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Review

A Review on the Modeling, Control and Diagnostics of Continuous Pulp Digesters

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Abstract: Being at the heart of modern pulp mills, continuous pulp digesters have attracted much attention from the research community. In this article, a comprehensive review in the area of modeling, control and diagnostics of continuous pulp digesters is conducted. The evolution of research focus within these areas is followed and discussed. Particular effort has been devoted to identifying the state-of-the-art and the research gap in a summarized way. Finally, the current and future research directions in the areas have been analyzed and discussed. To date, digester modeling following the Purdue approach, Kappa number control using model predictive controllers and health index-based diagnostic approaches by utilizing different statistical methods have dominated the field. While the rising research interest within the field is evident, we anticipate further developments in advanced sensors and integration of these sensors for improving model prediction and controller performance; and the exploration of different AI-based approaches will be at the core of future research.

Keywords: Kraft pulping; pulp digester; modeling; control; diagnostics

1. Introduction

With the widespread expansion of the Internet, electronic media and paperless communication, the demand for the graphic paper (i.e., newsprint and higher-value printing and writing paper) has been declining since 2000 [1]. Despite this downfall, the global pulp and paper market is growing steadily at a rate of over 1% per year [2]. A large part of the growth is attributed to packaging materials and the sanitary products as a result of growing e-commerce business and the modern lifestyle. In spite of the economic significance, the pulp and paper industry is lagging behind in embracing digitalization and state-of-the art process optimization techniques. Consequently, research in the area of modeling, advanced process control and diagnostics is grabbing much attention.

Pulp and paper mills convert wood chips into a fibrous mass called pulp, the raw material for different paper products. The production of pulp is commercially accomplished by a mechanical or chemical pulping process or a combination of both methods. In mechanical pulping, abrasive refining or grinding is used to reduce wood into fibrous pulp. As the name suggests, in chemical pulping the wood pulp is produced by means of chemical reactions. Sulfate pulping and sulfite pulping are two typical types of chemical pulping process. More than two-thirds of the globally produced pulp comes from sulfate or Kraft pulping mills [3].

A typical outline of the integrated Kraft pulping process is shown in Figure 1. Normally the process includes wood handling steps such as debarking, chipping and storage; Kraft cooking in the digester; screening and washing of pulp; bleaching and drying of pulp or paper/board; and pressing, drying and finishing. About 97% of the chemicals are recovered through the chemical recovery process [4]. To do so, the spent chemicals known as black liquor are evaporated, burnt in a recovery boiler and converted back to white liquor in a causticizing plant.

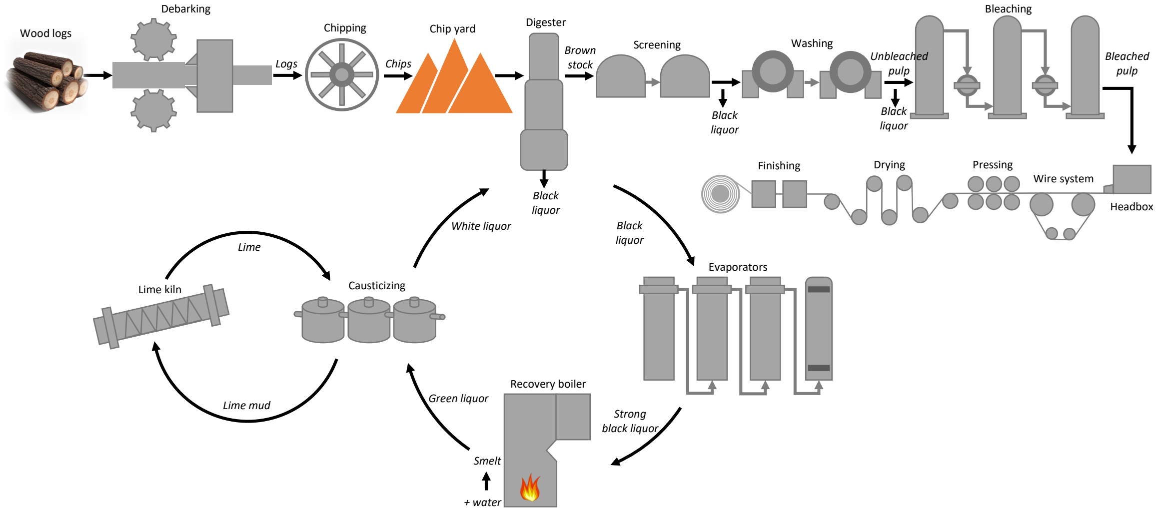

Figure 1. An overview of Kraft pulping process.

In the Kraft pulping process, the quality of the produced pulp is very much dominated by the raw material properties and the process conditions. All wood species are mainly composed of three basic structural elements called cellulose (∼40%), hemi-cellulose (∼30%) and lignin (∼25%). As depicted in Figure 2, cellulose and hemi-cellulose form the fibrous structure of the wood, and lignin acts like a "glue" that that holds the individual cellulosic polymers together. The conversion of wood chips into pulp mainly takes place in a long, upright, tubular vessel known as the pulp digester (see Figure 3). In the digester lignin is removed from wood chips to free the wood fibers by utilizing a thermo-chemical conversion process known as delignification. In this process, an aqueous solution of sodium hydroxide ($NaOH$) and sodium sulfide (Na_2S), also known as white liquor, is used, which dissolves most of the lignin and thus separates the cellulosic fibers from each other. However, the white liquor also reacts with the cellulosic fibers and thus not only degrades the physical properties of the produced pulp but also reduces the pulp's yield. Therefore the cooking conditions inside the pulp digester must be controlled in a way that fibers are separated without damaging them too much while maximizing the pulp yield. These factors are highly correlated, and hence a best compromise among residual lignin, yield and fiber properties is needed.

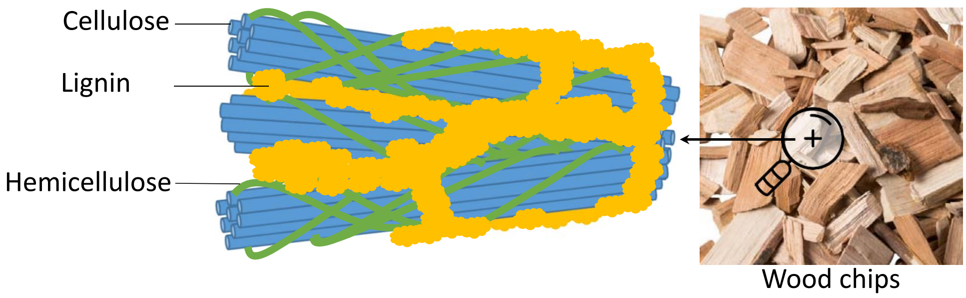

Figure 2. Arrangement of cellulose, hemi-cellulose and lignin in wood.

Two common types of pulp digesters that are widely used for Kraft pulping are batch and continuous digesters. Due to lower space requirements, less labor and lower energy costs, continuous digesters have become the dominant design in the realm of Kraft cooking [5]. As illustrated in Figure 3, after pre-steaming, wood chips are transported at the top of the digester via a circulating liquor system. Cooking liquor is also added at the top of the digester. The top part of the digester is called the impregnation zone where wood chips are soaked by the cooking liquor via penetration and diffusion mechanism. The delignification already starts in this zone at a typical temperature between 115 °C to 120 °C. Then in the heating zone, the temperature of the chip mixture is rapidly increased between

150 °C and 170 °C via two external heat exchangers. After that the chips enter the cooking zone where the majority of the lignin is removed at an elevated temperature. The spent liquor is separated and taken out of the digester in the extraction zone. The next zone is the counter current washing zone where cooked pulp is washed and cooled down with wash liquor. By doing so the delignification reaction is stopped and thus fiber properties are preserved. The cooked pulp is diluted to around a 10% concentration level and removed from the bottom of the digester. The produced pulp quality is mainly expressed by Kappa number which is the residual lignin content of the pulp.

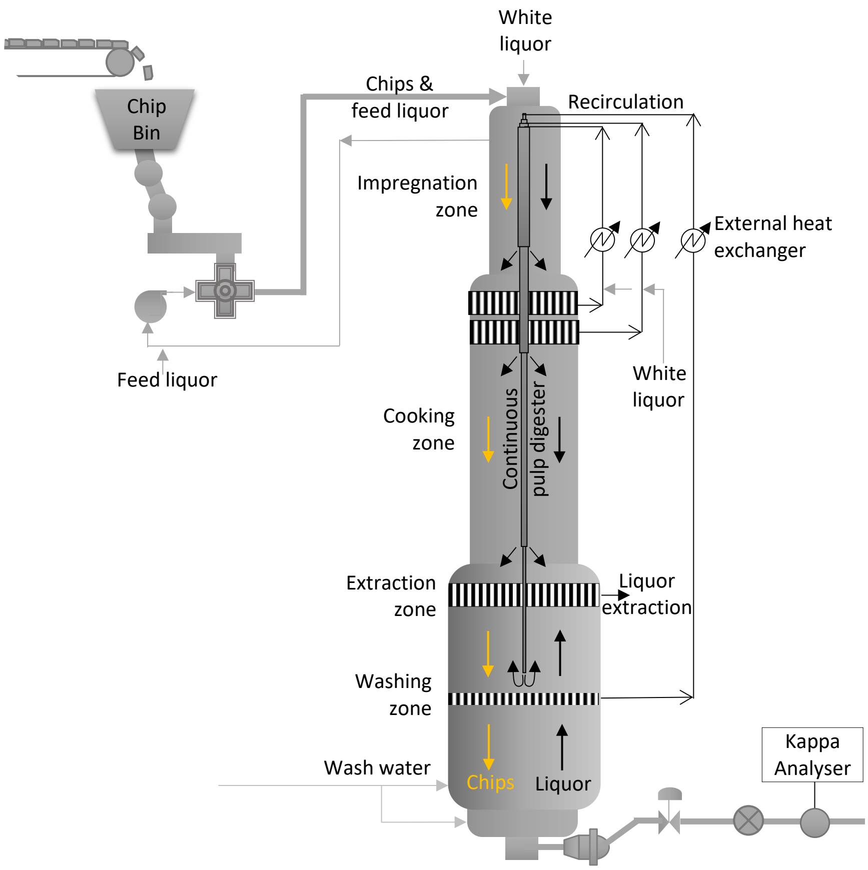

Figure 3. Schematic of a continuous pulp digester process flow [6].

Due to the naturally varying feedstock, long residence time, inadequate measurements and complex nature of the delignification process, controlling pulp quality at the digester outlet is a challenging task. Moreover, due to the non-ideal flow behavior in the digester, process faults often occur that lower the pulp quality and production rate considerably. Hence, controlling of the pulping process in an efficient way and early detection of underlying digester faults are matters of utmost importance for the economic operation of a pulp and paper mill. In this article the modeling, control and diagnostics of continuous pulp digesters are reviewed. Particular effort has been devoted to highlighting the state-of-the-art and the research gaps in a summarized way.

The paper is organized as follows. Firstly, the research methods along with a bibliographic analysis of the reviewed articles are provided that lay down the foundations of this study. Subsequently, the review of relevant literature on pulp digester modeling, control and diagnostics is presented. The outcome of the review is discussed, and concurrently, future research directions are proposed.

2. Materials and Methods

The present work focused on the review of available literature within the area of modeling, control and diagnostics of continuous pulp digesters. The purpose of considering the entire span of literature instead of basing our work on the previously published articles was to provide a truly comprehensive review by following the development in the field along the way. Though some of previously publish articles included rather narrow literature reviews to frame their work, to the best of the author's knowledge, no comprehensive review has been published covering this topic yet.

To conduct the review, three major bibliometric databases, the Web of Science, Google Scholar and Scopus, were queried using a comprehensive keyword list. Various combinations of keywords were utilized, including "pulp digester"; "kraft pulping"; "model"; "control"; "fault detection"; "diagnostics"; etc. To broaden the search, synonyms used by both industry and academia were included. Furthermore, references of relevant papers were also individually investigated to find new papers which were related to this topic. A manual sorting based on titles, abstracts and keywords yielded 210 articles to be potentially relevant for this review. These works, ranging from 1966 up to July 2020, were all published in white literature and written in English.

The yearly distributions of these publications are presented in Figure 4. Although the number of publications is unevenly distributed over the years, a gradual increment can be observed until 1997, followed by a rather slow descent. However, recently the number of publications within the area of this review seems to be rising again. This shows a positive trend of growing research interest within the topic. An overview of the origin of these publications can be visualized through Figure 5. If we look at the number of publications per country, the USA (63), Canada (16), Finland (14), China (14) and Sweden (11) have dominated the research area. This is no surprise, since they are also top pulp and paper producing countries.

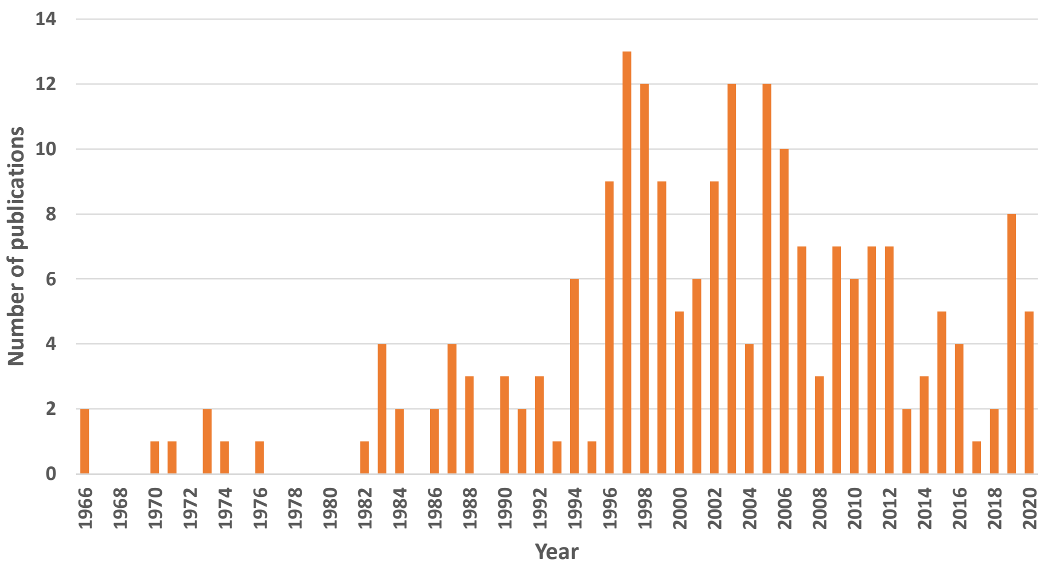

Figure 4. Distribution of publications over the years.

Using VOSviewer (https://www.vosviewer.com/), a bibliometric analysis tool, a network visualization of citation relationships between the publications was studied. Only publications that were connected to other publications in the network were considered for visualization; only 68 items met the requirement. As shown in Figure 6, 15 different clusters were identified based on their similarity. While the clusters are represented through different colors, the size of each node is proportional to the number of times the item has been cited. As expected, publications following the Purdue approach and MPC gained the most attention among the surveyed articles and are in the center of the network.

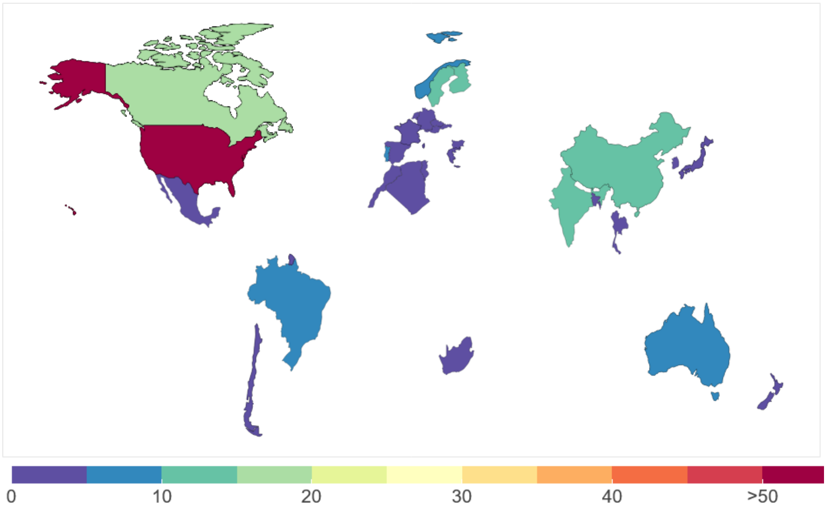

Figure 5. Number of publications per country.

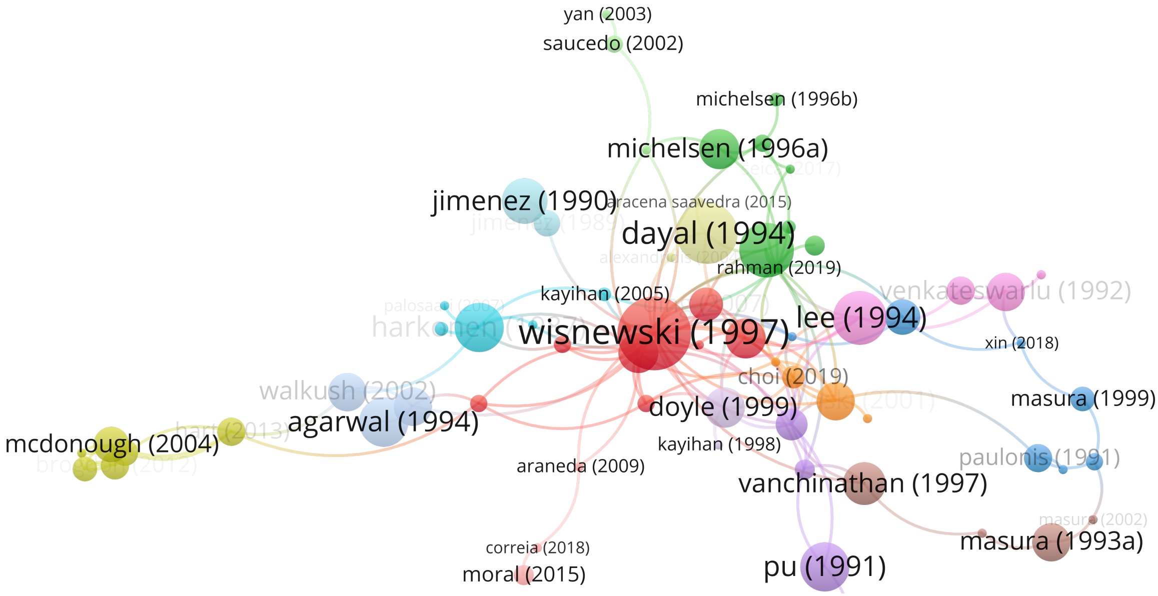

Figure 6. The network map showing the relationships between various publications based on citations.

To conduct the review in a structured way, the sub-topics of modeling, control and diagnostics were addressed independently. However, in reality there were noticeable overlaps among these sub-topics, especially modeling and control. In the following section, the outcome of the literature review is thoroughly discussed by highlighting the state-of-the-art and potential literature gaps.

3. Modeling of Pulp Digesters

Robust and reliable process models are prerequisites for optimal control and diagnostics of any complex industrial process. Over the years, extensive research effort has been devoted to exploring different approaches for modeling pulp digesters. Typically, pulp digester models can be classified into two broad categories: physics-based and data-driven (Figure 7). Physics-based models are based on mathematical equations that explain the underlying physico-chemical phenomena that take place inside the digester. On the other hand, data-driven models are based on historical data or observations, and mainly capture the relationships between inputs and outputs.

Widely explored data-driven approaches used for digester modeling are regression, the Box–Jenkins method, artificial neural networks (ANN), clustering and other model-order-reducing methods [7–11]. A comparative study on different data-driven modeling techniques based on their ability to predict Kappa number was performed by Correia et al. [12]. The study revealed that the Box–Jenkins method provides the best accuracy, followed by regression and ANNs. Even though data-driven models potentially allow rapid development and deployment due to their flexible structure, they have limited expressive capabilities and require high-quality data.

Physics-based models can be further classified into two groups, steady-state and dynamic models. The fact that distinguishes these two is that the steady state model depends on spatial variables (such as extent of delignification) while dynamic models depend on temporal variables (such as rate of delignification). Moreover, a steady state model is based on the assumption that the system is in equilibrium, and is thus time-invariant. This type of model is useful for system design but not for control applications. On the other hand, a dynamic model accounts for the time-dependent changes in a system and can therefore capture the transient behavior of the system, which is essential for dynamic control. Few researchers have investigated steady-state models for pulp digesters [13–15], whereas the majority of researchers have concentrated their focus on dynamic modeling. Some of these dynamic models are more focused on physical phenomena such as chip bed compaction, diffusion and detailed fluid dynamics, whereas others are more focused on reaction kinetics of lignin dissolution, carbohydrate degradation and alkali reactions.

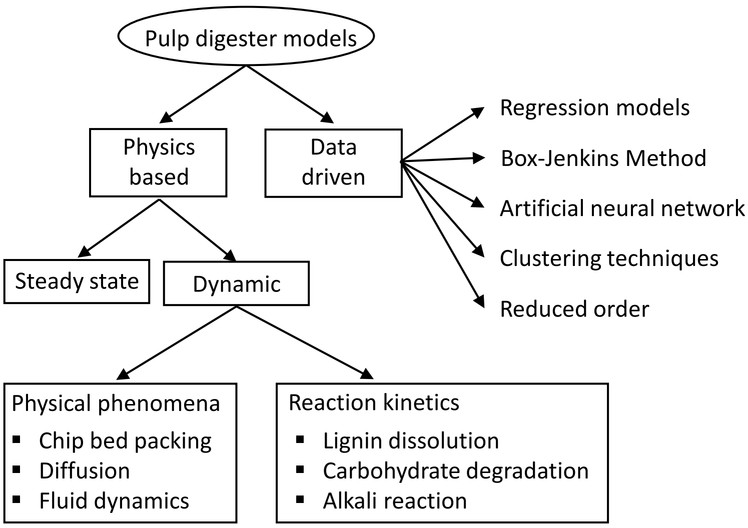

Figure 7. Overview of pulp digester models.

In reality, purely physics-based models rarely exist. They often incorporate statistical information based on the experimental observations whenever physical interpretations are not directly available. However, physics-based digester models are based on one very important assumption—that is, that the pulping reaction rates are kinetically controlled. One of the earliest well-known kinetic models was proposed by Vroom [16] that even today is widely used for control purposes. It describes the rate of lignin dissolution based-on Arrhenius-type expression (Equation (1)) to derive the H-factor (Equation (2)).

$$\frac{dL}{dt} = -k(T) = -\alpha e^{-\frac{\beta}{T}}, \quad (1)$$

where L is the lignin concentration; k is the temperature (T) dependent Arrhenius constant; and α and β are positive constants.

$$H = \int e^{43.20-\frac{16113}{T}}\, dt, \quad (2)$$

Vroom used the H-factor to combine the pulping time and temperature into a single variable that represents the extent of cooking in a batch digester. In reality, the factor is used to predict the temperature or cooking time needed to achieve a given Kappa number. Kleinert [17] theorized different reaction rates for bulk and residual phases of delignification. In Kleinert's model, the delignification reaction is assumed to be first order and dependent on temperature and alkali. Later, Kerr [18] improved Vroom's kinetic model by incorporating effective alkali (EA) and lignin concentrations into the delignification rate equation (Equation (3)).

$$\frac{dL}{dt} = -k[OH]L, \tag{3}$$

where OH is the alkali concentration.

Kerr used H-factor to account for time–temperature behavior while empirically estimating the Kappa number. Two linear functions are used to represent the alkali consumption rate for initial and bulk phases. However, in a later paper, Kerr and Uprichard [19] simplified the model by proposing a single first-order equation for softwood delignification. They also refined the model by empirically incorporating sulfidity, chip moisture, chip size and liquor to wood ratio into the kinetic equation. Later, Clarke [20] extended the model to be valid for hardwood too. LeMon and Teder [21] presented a three-stage approach by assuming initial, bulk and residual stages for wood substance dissolution.

Based on these early kinetic models, three broad groups of digester models have emerged that are widely used at present. These models are well-known as the Purdue, Gustafson and Andersson models, and have been the bases for developing digester models with increasing degrees of sophistication. The main conceptual bases of these kinetic models are similar. They all are based on the Arrhenius expression, which shows the effect of a change of temperature on the reaction rate constant for different wood components. In contrast, the main differences between the models arise from the numbers of wood components that are considered (particularly lignin); the assumption of consecutive or parallel reactions; and the assumption about how the delignification reaction takes place along the digester length.

3.1. Purdue Model

The Purdue model was originally developed by Smith and Williams at Purdue University in the 1970s [22]. This was one of the first kinetic models developed for both softwood and hardwood. The model was developed for simulation and control of a Kamyr digester by approximating series of continuously stirred-tank reactors (CSTR). In Smith's model, it is assumed that there are three phases in the digester: solid wood, entrapped liquor and free liquor phase. The wood substance is represented by five different components reacting in parallel: high-reactive lignin, low-reactive lignin, cellulose, galactoglucomannan and arabinoxylan. The reaction rate for each component is expressed as:

$$\frac{dC}{dt} = -(k_1[OH] + k_2[OH]^a[HS]^b)C, \tag{4}$$

where C is the wood component concentration, HS is the sulfide concentration, k_1 and k_2 are rate constants and a and b are exponents determined experimentally.

Christensen et al. [23] and Saltin [24] extended the Purdue model by adding a nonreactive lignin component in addition to the high-reactive and low-reactive lignin. Consumption of dissolved reagents and heat of reaction are also included in Christensen's model. Later, Michelsen [25] developed a dynamic model for a continuous digester by combining simplified reaction kinetics following the Purdue model and a modified bed compaction correlation following Harkonen [13]. He modeled the flow dynamics and thermodynamics in detail by using mass, momentum and energy balances. Thus, the model was able to capture the effect of flow variation on Kappa number better, but the model validity range reduced considerably due to simplification of reaction kinetics. Later, Kayihan et al. [26] developed a simplified two-phase benchmark model for a continuous digester by ignoring the heat of reaction and considering no diffusion limitation. Lindgren and Lindström [27] proposed a modification to the reaction kinetics where delignification of fast, intermediate and slow lignin is considered. The authors also incorporated the effect of sodium ion on the reaction rates. Miyanishi and Shimada [28] simulated a Lo-Solids Kamyr continuous digester to compare its performance with conventional digester. The authors also proposed a new equation for cellulose degradation. The results showed good agreement with the measured process data. Bhartiya et al. [29] integrated work from Kayihan et al. [26] and Michelsen [25] to extend the benchmark Purdue model with Michelsen's momentum transport description and control volume approach with three-phases. This allowed for simulation of the production rate change, feedstock grade change, chip level transition and plugging of the digester. Afterwards, Kayihan et al. [30] extended the Purdue model to incorporate dynamic compaction and stochastic changes in chip size distribution. Pougatch et al. [31] developed a three-dimensional numerical model for the continuous digester by using simplified, Purdue-like reaction kinetics. Ding et al. [32] used the Purdue model to estimate the parameters of a simplified linear model. Araneda et al. [33] adapted the Purdue model to simulate an industrial Lo-Solids pulp digester and thus showed 9.1% savings of white liquor can be achieved by adapting operating conditions. Recently, Rahman et al. [6] developed a dynamic continuous digester model for real-time simulation by following reaction kinetics similar to Bhartiya et al. [29] and simplified compaction similar to Fernandes and Castro [15]. The authors developed an object-oriented modeling library in Modelica language [34] for modeling various commercial digesters. The wood components dissolution rates are adapted as presented in Equation (5),

$$\frac{dC}{dt} = -(k_1[OH] + k_2[OH]^{0.5}[HS]^{0.5})(C - C_\infty), \tag{5}$$

where C and C_∞ represent the concentrations of instantaneous and nonreactive components in the solid phase and

$$K_n = A_n exp(\frac{-E_n}{RT_c}), \tag{6}$$

where T_c, A_n, R and E_n are the chip temperature, pre-exponential factors, universal gas constant and activation energies of the reaction, respectively.

In a more recent work, Choi and Kwon [35] extended the Purdue model to capture the evolutions of cell wall thickness and fiber length for batch digesters by integrating the macroscopic model with a microscopic model.

3.2. Gustafson Model

The Gustafson model, also known as the three-stage model, was developed by Gustafson at the University of Washington in the 1980s for softwood [36]. In Gustafson's model, the wood substance is represented by two components: lignin and carbohydrates that react consecutively. The dissolution of these wood components is modeled as three consecutive phases: initial, bulk and residual. The percentage of lignin is used to mark the transition from initial to bulk phase and so on.

The kinetic expression during the initial stage (lignin content > 22.5%):

$$\frac{dL}{dt} = -k_1\sqrt{T}L, \tag{7}$$

$$\frac{dCH}{dt} = c_1[OH]^{0.11}\frac{dL}{dt}, \tag{8}$$

During bulk stage (22.5% > lignin content > 2.5%):

$$\frac{dL}{dt} = -(k_{2a}[OH] + k_{2b}[OH]^{0.5}[HS]^{0.4})L, \tag{9}$$

$$\frac{dCH}{dt} = c_2\frac{dL}{dt}, \tag{10}$$

Finally, during bulk stage (lignin content > 2.5%):

$$\frac{dL}{dt} = -k_3[OH]^{0.7}L, \tag{11}$$

$$\frac{dCH}{dt} = c_3\frac{dL}{dt}, \tag{12}$$

Subsequently, Pu et al. [37] extended the Gustafson model by considering three wood substances: lignin, cellulose and hemi-cellulose, while assuming portions of cellulose and hemi-cellulose are nonreactive. The authors simplified the kinetic model by neglecting the residual stage and effect of $[HS]$ on the reaction rates. Vanchinathan and Krishnagopalan [38] implemented the Gustafson model for Kraft pulping of southern pine and identified kinetic model parameters using real-time liquor analysis data. Walkush and Gustafson [39] used the Gustafson model to analyze the operation of a continuous commercial digester operated in extended modified continuous cooking (EMCC) and LoSolids cook modes. Later, Rantanen et al. [40] adopted the Gustafson model for modeling of an industrial Downflow Lo-Solids cooking process. The authors optimised the model parameters for both softwood and hardwood. Ahvenlampi et al. [41] predicted the yield profiles of conventional and Downflow Lo-Solids digesters by combining the Gustafson model and fuzzy clustering. Santos et al. [42] studied the kinetics of hardwood carbohydrate degradation during bulk phase to better understand losses during the Kraft process.

3.3. Andersson Model

The Andersson model was developed by Andersson at Karlstad University in 2003 by combining Purdue and Gustafson models [43]. The Andersson model uses similar underlying kinetic expressions to the Purdue model, including the assumption of parallel reactions. One of the key assumptions that differs from the Purdue model is the three types of reactive lignin ($L1$, $L2$ and $L3$ in Figure 8) used to model the delignification reaction inside the digester. The concept of using transition points as a function of the cooking conditions in the distribution model is quite similar to Gustafson's model. This results in a total of 12 pseudocomponents representing the wood substance [44]. The component dissolution is expressed by Equation (13):

$$\frac{dC}{dt} = -k_1([OH]^a[HS]^b + k_2)C, \tag{13}$$

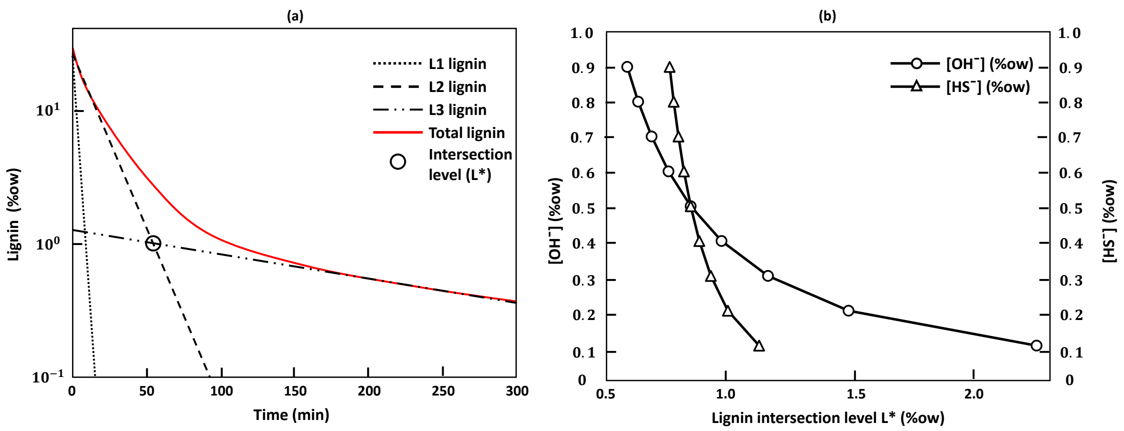

Figure 8. Schematic showing (**a**) $L1$, $L2$ and $L3$ lignin, and (**b**) dependence of the intersection level L^* on cooking conditions—in this case $[OH]$ and $[HS]$.

Using multivariable curve fitting, the authors derived Equation (14) for intersection level L^* that represents the cooking stage when the intermediate ($L2$) and slow reacting lignin ($L3$) amounts are equal. According to the experimental observations, the authors found that the intersection level depends on the cooking conditions, i.e., amounts of hydroxyl and sulphide groups and temperature.

$$L^* = 0.49([OH] + 0.01)^{-0.65}([HS] + 0.01)^{-0.19}(1.83 - 2.91 \times 10^{-5}(T - 273.15)^2), \quad (14)$$

Similar equations for intersection levels were also derived for the other wood components too. According to the authors, these modifications resulted in better fits with autoclave and circulation digester data when compared to prior models.

Later, Sixta and Rutkowska [45] extended the Andersson model by considering the influences of sodium ions on pulping kinetics for *Eucalyptus globulus*. Paananen et al. [46] followed Andersson's approach to study the impacts of alkali concentration, temperature and reaction time during the initial phase of Kraft cooking.

3.4. Other Models and Comparative Studies

He et al. [47] proposed one of the earlier computational fluid dynamics (CFD) models of a continuous digester based on Michelsen's fluid dynamics assumptions, Härkönen bed compaction and a simplified kinetic model. Continuing the work of He et al. [47], Fan [48] developed a detailed CFD model by considering inter-phase friction, thermal dispersion and chip compressibility. The reaction model was based on regression method from extensive experimental data. Pourian [49] extended the digester CFD model by incorporating factors such as chip quality, variations in the concentrations of active ions and energy balance to describe the temperature distribution in the digester.

Burazin and McDonough [50,51] used non-linear regression and parameter estimation to choose the best models out of 200 model candidates for delignification and carbohydrate degradation of softwood. For delignification, the best model incorporated three parallel pathways for lignin solubilization, a pathway for lignin condensation, and a pathway for residual delignification. For carbohydrate dissolution, the best model incorporated two parallel pathways for peeling, two for stopping and one for chain cleavage. Giudici and Park [52] modified Burazin's model for hardwood. Masura [53] derived a model for Kraft pulping by relating the lignin content and the alkali concentration of a cooking liquor.

Grenman et al. [54] combined the work of Purdue, Gustafson and Andersson to model delignification kinetics by considering the influences of wood anisotropy and internal diffusion. The authors proposed a dynamic, three-dimensional model that can be used for pulping process intensification and optimization, and future digester design. The authors also attempted to benchmark the performances of three well-known kinetic models, and concluded that the trends predicted by these kinetic models are quite similar, but the details differ depending on which kinetic model is used. Nieminen et al. [55] developed a detailed kinetic model for carbohydrate degradation in Kraft pulping. The carbohydrate degradation is modeled based on the reaction mechanism of peeling, stopping and alkaline hydrolysis. Another Kraft cooking modeling approach was proposed by Bogren et al. [56], which is based on the assumption that the wood species consist of infinite numbers of components that react with a continuous distribution of time and concentration-dependent rate constants.

$$\frac{dC}{dt} = -(S_0[OH]^{(m+nC)}[HS]^{(o+pC)}[Na]^{(q+rC)}e^{-\frac{E_a}{RT}})^{\gamma}\gamma^{1-\gamma}\Gamma(-\frac{1}{\gamma})^{\gamma}t^{\gamma-1}C, \quad (15)$$

where Γ denotes the gamma function, S represents concentration-dependent function and γ represents temperature-dependent function. S_0, m, n, o, p, q and r are parameters that need to be determined by fitting the experimental data. While Bogren's model provides reasonable results, the higher mathematical complexity and many tuneable parameters make it challenging to use.

Andersson et al. [57] used data collected from an well-instrumented circulation digester to compare eleven kinetic models by categorizing them into three broad families (i.e., simplified kinetics model, Purdue Model and three-stage model). The results showed that the three-stage model was good at capturing the end point for lignin, while the Purdue model followed the trajectory better. Later, Nieminen and Sixta [58] performed a similar study that compared the Purdue, Gustafson, Andersson and Bogren models. The authors used these kinetic models to simulate a well-controlled laboratory-scale batch digester. The results demonstrated that the Purdue model had the best structure, weighing the complexity and computational efficiency. It was able to follow the trajectory of the cook with higher accuracy, given that good adjustments of its parameters were performed. Recently, Fearon et al. [59] studied phenomena-based detailed modeling of the delignification process by considering macromolecular aspects of lignin. Concurrently, Fearon et al. [60] also studied the detailed chemistry and essential phenomena of carbohydrate reactions at the molecular level. While all of these detailed models are quite useful to help with understanding the Kraft pulping process in more detail and creating in-depth knowledge on the existing and possible new cooking processes, these are not very suitable for online prediction and advanced control of commercial digesters.

3.5. Discussion and Future Research Directions for Pulp Digester Modeling

Modeling of pulp digesters is well studied in the literature. Many variants have been studied; some were devoted to studying the influences of only one or a few variables on the delignification kinetics or carbohydrate degradation in detail; others were devoted to developing overall models. The chemical engineering community has explored models that are more complex in nature by studying fundamental physical and chemical phenomena. Nonetheless, the control community always strives for model simplification; in-fact, they often utilize linear state-space models for controller design. Still, the control community has also explored kinetic models with variable degrees of complexity in order to study different controller performances. The majority of these works studied diffusion effects in a pseudokinetic approach by combining mass transfer and intrinsic kinetics together in a single equation. Such an approach provides a good approximation of the diffusion effect within the nominal operating region. However, using such equation systems beyond the studied experimental domain can be prone to errors. This is also true for estimates of Kappa number, chip pressure and in many cases bed compaction that are often based on empirical constants identified from experimental data.

Interestingly, the earlier scientific articles addressing pulp digester modeling devoted substantial effort to describing the solution procedure to ensure model convergence. As different software packages for solving differential-algebraic system of equations (DAEs) have became readily available, the solution procedure has become less of a concern. If we look at recent trends, pulp digester modeling studies are more application focused. Nevertheless, using pulp digester models for online applications is still challenging due to the poor accuracy, high development costs and complex adaptive schemes. One of the reasons behind the poor accuracy is that most of the earlier models only considered physico-chemical phenomena along the digester's length. Radial phenomena were often neglected—a simplifying assumption.

The obvious reason for often using very simplified models is the challenge of the problem itself. The delignification process is very complex by nature, involving hundreds of parallel reactions that are still not well-known. Moreover, the wood chip is a very heterogeneous material that is subject to natural variations. Both the properties and compositions vary depending on the type of wood, geographical location, land elevation, seasonal variation and climate. The properties of wood chips even differ depending on age and which part of the tree they originate from. These variations are the major source of unmeasured process disturbances. Ding et al. [61] stated that the variation of wood chip quality is responsible for 30–40% of process variability. Moreover, wood chips undergo both structural and chemical changes during delignification. The process is not only dynamic in nature but also has long dead times. Much work has been carried out toward online characterizations of wood chips, black liquors and pulp to measure the amounts of moisture, lignin and carbohydrates, and the reactivity [62,63]. However, model improvements using such inputs are still uncharted territory for the research community. Some researchers studied the residence time distributions (RTDs) of pulp digesters and emphasized on RTD's importance for digester modeling [64,65]. Besides, integrating RTD in pulp digester modeling has never materialized.

To reduce the development cost, there is a growing need for developing a generic library that could be used to model different digesters with different dimensions, configurations and types. Data-driven modeling is one of the growing research domains that has been capturing much attention recently. While it is not uncommon to position data-driven and physics-based approaches as opponents to one another, real opportunity lies within combining them to exploit the benefits of both. Using data-driven techniques to improve physical models by incorporating parameter tuning, real-time adaptations and virtual sensors remain unexplored. Moreover, physical models can also be used to perform optimal tests or in the training of data-driven models for fault detection.

4. Control of Pulp Digesters

The ultimate objective of a pulp and paper mill is to ensure the specified quality of the end products while meeting the production targets and minimizing the operational costs. On the pulp digester side, this can be translated to producing pulp with a specific Kappa number with minimum chemical and energy inputs [66]. Pulp with a higher Kappa number can lead to screen clogging that often affects production rate negatively and sometimes even creates rejects. This also affects the downstream processes; i.e., chemical uses in bleaching plants and organic uses in the effluent treatment plants are increasing significantly. Though a lower Kappa number does not lead to rejects, it is not desirable either. It is linked with lower fiber strength due to carbohydrate degradation and thus results in lower yield [67]. Hence, Kappa number control is mostly a constrained control; digesters are operated in such a way that the produced pulp Kappa number stays below the upper limit. Hence, the Kappa number target is set conservatively based on the ability of the control system to account for process variability. As illustrated in Figure 9, improved control can lead to reduction in process variability. Consequently, the Kappa number target can be shifted upward, closer to the upper limit. Typically, this results in higher yield and thus lowers the operating cost significantly.

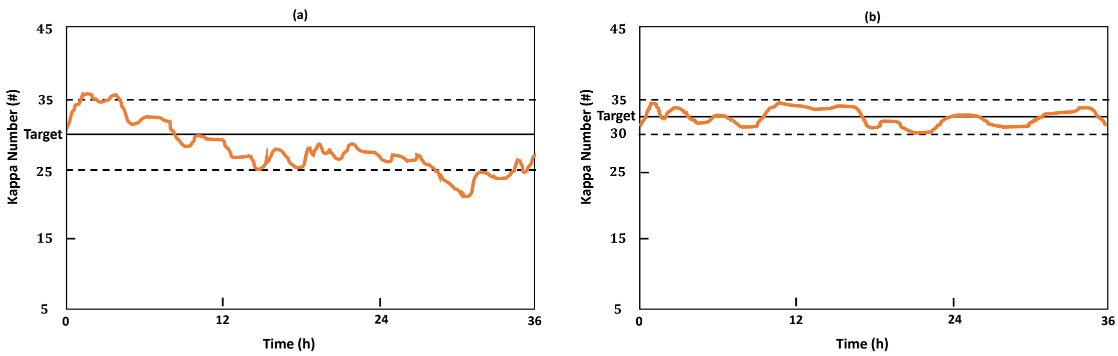

Figure 9. Graph showing Kappa number variability: (**a**) before and (**b**) after improved control.

In addition to the Kappa number control, stable operation of the digester requires chip-level control. Chip level influences the downward movement of chip column inside the digester. Frequent variation in the chip column movement result in disturbances in the cooking process and hence inconsistent pulp quality [68]. A higher chip level leads to under-cooking of the pulp, thereby resulting in increased Kappa number and vice-versa. Furthermore, residual alkali control at the extraction is necessary to minimize the white liquor demand for the cooking process. Since the pulp quality and black liquor composition are closely related, residual alkali control also results in reductions in Kappa number variability, white liquor and energy consumption.

4.1. Kappa Number Control

Controlling the Kappa number at the continuous digester outlet is a difficult problem, mainly due to the fact that all the main control manipulations are performed in the top part of the digester, but the Kappa number is physically measured at the outlet of the digester (see Figure 3). The residence time between these points can be between four to six hours. This literally means that the instantaneous Kappa number measurement is a result of past process input parameters that existed four to six hours earlier [6]. Moreover, blow-line Kappa number is affected by a huge number of process variables. Due to the complexity involved, continuous cooking requires multi-variable process control [68]. Kappa number control is usually achieved by monitoring the properties of chips and liquor at the digester inlet and by manipulating several liquor flows and reaction temperatures [66].

Although many strategies for Kappa number control have been studied and utilized over the years, the H-factor control remains the legacy control strategy taken originally from the control of batch digesters [69]. This type of conventional control strategy utilizes the measured Kappa number for feedback control, often a proportional-integral-derivative (PID) controller that manipulates the H-factor target. Since for a stable chip level the preceding production rate dictates the retention time, in reality the H-factor manipulation is achieved by adjusting the lower heating circulation temperate [68]. However, the multivariate nature of the delignification process and long retention time make PIDs inappropriate for Kappa number control and eventually results in manual digester control by the operators [70]. Therefore, different model-based control strategies were widely explored by both academic and industrial researchers. Particularly, model predictive control (MPC) has been at the center of attention for research efforts within this area [71].

In one of the pioneering studies, Cegrell and Hedqvist [72] deployed a simple but adaptive model of the continuous digester to control a predicted Kappa number by manipulating the cooking temperature. Liao and Wu [73] proposed a double loop Kappa number and H-factor control of a Kamyr digester based on a lower-order auto-regressive (AR) model for Kappa number estimation. The proposed control strategy does not appear to have been implemented for online digester control. A comprehensive survey of earlier control strategies can be found in Dumont [74]. Michaelsen et al. [75] employed an MPC optimization on a Kamyr digester using a real-time mechanistic model compensated by an optimal state estimator. The MPC performance proved to be superior when compared with proportional-integral (PI) control in offline simulations.

Funkquist [76] tested a 2×2 multivariate controller for washing zone control using a low-order linear model identified from a high-order nonlinear model. The control design was based on a Smith predictor in combination with a H-infinity stabilization. Sidrak [77] used the Purdue model to calculate set of optimal operating condition for blow-line Kappa number control though offline simulations. The author also proposed an online control architecture for online model adaptation and optimal control of pulp digester. Wisnewski and Doyle [78] analyzed the performance of linear MPC and nonlinear MPC for set-point tracking and unmeasured disturbance rejection. The authors used Hankel-norm approximation to obtain a low-order linear model from an extended Purdue model. It was shown that the nonlinear MPC provides better performance in terms of set-point tracking. However, no improvement in unmeasured composition disturbances was noticed. Wisnewski et al. [79] and Wisnewski and Doyle [80] explored a systematic method for selecting manipulated variable (MV) and secondary measurements to design a multi-rate linear MPC for Kappa number control. The authors concluded that either modified continuous cooking (MCC) or EMCC trim flow rates should be used for the Kappa number control. Amirthalingam and Lee [81] and Amirthalingam and Lee [82] examined a data-driven stochastic system model through subspace identification in order to design a multi-rate Kalman filter coupled to a MPC for the Kappa number control. Kayihan [83] and Kayihan [84] studied Kappa number profile control along the digester using a 5×5 unconstrained MPC. While the method is more likely to guarantee stable fiber properties and target Kappa number, having only one direct Kappa number measurement available at blow-line makes this approach difficult to apply in reality.

Al-Awami et al. [85] compared the performance of dynamic matrix control (DMC) with the performances of classic single-input-single-output (SISO) and multi-inputs-multi-outputs (MIMO) controllers. The author showed that a SISO feedback controller performed better than a MIMO controller based on 4×4 transfer function matrix. Both constrained and unconstrained DMC shown superior performance over all classical control methods. Clarke-Pringle and MacGregor [86] developed and compared two SISO reduced dimension controllers (RDCs) to a full-dimension DMC for a Kamyr digester. Despite the simpler structure, the performances of the RDCs were comparable with DMC at operating point and showed very mild degradation in operating conditions.

Wisnewski and Doyle [87] performed a comparative study where two linear MPCs, one obtained though subspace identification and the other through linearization, were compared with a nonlinear MPC. The nonlinear MPC and linear MPC with a linearized model had better closed-loop performances than MPC with a subspace identified model. Castro and Doyle [88] studied MPC and SISO PI control for plant-wide control of a fiber line. The authors performed relative gain array (RGA) analyses to prove that EMCC temperature was the best MV in terms of interaction, but MCC temperature had a gain almost three times that of EMCC temperature. Hence, it was concluded that both MCC and EMCC temperatures should be used for Kappa number control. The authors also concluded that the multivariate compensation by MPC was useful in the digester, but did not affect the bleach plant's performance. Mori et al. [89] utilized multiple linear regression (MLR) for Kappa number control of a Kamyr digester during wood species change. Silva and Biscaia [90] applied a multi-objective optimization based on the genetic algorithm (GA) for Kappa number and yield control of a Kamyr digester. By using an improved Purdue model, the authors showed that for each Kappa number there was a maximum yield associated and concluded that GA was able to overcome the conflicting optimization goals. Alexandridis et al. [91] demonstrated a MPC for Kappa number control by using a multi-input single-output (MISO) partial least square (PLS) model. The paper showed the effectiveness of the PLS method for developing an accurate Kappa number prediction model and MPC. Alexandridis et al. [92] and Alexandridis and Sarimveis [93] employed an adaptive MPC based on a radial basis function (RBF) ANN model for Kappa number control of continuous pulp digesters. The authors found that the tracking performance of the adaptive MPC was superior to that of a non-adaptive MPC. Padhiyar et al. [94] extended the work presented in [84] by employing a multi-rate extended Kalman filter (MR-EKF)-based nonlinear inferential MPC for Kappa number profile control of a continuous pulp digester. The authors used a first-principles nonlinear model as the controller model, while most of the previous authors used some simplified controller models. They illustrated Kappa number control at three different locations along the length of the digester. The developed controller showed superior performance even under significant mismatches in parameters, initial state errors and stochastic disturbances in the feed-stock composition.

Rantanen [95] proposed an iterative control strategy for Kappa number control of the Downflow Lo-Solids digester wherein set points for chemical charge and cooking temperature are iteratively solved by using a mechanistic digester model. Later, Ahvenlampi and Rantanen [96] extended the approach presented in [95] and tested a fault tolerant control strategy with the combination of diagnosis and control of the Kappa number in the continuous cooking plant. The authors used a self-organizing map (SOM) to monitor the process and the information was used to switch on the controller or switch it off. Padhiyar and Bhartiya [97] proposed a lexicographic optimization-based MPC that enforces priorities to achieve the blow-line Kappa number target when the target Kappa number profile is unachievable due to model–plant mismatch, unmeasured disturbances and input limitations. Galicia et al. [98] showed that the closed-loop performance of PID can be significantly improved by feedbacking Kappa number prediction from a recursive reduced order dynamic PLS model. Choi and Kwon [99] tested a model-based feedback controller for Kappa number and porosity control of a batch digester with simulation studies. The reduced order controller model was built using the simulation data to design a Luenberger observer for state estimation. Recently, Rahman et al. [6] examined a feedforward MPC approach by combining a state-space model identified from complex first-principles model and a near infrared (NIR) soft-sensor for online lignin content measurement. The authors demonstrated that the feedforward MPC performed superiorly to both PID and MPC without feedforwarding lignin content.

4.2. Chip Level Control

In practice, digester chip level or column height varies significantly due to unmeasured changes in chip size, density and composition; unstable movement; and elasticity of the column caused by different cooking conditions. Chip level influences the residence time of the chips in the digester [100]. Hence, a fluctuating chip level results in varying degrees of cooking, and thus an inconstant Kappa number. Digester chip level can be controlled either by adjusting the chip inflow or by manipulating the pulp outflow. Typically chip inflow is manipulated by varying the chip meter speed, and the pulp outflow is manipulated by adjusting the blow flow [101]. However, the less the blow valve has to move to maintain the digester level, the more likely the chip column is to remain compact and stable [102]. Hence, the chip meter speed is often preferred over blow flow. In some mills, both chip feed and blow flow rate are used, as primary and secondary MVs respectively. In addition to the blow flow, the bottom scraper speed also influences the pulp outflow from the digester. Due its effect on pulp consistency, bottom scraper speed can be used for chip-level control in combination with chip meter speed and blow flow [68]. It is important to note here that different types of disturbances may require different manipulation strategies [103]. For example, chip level change due to bulk density variation will require blow flow manipulations for residence time control and manipulation of chip meter speed for throughput control.

A wide range of control strategies have been applied over the years for digester level control, but only a few research articles could be found in reality. Dumont et al. [104] and Belanger et al. [105] showed self-tuning regulators (STR) using both chip feed and blow flow rate had comparable performances for Kamyr digester level control. Allison et al. [106,107] demonstrated a MISO generalized predictive control (GPC) where the blow flow and the chip feed rate were manipulated simultaneously to control the chip level. However, the controller was discontinued after six months of operation due to increased Kappa number variability. Lindgren et al. [108] implemented a MPC for chip-level control through manipulation of chip meter speed at M-real Husum mill. Though the control strategy did not reduce the chip-level variations significantly, the reduction of the blow flow manipulations resulted in lower Kappa number variations. Badwe and Satini [68] emphasized the need for a multivariate controller over linear MPC for a continuous digester by highlighting the nonlinear behavior of the chip level. Subsequently, they implemented a nonlinear MPC for the level control to compute optimal bottom scraper speed and blow flow as primary MVs, bottom wash liquor flow as the secondary MV and chip meter speed for situations when the chip level is significantly high or low. The authors suggested the use of a soft-sensor or bottom differential pressure for blow consistency control if direct measurement is not available.

4.3. Residual Alkali Control

Residual alkali or residual EA of the black liquors is the amount of unused EA that is left after the cook [109]. Residual alkali concentration should not be too high or too low. High residual alkali increases chemical consumption and increases load on the recovery cycle, and thus also raises energy consumption. This is often linked to high EA at the beginning of the cook that results in higher cellulose degradation, which reduces pulp yield [110]. On the other hand, too low a concentration of residual alkali can lead to lower pulp quality and bleachability. Lignin starts to re-precipitate if the EA drops too low at any stage of the cook [111]. This can result in high chemical consumption, low pulp strength and low yield [112]. Hence, modern digester control should not only minimize the initial alkali levels but also control the alkali profile along the digester's length [113].

Only a few scientific articles can be found that address the important issue of residual alkali control. This is probably due to the fact that Kappa number is the main quality key performance indicator (KPI) and thus the primary objective of any digester control system. Gough and Kay [114] applied a transfer function-based predictive adaptive controller for closed loop control of residual alkali in an effort to reduce Kappa number variability. Luo et al. [115] studied the control of residual alkali content during Kraft pulping by employing empirical prediction model for residual alkali and Kappa number. The simulation study revealed that residual alkali control requires co-regulation of H-factor, initial alkali charge and sulfidity.

4.4. Discussion and Future Research Directions of Pulp Digesters Control

Control of continuous pulp digesters has been widely studied by both academic and industrial researchers. Initially, the research focus was set on the control of the chip level of continuous pulp digesters [104,106,107]. Eventually, the focus shifted to achieving maximum pulp production at a specific Kappa number with minimum chemical and energy consumption. Apart from MPCs, a wide variety of control approaches, such as DMC, RDC, Smith predictor and GA were explored to accomplish these goals [76,85,86,90]. Due to its superiority, researchers have investigated different MPC concepts for continuous pulp digesters. Some of the studies are focused on the linear MPC concept that tackles problems with linear constraints and dynamics [75,78,82]. Both linearization of the physics-based models and subspace identification from the data were adopted. On the other hand, nonlinear MPC based on complex physics-based methods, and data-driven methods such as ANN, MLR and PLS, have also been studied [94,97,116,117]. Interestingly enough, the focus shifted along the way from end-point Kappa number control to Kappa number profile control.

Even though level control, residual alkali control and a few others also gained heed in the realm of digester control, the ultimate goal of all these control strategies was typically linked to stabilizing the end-point Kappa number. If a control strategy impacts the end-point Kappa number negatively, it is most likely to be discontinued despite any other gains in performance.

Despite the extensive research, end-point Kappa number variability at the digester outlet is still a major concern for the pulp mills. With the skyrocketing computing power, the use of nonlinear MPC by employing complex digester models is gaining traction. Particularly, integrating advanced measurement techniques with MPC can enable tighter control of continuous digesters. However, reliable measurement devices targeting digester control are not well developed [118]. Conventionally, reliable measurements of chip moisture, lignin and carbohydrate contents, white liquor EA, sulfidity, residual alkali, pulp consistency and end-point Kappa number, have mostly been achieved by laboratory testing and rarely by in-situ testing. Nonetheless, advanced measurement techniques for reliable online measurements of important process parameters are emerging [119–121]. Till date, most of these advanced sensors have primarily been used for process monitoring rather than process control. We anticipate that integration of state-of-the-art sensors and advanced controllers will be extensively researched in coming years. On that front, measurement techniques targeting digester operation and control need further research exploration. Particular focus needs to be on improving the robustness of these sensors.

In recent years, applications of different artificial intelligence (AI) techniques, i.e., ANN, reinforcement learning, etc., gained much attention in the area of process control [122]. Particularly, employing reinforcement learning to approximate the cost function of a nonlinear MPC seems very promising [123]. Approaches such as deep reinforcement learning eliminate the need for tailor-made feature descriptors, controller tuning, deriving control laws and developing mathematical models [124]. It is expected that in the near future deep reinforcement learning and other AI approaches will be extensively researched for control of complex industrial processes like pulp digesters. However, the actual industrial application might need to wait until such approaches have been fully developed and gained trust through pilot applications.

5. Diagnostics of Pulp Digesters

Pulp digesters are the main production bottleneck that can considerably limit the production capacities of pulp mills. Therefore, early detection of process abnormalities or faults is necessary. Process abnormalities or faults can be referred to as unwanted process conditions when the process changes abruptly or gradually. These situations can be better described as soft-faults, since they often do not result in instant shutdowns of plants. Rather, the quality of the product and/or the production rate can be substantially degraded. They may also result in energy and chemical wastage, and high waste generation. Thus, soft-faults can significantly affect plant economics. Typically, soft-faults are almost impossible to detect through monitoring the process parameters only. Normal control actions under such faulty conditions may further deteriorate the plant's operation and result in major shutdowns. The most problematic soft-faults that can occur in a continuous pulp digester with major effects on the blow-line pulp quality and/or the production rate are hang-ups, channeling and screen clogging [125,126].

Over the years, fault detection and diagnostics for different chemical processes have been studied in many articles [127,128]. However, only a small number of studies have focused on fault detection and diagnostics of continuous pulp digesters. In an early study, Puranen [129] proposed a disturbance index to monitor the status of the chemical pulping process, which was calculated by combining measurements, means and deviations using fuzzy logic. Alhoniemi [130] used SOM to identify the faulty states related to chip column movement in a digester. The author highlighted the ineffectiveness of the control system under the faulty states. Dufour et al. [131] evaluated three different data-driven approaches to diagnose a pulp digester. A Gross error-detection approach for sensor fault detection and two ANN approaches for the detection of product quality related changes and feedstock composition changes were investigated . The third approach was further investigated in Dufour et al. [132]. Due to the lack of plant measurements, the ANN approach was developed and validated based on data generated from a first-principles model of the pulp digester. A Bayesian network (BN)-based root cause analysis method for pulp digesters was proposed and validated using a simulation model by Weidl and Dahlquist [133]. The proposed model needed many inputs that were not readily available from pulp mills. Ahvenlampi et al. [134] used fuzzy logic and principal component analysis (PCA) to compute key factors for the digester diagnosis by combining measurements and some statistical variables. The authors showed the applicability of the approach by using offline data. In another paper Ahvenlampi and Kortela [10] applied SOM and fuzzy clustering to identify faulty state of continuous digesters. Later, Ahvenlampi and Uusitalo [135] studied extraction screen plugging by analyzing data from a Downflow Lo-Solids digester. Lee et al. [136] examined a hybrid fault diagnosis method based on a combination of the signed directed graph (SDG) and the PLS. The regression result revealed that the method performs better if the time delays of the measurements are also included as inputs. To reduce disturbances related to chip retention in the digester, Correia and Lana [137] proposed a digester criticity index based on different correlation tests and process measurements. The index was intended to provide an estimation of the stability of the digester as well as suggestions to the operator if corrective actions are required. Another performance index-based method for digester monitoring and root cause identification was examined by Tervaskanto et al. [138]. The authors used seven performance indices—each corresponding to a sub-process in the chemical pulping mill—that were developed based on process statistics and physics-based models. Yli-Korpela et al. [139] evaluated the digester runnability problem by utilizing process performance indices and k-means clustering to find failure pathways. Pourian and Dahlquist [140] studied the channeling phenomenon in pulp digesters by using a porous medium model with CFD. The result showed higher circulation flow and lower pressure in the nearest circulation pipe, which can be used as indicators of channeling situations.

5.1. Discussion and Future Research Directions in Pulp Digester Diagnostics

According to the review of relevant literature, the data-driven and knowledge-based methods have so far been largely preferred over physics-based approaches for digester diagnostics. However, in terms of accuracy level, none of the methods explored to date seem to be superior to the others or mature enough for industry-wide application. One of the possible ways forward to improve the performance of diagnostics systems could be by combining results from different methods, particularly through data fusion. This has the potential to enhance the benefits as well as diminish the drawbacks of different methods [141].

Due to the abundance of historical data, many novel AI approaches for fault detection and diagnostics of chemical processes have been appeared during last few years [142]. However, the potential applications of these techniques for pulp digester diagnostics have not been materialized yet. Many challenges lie ahead before industry wide applications of these AI approaches can take place. One of the major challenges is the lack of labeled data that is necessary for supervised AI approaches. Contrarily, unsupervised AI approaches often fail due to the lack of domain knowledge that is required to achieve explainable outcomes. Another key issue is that historical data are often clustered around a specific (or nominal) operating condition. This is not very useful for the AI approaches that tries to segregate normal and faulty process behavior over a wide range of operating condition. In this regard, physics-based approaches can have the upper hand over AI approaches. Hence, combining both in a hybrid approach would be beneficial.

6. Conclusions

The pulp and paper industry accounts for almost half of the total gross value added from the forestry sector at the global level [143]. Despite its economic significance, the industry is lagging behind in terms of adopting state-of-the-art operation and control techniques. It is likely that multiple factors led to this situation. During the past decade, R&D spending has dropped substantially due to the difficult financial situation faced by the pulp and paper industry [144]. The need for a major infrastructure overhaul, resistance from the workforce and the lack of pilot applications proving the robustness of new technological solutions are some of the things that are currently hindering the advancement within the field. The sector is also occupied by only a small number of multinational conglomerates which poses a penetration barrier for new technology niches. In this context, research to develop new methods, tools and algorithms for improving product quality and process efficiency while reducing production cost and plant downtime is drawing attention.

Bearing this in mind, a comprehensive literature review has been presented in the present work focused on the modeling, control and diagnostics of continuous pulp digesters, one of the major elements of a pulp mill. According to the bibliometric analysis, the USA dominates the research field, being the main driving force behind past research efforts. Furthermore, the research interest with the domain seems to be growing gain. In the area of digester modeling, although many approaches have been studied, models following the Purdue and Gustafson approaches have dominated the field. In a nutshell, the Purdue model has the best structure and succeeds in following the Kappa number trajectory better, while Gustafson's model is good at capturing the end point of delignification reaction. When it comes to digester control, minimizing the end-point Kappa number variability seems to have been the top priority for pulp mills, with MPC being the most studied control strategy. Both linear and nonlinear MPCs have been studied extensively, but online applications of nonlinear MPCs are not evident in the literature. Being the least studied research area, digester diagnostics have mostly focused on different statistical techniques.

The present work has also summarized the current and future research directions within the digester modeling, control and diagnostics. In recent years, a noticeable trend towards the development of new measurement devices around pulp digesters has been visible. Particularly, online characterization of wood chip, black liquor and pulp has been extensively researched. It is expected that this trend will continue in the coming years, explicitly focusing on robustness improvements for such devices. We argue that in the future we will see further integration of such advanced sensors for the improvement of model prediction and controller performance. The fear of lagging behind is forcing the pulp and paper industry to embrace AI and digital transformation. We anticipate that research on different AI-based approaches for modeling, control and diagnostics of pulp digesters will accelerate in the future.

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Notation and Symbols

The following notation and symbols are used in this manuscript:

α, β	Positive constants
H	H-factor
γ	Temperature dependent function
L	Lignin concentration
Γ	Gamma function
L^*	Intersection lignin level
a, b	Exponents of concentration
L_1, L_2, L_3	Fast, intermediate and slow lignin concentration
c_1, c_2, c_3	Carbohydrate reaction rates
R	Universal gas constant
k_1, k_2, k_3	Lignin reaction rates
S	Concentration dependent function
m, n, o, p, q, r	Fitting parameters
T	Temperature
t	Time
T_c	Chip temperature
A_n	Pre-exponential factor
CH	Carbohydrate concentration
C	Wood component concentration
HS	Sulfide concentration
C_∞	Nonreactive wood component concentration
Na	Sodium concentration
E_n	Activation energies
OH	Alkali concentration

Abbreviations

The following abbreviations are used in this manuscript:

EA	Effective alkali
MLR	Multiple linear regression
CSTR	Continuously stirred-tank reactor
GA	Genetic algorithm
CFD	Computational fluid dynamics
MISO	Multi-input single-output
PID	Proportional-integral-derivative
PLS	Partial least square
MPC	Model predictive control
RBF	Radial basis function
AR	Auto-regressive

ANN	Artificial neural network
PI	Proportional-integral
MR-EKF	Multi-rate extended Kalman filter
MV	Manipulated variable
SOM	Self-organizing map
MCC	Modified continuous cooking
NIR	Near infrared
EMCC	Extended modified continuous cooking
STR	Self-tuning regulator
DMC	dynamic matrix control
GPC	Generalized predictive control
SISO	Single-input-single-output
BN	Bayesian network
MIMO	Multi-inputs-multi-outputs
PCA	Principal component analysis
RDC	Reduced dimension control
SDG	Signed directed graph
RGA	Relative gain array
DAE	Differential-algebraic equation
RTD	Residence time distribution
AI	Artificial Intelligence

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