

Fuzzy logic modeling and optimization of a wood chip refiner

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ABSTRACT: *The authors develop a fuzzy logic model for a wood chip refiner. In conjunction with an optimization technique, this model will either minimize energy consumption of a refiner while maintaining the pulp properties within acceptable limits or optimize pulp properties within the refiner operation range. There is a case study investigating the effects of different operating conditions on chip refining optimization.*

KEYWORDS: *Chips, equations, logic, mathematical analysis, models, optimization, pulp properties, quality, refiners, wood.*

To respond to increasingly demanding customers, it is necessary to improve pulp quality while lowering manufacturing costs at the same time. Process control and optimization techniques can help achieve these goals. The development of optimization techniques requires a reasonably accurate mathematical description of the process, however. Unfortunately, such accurate models are unavailable for many pulp and paper processes including wood chip refining.

Because the interactions between refiner operating conditions and pulp quality are complex, there is no systematic and quantitative study and model. The few models that exist are generally empirical. They may only describe the relationships between a few variables while ignoring others. Years of industrial practice and re-

search, however, have led to an accumulation of experience and knowledge. This knowledge comes from various sources and is available in different forms. There are qualitative descriptions, semi-empirical correlations, and heuristic rules. Because of its empirical nature, this knowledge is often only valid for use in conditions close to those from which it came. Although the knowledge may be less accurate in different circumstances, it may still have some use, however.

In this paper, we offer a fuzzy logic modeling and optimization approach which makes maximum use of available knowledge sources. We use collection, reconciliation, verification, and consistent representation of different pieces of empirical knowledge to model a wood chip refiner and to optimize process operation and pulp quality. In

some instances, we consulted mill engineers and experts to verify the accuracy and reliability of the knowledge. For other cases, we used mill records over different process operations, fiber property tests, and pulp quality data to test the consistency and validity of the model.

Relationships and interactions among refiner variables

A set of equations representing the interactions among a set of variables describes the state of a wood chip refining system. Before building a model to simulate and to optimize the process, one must first identify the process variables and the phenomena that occur.

The interactions among wood chip refining process variables are extremely complex. Pulp quality (generally expressed in terms of freeness and fiber fractions) and handsheet properties (tear, burst, breaking length, scattering coefficient, etc.) depend upon intrinsic properties of the raw fibers such as fiber strength, length, coarseness, specific surface, etc. The thermal, chemical, and mechanical treatment of wood chips in a pulp mill will modify these intrinsic properties. **Figure 1** shows the interactions among these different groups of variables. These interactions show the most commonly used variables to represent a wood chip refining operation. From a modeling point of view, we distinguish two classes of operating variables. There are independent variables including operating condi-

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tions and raw chip quality. These form the smallest set of variables necessary to describe the refiner operating conditions. There are also dependent variables such as intrinsic fiber property, fiber characteristics, and pulp and paper quality. These derive from the independent operation variables.

Mill operators generally use the screw feeder speed, the dilution water flow rate, and the motor load as the three main operation variables to control refiners. To facilitate the incorporation and comparison of data from the literature and from different mills, we use another set of independent variables here. These are production rate, refining consistency, specific energy, and plate wear. Besides these four variables, a number of other process variables such as chip temperature, dilution water temperature, plate pattern, disc rotating speed, and energy split between primary and secondary refiners can also affect refining. To simplify the investigation, we treated these variables as constants during the refiner operation.

To ascertain wood chip quality, we considered changes in wood chip moisture content and density but assumed that the wood species and chip size distribution were relatively constant.

Of the many tests useful to characterize the effects of refining on fibers, we selected fiber strength, length, coarseness, Bauer McNett fiber fractions, and shive content to differentiate fiber.

Equation 1 shows the definition for a paper quality parameter, Q , from another investigator (1):

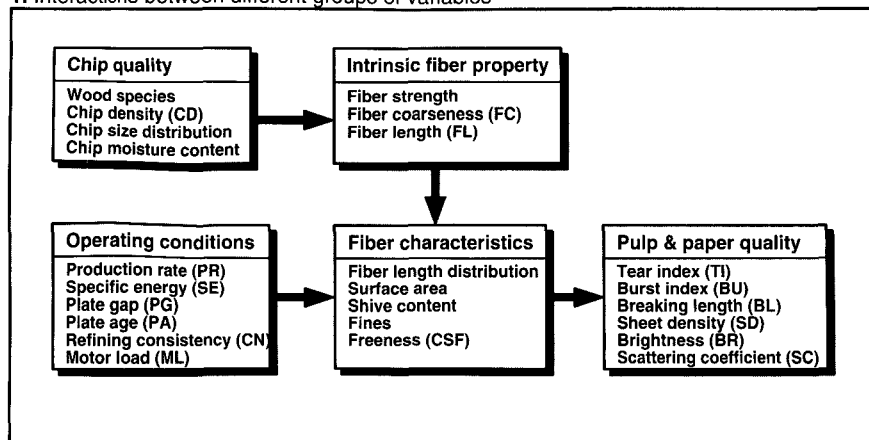
$$Q = (TI/9)^{2/3} (BL/8)^{1/3} (SC/800)^{4/3} \quad (1)$$

We prefer using a set of inequalities to indicate upper and lower bounds necessary for refiner pulp and paper properties. Usually, customers require different specifications depending upon the products.

Fuzzy logic modeling and optimization

A mathematical model describing the input to output relationships among

1. Interactions between different groups of variables



1. Some empirical equations of the chip refining process

$$\begin{aligned} \Delta PG &= -0.78\Delta SE - 0.184\Delta PR - 4\exp -5\Delta PA + 0.01\Delta CN \\ \Delta CSF &= -250\Delta SE - 104\Delta PR - 0.05\Delta PA \\ \Delta CSF &= -200\Delta SE - 32\Delta PR \\ CSF &= 1130\exp\{-0.02 - 0.033FL[1 + (2 - 0.11CN)SE]\} \\ TI &= 0.103CD + 11.5FL - 57.9 \\ \Delta BU &= 1.2\Delta SE - 0.11\Delta PR - 0.0023\Delta PA \\ BL &= 0.11SD + 5.8FL - 0.99FL^2 - 7.01 \\ \Delta SD &= -40.2\Delta FL - 0.58\Delta CD \\ \Delta SC &= -0.56\Delta SD - 16.8\Delta FC \end{aligned}$$

the process variables would be useful for pulp quality optimization and control. Unfortunately, such a sophisticated model does not exist. Nevertheless, earlier work does improve our understanding of the fundamentals of chip refining. Major pulp and paper research institutes have studied fiber physics, developed empirical equations derived from pilot plant or mill data, and performed statistical analyses based on common factors (2-4). Using this information, we have developed a fuzzy logic model to optimize refiner pulp properties.

In a previous paper (5), we presented a new approach for the modeling and optimization of poorly understood processes. The following description presents the basic ideas.

Fuzzy logic modeling

Equation 2 shows the form for empirical and approximate equations which describe the empirical knowledge from different sources:

$$f_i(x) = 0 \quad (2)$$

where

$x = x_1, x_2, x_m$, a set of process variables

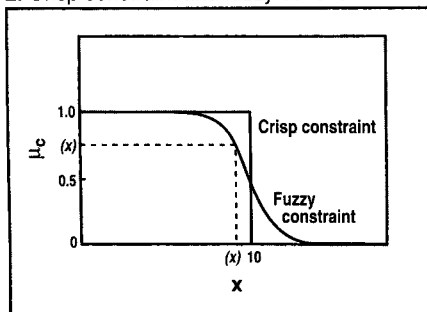
$i = 1, 2, N$.

In Eq. 2, N is greater than m , because there are usually more equations than the number of process variables. This indicates a redundancy of information.

We collected quantitative data, empirical equations, and qualitative descriptions from about 45 sources that relate chip quality and refiner operations to fiber characteristics and pulp and paper quality. Because of the empirical nature of those relationships, however, some of them were imprecise or even contradictory. We therefore had to perform some kind of screening to remove conflicting information before using these different pieces of information in a fuzzy logic model.

Consultation of domain experts provides discrimination between knowl-

2. Crisp constraint and fuzzy constraint



edge sources and information telling what is inappropriate due to differences in process configurations, feed stocks, or operation ranges. It is sometimes difficult, however, even for an expert to identify an empirical statement of a system characteristic as absolutely right or wrong. Nevertheless, with experience and examination of the data collection and equation correlation, the expert can tell if one piece of information is more reliable and accurate than another. It is therefore possible to assign a credibility factor, w_i , to each equation.

After weighting the approximate equations, it is possible to define a membership function for each equation as follows:

$$\mu_i = \exp[-w_i f_i^2(X)] \quad (3)$$

where

- μ_i = membership function from 0 to 1
- w_i = credibility factor
- X = vector of dimensionless process variables

When $f_i(X) = 0$, membership is 1. This means the equation, f_i , satisfactorily describes a relationship between the system variables, X . Alternately a membership lower than 1 indicates that the equation is not compatible with the other equations of the set. For the model to represent successfully the true process, it is necessary to remove equations with extremely low memberships from the set.

We tested the memberships of the 45 empirical equations in our model and removed 3 equations with memberships lower than 0.45 from the

model. The 42 remaining empirical equations with memberships ranging from 0.7 to 1.0 formed the fuzzy model of the wood chip refining process. This fuzzy model constituted the basis for developing the simulation and optimization. **Table I** lists some of the empirical equations.

Equation 4 defines the average membership of all screened equations:

$$\mu_M = \frac{1}{N} \sum_{i=1}^N \mu_i = \frac{1}{N} \sum_{i=1}^N \exp\left(-w_i f_i^2(X)\right) \quad (4)$$

where

μ_M = degree of fuzziness of the model.

The degree of fuzziness of the model indicates the consistency of the whole set of empirical equations. When μ_M equals 1, the model is mathematically precise. Alternately, a model with μ_M less than 1 is imprecise or conflicting.

In a mathematically precise model, a set of variables, X^* , can be the solution only when they completely satisfy the equation set. Thus $f_i(X^*) = 0$, where i equals 1, ..., N . In a fuzzy model, however, a set of variables, X^* , is the solution when it minimizes inconsistency among the empirical equations or, equivalently, maximizes memberships of the remaining equations as Eq. 5 indicates:

$$\mu_M(X^*) = \max \mu_M(X) \quad (5)$$

Fuzzy constraints

There are different types of process constraints. These include operating condition limitations and product specifications. A conventional approach for representing constraints is a crisp step function, μ_c . When a variable, x , is too close to the boundary, a slight disturbance can result in totally different consequences. Process models operated on this kind of constraints would behave sensitively in those boundary regions. In the fuzzy logic modeling approach, constraints are viewed as "soft" constraints. When x moves away from the inside to the outside of a constrained region, the membership of the

fuzzy set changes gradually from 1.0 to 0.0. This means it changes from fully allowable to completely forbidden. For example, the membership function of Eq. 6 represents the fuzzy constraint less than or approximately equal to 10 with a tolerance, $r = 2$:

$$\mu_c(x) = 1 / \{1 + \exp[(x - 10)/2]\} \quad (6)$$

Figure 2 shows the difference between a crisp constraint and a fuzzy constraint. The decisive constraint of the whole system depends upon the toughest constraints in the system. Membership of the general constraint, $\mu_c(X)$, is the least of all membership constraints.

Fuzzy optimization and decision making

There is usually not a clear definition of the process optimization objective. A membership function of fuzzy sets, $\mu_G(X)$, can represent it. When operating the system at a set of variables, X , $\mu_G(X)$ gives a range from 0 to 1 to denote degree of satisfaction with the objective.

Every day process engineers and mill managers make decisions in the presence of uncertainty and imprecise information. Usually, multiple perspectives characterize such decision making. These include minimal production cost, best product quality, varying production rate according to the orders from the sales department, minimal environmental and social effects, etc. In our approach, decision making is a fuzzy set, $\mu_D(X)$. It comes from the compromising solution for the fuzzy model, $\mu_M(X)$; the fuzzy constraints, $\mu_c(X)$; and the general fuzzy objective function, $\mu_G(X)$. Equation 7 shows that $\mu_D(X)$ is equal to the smallest membership of the three fuzzy subsets:

$$\mu_D(X) = \min [\mu_M(X), \mu_c(X), \mu_G(X)] \quad (7)$$

A solution, X^* , provides process optimization. This maximizes the membership of the general fuzzy set, $\mu_D(X)$, as Eq. 8 indicates:

$$\mu_D(X^*) = \max \mu_D(X) \quad (8)$$

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The work above constitutes a systematic approach to modeling and optimizing for poorly understood industrial processes. **Figure 3** provides a schematic diagram for the approach. To solve this fuzzy optimization problem, we use a genetic algorithm (6). Genetic algorithms behave well in multimodal function optimization. In the poorly structured system with 20 variables and 42 equations described later in this paper, it requires approximately 25 min for the genetic algorithm to find the global optimal using a work station.

Verification of the fuzzy model

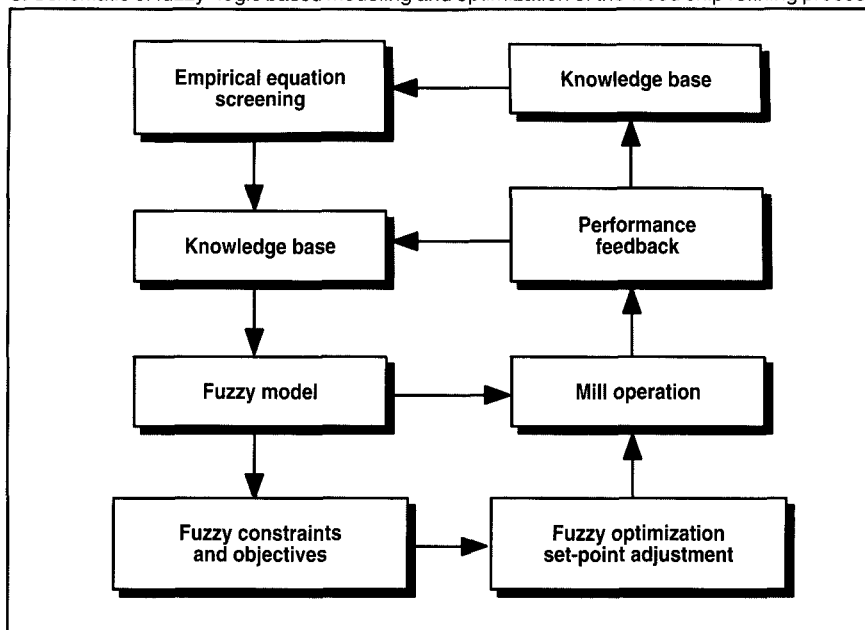
We compared the proposed chip refining model with a set of published data obtained in pilot-scale refiner runs (7). The refiner was a normal single-stage thermomechanical process. Production was approximately 12 tons/day. The feeding consistency was 20%. **Figure 4** shows a comparison of the model prediction (solid lines) and the refiner data (circles). The model results are satisfactory in predicting the trend of changes of several main variables addressing pulp and papermaking qualities such as freeness, shive content, breaking length, and long fiber content.

Refining process optimization

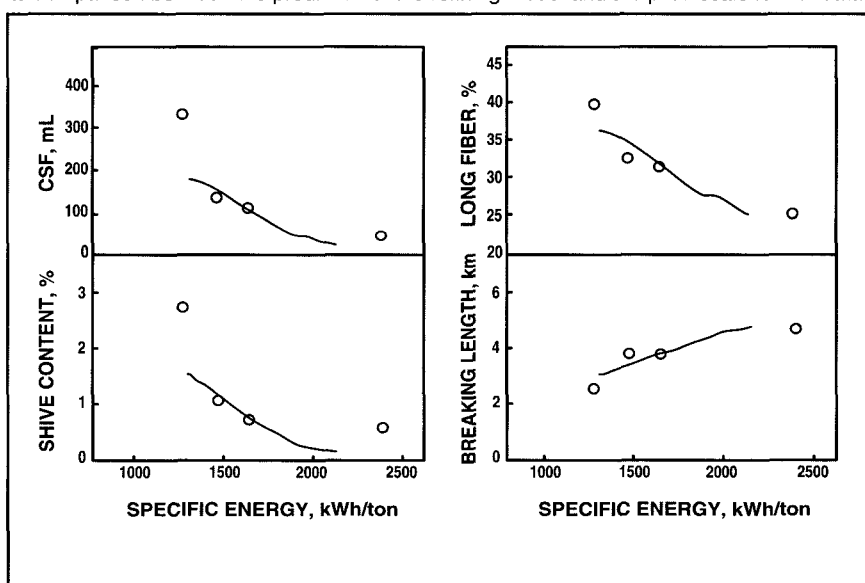
To apply the proposed modeling and optimization system to the pulp and paper industry, we chose a 175 tons/day TMP line in a western Canadian newsprint mill as a case study. The line uses hemlock and balsam and consists of two commercial refiners. The primary refiner operates under pressure, and the secondary refiner operates at atmosphere pressure. **Table II** shows the data representing the typical operating conditions for the modeling and optimization.

There were two different types of optimization. The first optimization tried to minimize the energy consumption while maintaining the same pulp

3. Schematic of fuzzy-logic based modeling and optimization of the wood chip refining process



4. Comparison between the prediction of the refining model and the pilot-scale refiner data



quality. The second was an attempt to improve pulp quality while keeping the operating conditions within certain constraints.

Energy consumption minimization

Table III shows the first optimization simulation for the chip refining process. In Test I, we examined the possibility of reducing energy consumption by adjusting other operat-

ing variables while maintaining a constant breaking length. We achieved this by slightly increasing the production rate. There was a reduction in tear index, however. Typically, for the same breaking length, a 4.5% increase in production rate resulted in an 8.2% decrease in tear index.

In Test II, we tried to minimize the energy consumption while maintaining the tear index at a level not below 90% of the initial value. **Table IV** shows

II. Mill data from a TMP line

Variable	Typical value	Operating range	σ
Production rate, o.d. metric tons/day	175	145–210	5
Specific energy, MW•h/o.d. metric ton	1.85	1.20–2.20	0.05
Consistency, %	25	20–30	1
Plate age, h	500	<1600	-
Motor load, MW	13.5	8.0–15.0	0.5
Dilution water flow rate, tons/h	14.0	10–18	1.0
Chip feed rate, m ³ /h	117	100–150	8
Chip moisture, %	52.0	48–55	2.0
Chip density, kg/m ³	325	300–350	14
Fiber length, mm	1.34	1.0–3.0	0.2
Fiber coarseness, mg/100 m	16.6	10–35	2
Long fiber content, %	33	29–36	3
Middle fiber content, %	17	15–19	2
Short fiber content, %	20	17–24	2
Fines content, %	30	26–34	3
Shives content, %	1.0	0.0–1.5	0.3
CSF, mL	110	80–180	15.0
Tear index, mN•m ² /g	9.6	6.6–11.5	1.3
Burst index, kPa•m ² /g	1.90	1.2–2.3	0.24
Breaking length, km	3.1	2.0–4.3	0.55
Sheet density, kg/m ²	368	334–585	30
Brightness, %	52.1	49.7–55.5	1.3
Scattering coefficient, cm ² /g	555	323–610	55
Opacity, %	97.2	96–98	0.4

III. Energy consumption minimization

Variable	Initial	Test I		Test II	
		Goal or constraints	Optimal	Goal or constraints	Optimal
Production rate, o.d. metric tons/day	175	$170 \leq PR \leq 190$	183	$170 \leq PR \leq 190$	186
Specific energy, MW•h/o.d. metric ton	1.825	Minimization	1.78	Minimization	1.76
Consistency, %	25	Fixed	25	$22 \leq CN \leq 28$	26.7
CSF, mL	110		107	$CSF \geq 102$	118
Tear index, mN•m ² /g	9.6		8.8	$TI \geq 9.1$	9.3
Burst index, kPa•m ² /g	1.9		1.9	$BU \geq 1.7$	1.84
Breaking length, km	3.1		3.1	$BL \geq 2.8$	2.9

IV. Pulp quality window

$$0.92 \text{ CSF}_0 \leq \text{CSF} \leq 1.08 \text{ CSF}_0$$

$$TI \geq 0.95 \text{ TI}_0$$

$$BU \geq 0.90 \text{ BU}_0$$

the pulp quality window. In that, the subscript indicates the initial value of the corresponding variable.

The Test II column in Table III summarizes the results of the optimization. CSF, tear index, and burst remained in the specified window while

the production rate increased by 6% and the energy consumption decreased by 3.6%. These results came from increasing the inlet consistency from 25% to 26.7%. Assuming the chip moisture was 52% before the refiner, the increase in consistency represents a 13% decrease in the dilution water flow rate. In the case of the other properties (sheet density, brightness, and scattering coefficient), the changes were within 2%. The price for the 3.6% decrease in specific energy was a 6.9% decrease in the breaking length, however.

In classic optimization problems, there is often a solution at the boundary of the constraint conditions. In an imprecise system, however, the risk of violating the constraints is high. In our approach described in the previous section, we view constraints as soft restrictions and represent them as descending or ascending functions. When the system approaches the boundary too closely, the constraint functions have low fitness values, and the optimization procedure forces the system away from the constraint boundary. In this example, constraints are $CSF < 1.08CSF_0$, $TI > 0.95TI_0$, and $BU > 0.95BU_0$. Table III indicates that the optimal solutions for the three variables are $1.076CSF_0$, $0.97TI_0$, and $0.97BU_0$, respectively. This approach gives the process some degree of tolerance to cope with stochastic fluctuation of process variables.

Pulp quality optimization

Our objective was to maximize pulp quality while maintaining the manipulated operation variables within a desired range. It is obviously not possible to improve all properties at the same time, however. Compromises are necessary. These should depend upon the customer's requirements.

As an example, we tried to achieve a higher burst index while keeping freeness at a value no less than 90% of its initial value, as Table V indicates. The fuzzy optimization approach shows that it is possible to achieve this result by changing the specific energy

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alone (Scheme I) or by changing both the specific energy and the consistency (Scheme II). Table V gives the results of the optimization. In both cases, the burst index can increase by 8–9% with a decrease in freeness of less than 10%.

Conclusion

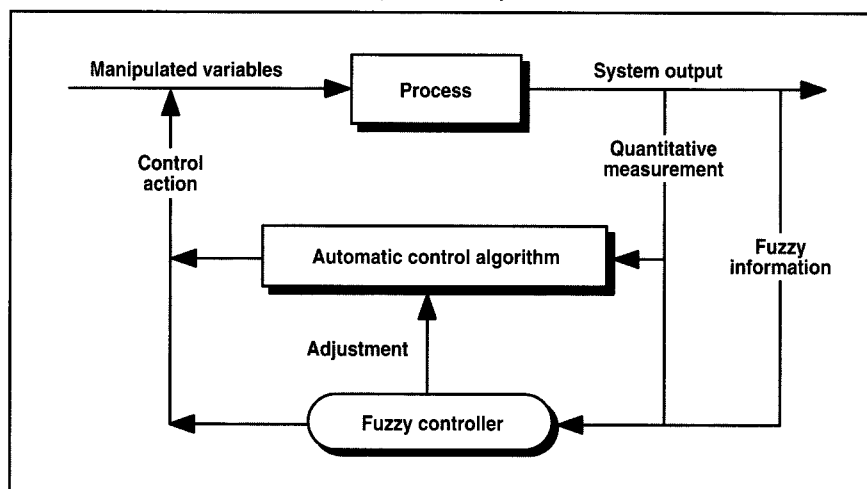
We have developed a wood chip refining model based on fuzzy relation equations that facilitates the maximum use of available empirical, imprecise, and even conflicting information and data from different sources. The model can serve as a simulation and optimization tool for the refiner process. It will either minimize the refiner energy consumption while maintaining a stable pulp quality window or optimize pulp quality within a reasonable operation range. It is possible to incorporate the model in a mill operation and control system as a consulting adviser to suggest which set points will be optimal as Fig. 5 shows. This will increase the potential savings in overall operating costs as well as decrease variations in pulp quality.

The current model software is in C language. With implementation in a specific mill, the knowledge base and the process model require modification and screening according to local practical data. It is possible to develop a user interface for the convenience of the operator. When there is process data, the model can predict the process performance. When process objectives or product specifications change, the model can suggest setpoint adjustments. An interface to the existing mill DCS would also be necessary for the model to respond to changes quickly. ■

V. Maximization of burst index subject to freeness lower bound constraint

Variable	Initial	Scheme I		Scheme II	
		Goal or constraints	Optimal	Goal or constraints	Optimal
Production rate, o.d. metric tons/day	175	Fixed	175	Fixed	175
Specific energy, MW•h/o.d. metric ton	1.825	$1.70 \leq SE \leq 1.95$	1.85	$1.70 \leq SE \leq 1.95$	1.86
Consistency, %	25	Fixed	25	$22 \leq CN \leq 28$	26.3
CSF, mL	110	$CSF \geq 100$	101	$CSF \geq 100$	102
Tear index, mN•m ² /g	9.6	$TI \geq 9.4$	9.93	$TI \geq 9.4$	9.49
Burst index, kPa•m ² /g	1.9	Maximization	2.05	Maximization	2.07
Breaking length, km	3.1	$BL \geq 3.1$	3.28	$BL \geq 3.1$	3.19

5. An integrated industrial control and optimization system



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