gas flow, and lower furnace temperature have the highest



2. Score scatter plot for mill A data.



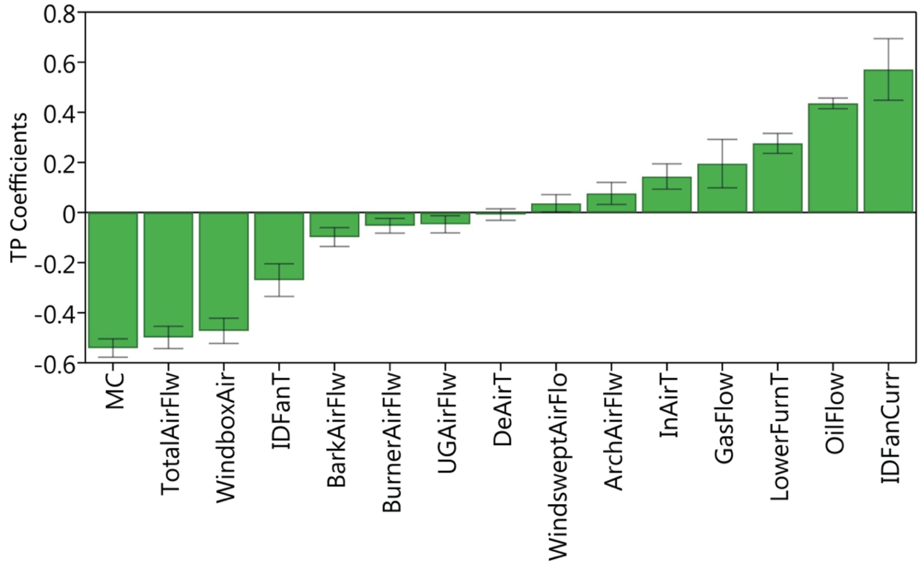
3. Loading scatter plot for mill A data.



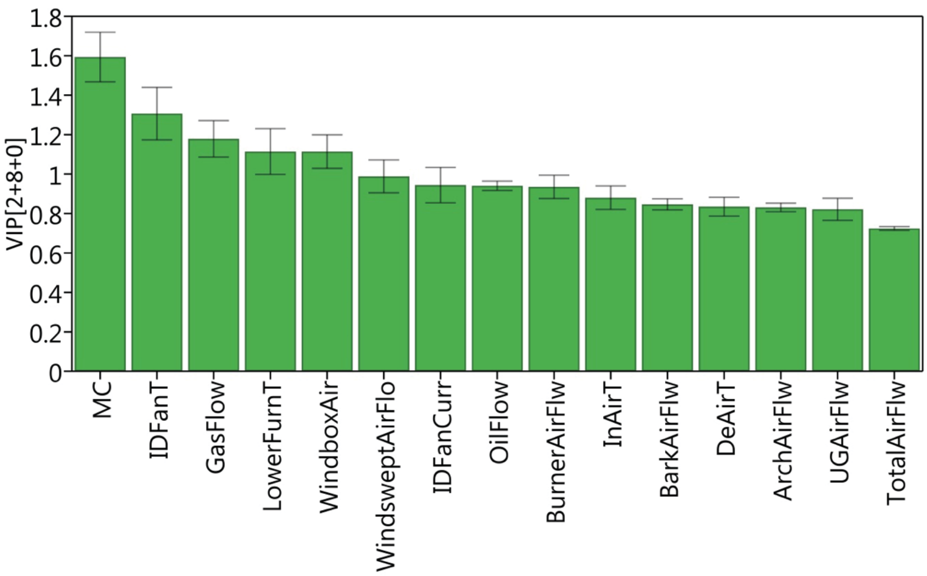
4. Coefficient plot for excess O_2.

negative coefficients, whereas total air flow and windbox air flow rate have the most significant positive effect on excess O_2. The positive effect of air flow rate on excess O_2 is intuitive; the negative coefficients could also be explained by process characteristics.

Low excess O_2, as explained earlier, is a good indicator for combustion quality provided that adequate air is provided for stoichiometric combustion. Also, when the biomass feedstock burns completely, more flue gas is produced and the ID fan current increases to remove the increased amount of flue gas to maintain the negative draft inside the boiler. The relationship between gas flow and excess O_2 could be explained by the same principle: burning more biomass would produce more flue gas and at the same time consume more O_2, resulting in less excess O_2. Furthermore, better combustion would increase the furnace temperature which, in turn, would improve combustion and result in more fuel being burned and less excess O_2 at the boiler exit.



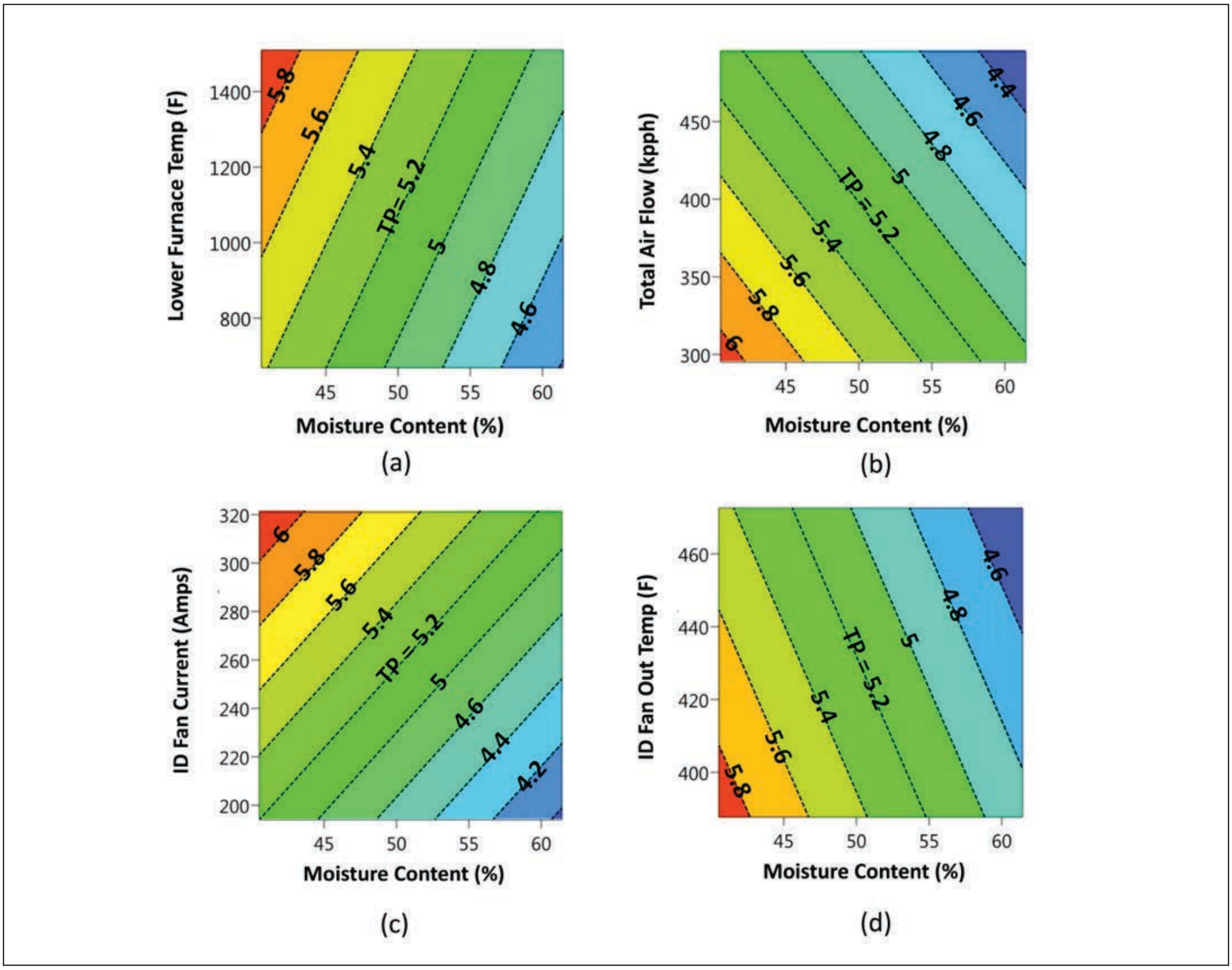
5. Coefficient plot for TP.



6. Variable importance for projection plot for orthogonal partial least squares analysis model.

Figure 5 shows the coefficient plot for TP. The positively correlated parameters with TP are ID fan current, lower furnace temperature, and oil flow. When more fuel is burned, whether biomass or oil, furnace temperature increases and more flue gas is produced, which results in more steam and an increase in TP. The negative coefficients for TP are MC, windbox air, and total air flow. The negative correlation between MC and TP will be explained in more detail in the following sections. Increase in air flow rate has a negative impact on TP because high air flow rate dilutes the flue gases and reduces the heat content available for steam production.

To choose the parameters that need to be followed closely for optimizing the performance of biomass boilers, the variable importance for projection (VIP) plot needs to be studied. The VIP plot for this model is shown in **Fig. 6**, where variables with VIP value larger than 1 have considerable impact on the model. The VIP plot for the OPLS model built for mill A clearly indicates that MC has the most significant impact on the model. This is also evident from Figs. 4 and 5, where MC is among the top three contributing variables to changes in excess O_2 and the most significant variable with the highest coefficient for TP.



7. TP response contour for changes in moisture content and (a) lower furnace temperature, (b) total air flow, (c) induced draft (ID) fan current, and (d) ID fan outlet temperature.

Because moisture content is the most influential variable in this model, a more in depth analysis is needed for the effect of MC on TP while considering other influential variables to help better understand their interaction. **Figure 7** shows response contours for TP with changes in MC. Each graph looks at TP response contours while considering changes in MC, shown on the x-axis, and one other influential parameter, shown on the y-axis.

Figure 7a shows the effect of lower furnace temperature and MC on TP, and the highest TP is for high furnace temperature and low MC. This is in agreement with the findings from the four boilers investigated (see Fig. 1) where it was speculated that lower furnace temperature has a significant impact, especially for high MC values. Figure 7b shows total air flow and MC with TP. High TP values occur for low total air flow and low MC. This shows that increasing total air flow results in diluting the flue gases and decreases the heat content available for steam production and therefore lowers TP. Induced draft fan current and temperature are representatives of flue gas flow rate and temperature, respectively. As mentioned previously, increase in flue gas flow rate is an indication of more fuel burned in the boiler and therefore more heat available for steam production, which results in higher TP if combustion takes place efficiently (Fig. 7c). The flue gas temperature, on the other hand, shows a negative correlation with TP (Fig. 7d). When the temperature of the flue gas is high, it means the heat content of the flue gas has not been used to its fullest at the superheaters, economizer, or heat exchangers, and the result is lower TP.

The response contours in Fig. 7 clearly show that regardless of the y-axis variable, TP decreases with increasing MC. However, to predict TP values more accurately, other influential variables shown must be taken into consideration.

IMPLICATIONS

When the TP of a biomass boiler decreases (e.g., due to variability in the fuel), a combination of operating parameters could be changed to optimize boiler operation and bring the TP back to the desired value. Only a handful of process parameters are independent variables, especially those that could be changed without adverse effects on the rest of the process. For this reason, the interconnectivity of process variables and net effects on process outputs must be taken into consideration.

For example, a common practice is to increase the undergrate air flow rate when the operator is aware of wet biomass entering the boiler. This is thought to facilitate drying of high moisture material on the grate and expedite combustion to minimize process upset. The adverse effects of changing this parameter must also be considered. Depending on the air temperature, increasing the undergrate air might cause the lower furnace area to become cooler. It also results in an increase in total air flow entering the boiler, which in turn causes an increase in excess O_2. All of these lower the TP; therefore, the net effect must be considered beforehand to determine the maximum degree of change allowable.

The MVA results discussed here, as for any other statistical model, show correlations only and causality should not be concluded; when two parameters are closely correlated, one does not necessarily cause the occurrence of the other. Therefore, optimization methods for each boiler must be derived from individual assessment of boiler design, operation, and fuel types.

CONCLUSIONS

Optimized operation of biomass boilers depends on many factors, including fuel quality, operating conditions, and mill steam demand. The interaction of these parameters was investigated in a multivariate model to find which parameters have the most significant effect on TP. The most influential parameter on TP is MC, and excess O_2 and TP are negatively correlated. Induced draft fan current, gas flow, and lower furnace temperature have negative coefficients in relation to excess O_2, and windbox air and total air flow have positive coefficients in relation to excess O_2. Finally, ID fan current, lower furnace temperature, and oil flow have the most significant positive impact on TP, and the negative coefficients for TP are MC, windbox air, and total air flow. **TJ**

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Biomass combustion for the purpose of steam production is a viable solution for handling wood waste. Biomass is a carbon neutral fuel and therefore, finding ways to efficiently burn this type of sustainable fuel in biomass boilers has great potential. The main challenge, which is the variability of fuel quality, needs further research and exploration so that biomass boiler performance can be optimized.

Many researchers have developed numerical models for boiler optimization. However, we wanted to develop a practical solution for improving boiler operation using multivariate analysis as well as case studies to complement these statistical tools.

The most difficult aspect of this research was finding a suitable way to compare different biomass boilers. Boiler type, design, operation, and steam demands vary from mill to mill. To address this issue, we defined the thermal performance (TP) parameter with normalized steam properties to draw meaningful conclusions.

The power of statistical analysis was the main discovery for me (Orang) from this research. Specifically, multivariate analysis can be used to solve today's complex problems. The operating parameters that affect TP negatively were an interesting finding. Also, it was interesting to see the complexity in finding the desired balance between positively and negatively correlated parameters to improve TP.

The main takeaway from this work is that each boiler needs to be studied closely and in detail to find the most suitable way to optimize boiler operation with minimal process upsets. The next step is to conduct more case studies and develop a generalized guideline for biomass boiler operation and optimization.

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