Control of continuous digester kappa number using generalized model predictive control

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ABSTRACT: Kappa number variability at the digester impacts pulp yield, physical strength properties, and lignin content for downstream delignification processing. Regulation of the digester kappa number is therefore of great importance to the pulp and paper industry. In this work, an industrial application of model-based predictive control (MPC), based on generalized prediction control, was developed for kappa number feedback control and applied to a dual vessel continuous digester located in Western Canada. The problem was complicated by the need to apply heat at multiple locations in the cook.

In this study, the problem was reduced from a multiple to a single input system by identifying three potential single variable permutations for temperature adjustment. In the end, a coordinated approach to the heaters was adopted. The process was perturbed and modeled as a simple first order plus dead time model and implemented in generalized predictive control (GPC). The GPC was then configured to be equivalent to Dahlin's controller, which reduced tuning parameterization to a single closed loop time constant. The controller was then tuned based on robustness towards a worst-case dead time mismatch of 50%.

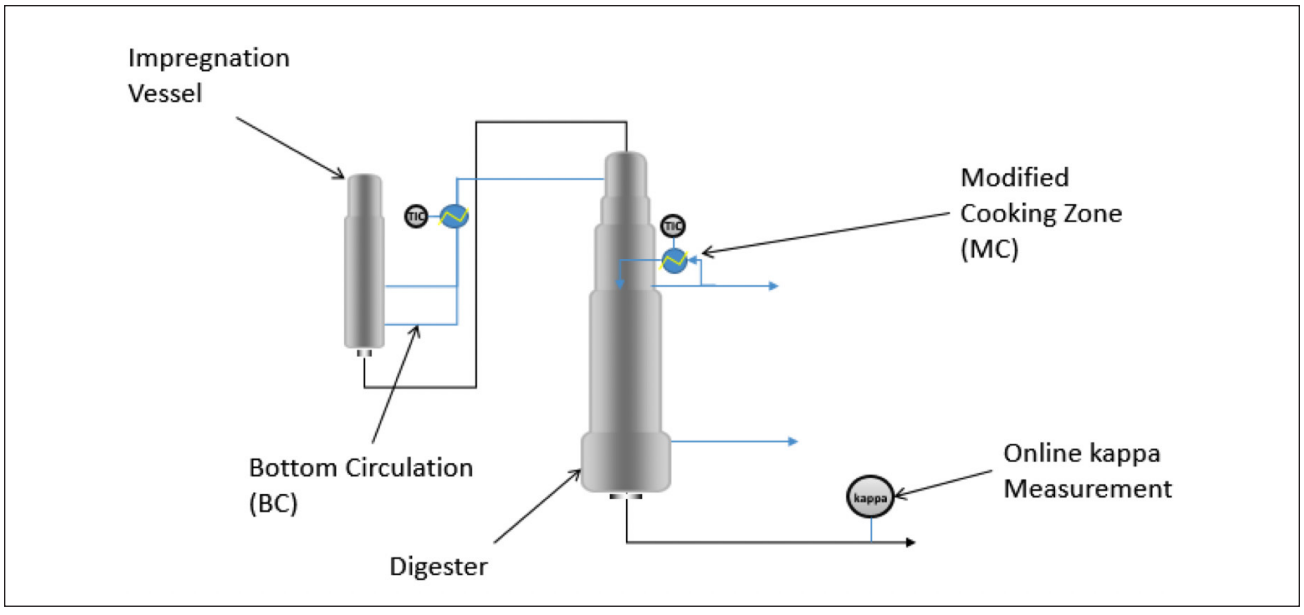
The control held the mean value of the kappa number close to the setpoint, and a 40% reduction in the kappa number's standard deviation was achieved. Different kappa number trials were run, and the average fiberline yield for each period was evaluated. Trial results suggested yield gains of 0.3%–0.5% were possible for each 1 kappa number target increase.

Application: This paper outlines the application of generalized predictive control to controlling kappa number of a continuous digester.

Wood chips are primarily comprised of a mixture of carbohydrates and lignin. In kraft pulping, the lignin is liberated from the carbohydrates using a combination of chemicals and energy. Kappa number is a measure of the amount of residual lignin remaining in a kraft pulp and is monitored and controlled at various stages of the manufacturing process. Most of the lignin is removed in the digester, with smaller amounts being removed in subsequent oxygen delignification and bleaching stages. Thus, excessive kappa number variability at the digester outlet is still a major concern for the pulp and paper industry. Pulp with too low of a kappa number typically has lower yield [1] and physical strength properties [2]. Pulp with too high of a kappa number is more difficult to bleach, i.e., has a lower brightness ceiling [3]. Thus, the ideal situation in digester control is to operate with low variability around a kappa number target that is chosen to yield pulp with the desired end use properties at the lowest possible cost. The main source of disturbances is raw material (wood chip) property variability, including species mix; degree of decay; chip geometry, including fines and overs content; and moisture content.

Prior to the widespread availability of online kappa number analyzers, early attempts at continuous digester kappa number control were inferential in nature. Many of these strategies used a Hatton-type empirical model [4] that related pulp yield and kappa number to H-factor and applied effective alkali (EA). This allowed the calculation of cooking temperature and/or EA level given the kappa number target and pulp residence time, but was unable to handle unmeasured disturbances that cause process-model mismatch due to changes in wood chip properties. A modification of the scheme [5] addressed this deficiency by proposing to monitor the residual effective alkali (REA) at a point partway through the cook, thereby enabling a feedforward control strategy to reset the EA level or cooking temperature in response to chip quality variations. A commercial digester control package from MoDo-Chemetics [6] based on similar ideas was widely applied in industry for years, and the strategy was further improved by feedback of kappa number manual tests to maintain long-term model accuracy. Gough and Kay [7] showed that, through the use of a model-based predictive controller, direct feedback control of REA is also a feasible way to reduce kappa number variability despite the long time delay between white liquor flowrate manipulations and the measured REA.

Online kappa number analyzers started to become available in the 1990s. Since then, numerous advanced di-



1.Dual vessel hydraulic digester with multiple heaters.

gester kappa number control approaches using kappa number feedback have been reported in the literature. Many of these developments were recently reviewed by Rahman, Avelin, and Kyprianidis [8]. Based on their survey, model-based predictive control (MPC) has been at the center of attention for research efforts in this area. Some of the advantages of MPC are that it combines dead time compensation, decoupling, feedforward control, constraint handling, and optimization all in one software package. Model-based predictive control has previously been applied to continuous digester chip level control [9] and REA control [7]. For kappa number control, numerous approaches have been reported for MPC based on linear, linearized, reduced-order, and nonlinear models. Rahman, Avelin, and Kyprianidis [10] state wood chip lignin and moisture contents are the two major disturbances impacting kappa number. While compensation for moisture was presented by Gilbert et al. [11], Rahman, Avelin, and Kyprianidis investigated MPC approaches with and without feedforwarding a near-infrared based wood chip lignin measurement and evaluated these against a proportional-integral-derivative (PID) scheme on a first principles nonlinear model of the digester. They also used the model to perform a controllability analysis to determine the best choice of manipulated variables. With only a few exceptions, the vast majority of the schemes reported in the literature have been tested in simulation only.

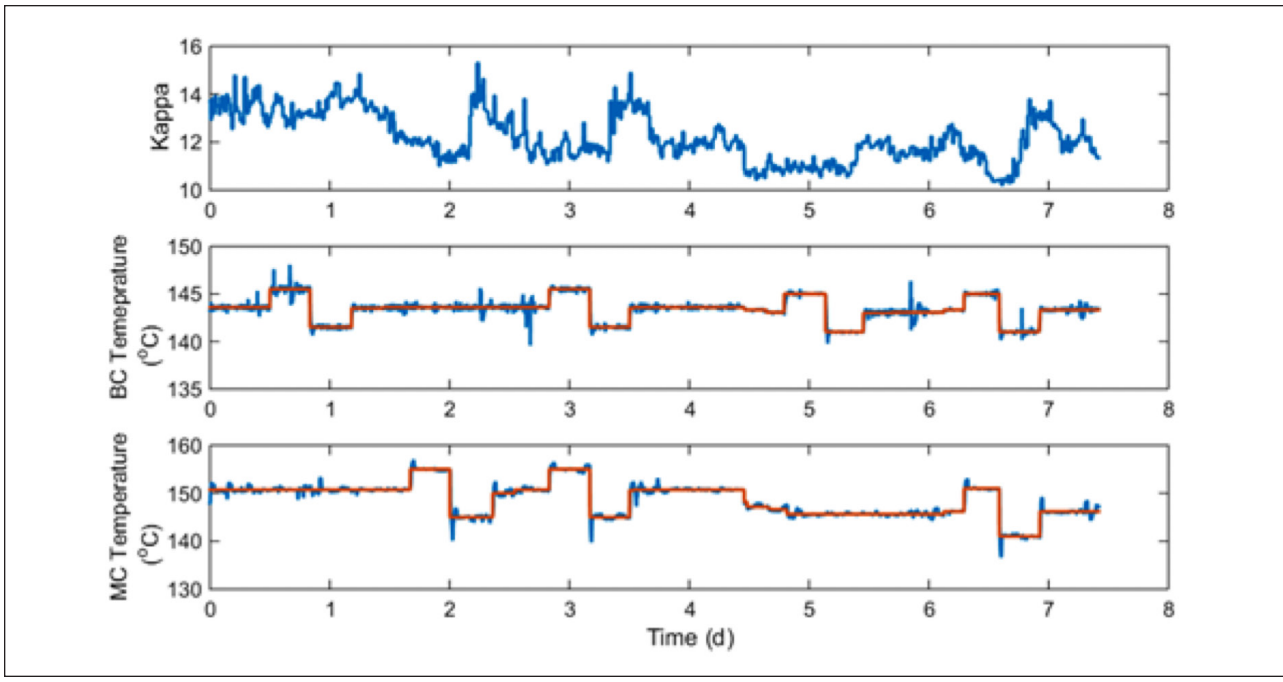
In this paper, an industrial application of MPC to digester kappa number feedback control is described. This report describes the dual vessel continuous digester process at the collaborating Western Canada kraft mill that produces predominately hardwood market kraft pulp. It also describes the experimental approach used to identify a process model and corresponding choice of manipulated variables. Simulation studies used to tune the MPC and the impact of tuning on closed-loop robustness compared to PID control are also discussed. Finally, this paper presents the application results, which show that feedback control of kappa number achieves significant variability reduction, and provides conclusions. In this work, the particular MPC applied is based on generalized predictive control (GPC), the salient features of which are discussed in the Appendix and in [12,13].

PROCESS DESCRIPTION

The process under investigation in this study, shown in **Fig. 1**, is a dual vessel hydraulic digester that produces both hardwood and softwood kraft pulp. Originally, the digester was designed to operate in extended modified continuous cooking (EMCC) mode. The EMCC configuration had a bottom circulation (BC) zone, a trim zone, a main extraction zone, a modified cooking (MC) zone, and a wash zone. The EMCC design was intended to operate in downflow from the BC to the main extraction and in up-flow from the bottom of the vessel to the main extraction. This posed significant issues due to the low density of the hardwood furnish, resulting in channeling and plug consolidation concerns.

In 2001, the digester was modified to operate in a downflow low solids mode to reduce issues with channeling and plug consolidation. To achieve this, the extraction was relocated and only the MC zone recirculated. The extraction is now from both the MC zone and the wash zone. Fresh weak black liquor is also added to the MC and wash zones to help displace the heavier spent black liquor in the vessel.

The digester has three cooking heaters in the BC zone, with one offline as a spare, one MC zone heater, and one wash zone heater. After the conversion to downflow low



2. Process tests on aspen hardwood.

solids cooking, the piping was modified to operate the wash and MC heaters in series as the wash circulation was taken out of service. Kappa number control is achieved by manipulating the temperatures in the BC and MC zones in a coordinated fashion, as discussed in more detail later. The remainder of this paper is focused on hardwood production only.

CONTROL DEVELOPMENT

In this work, continuous time models were identified using process bump tests and then converted into their discrete time counterparts for use with GPC. As multiple adjustments to the cooking profile are possible, a series of process experiments were conducted to identify the manipulated variables for control.

Model identification and control strategy development

There are two potential adjustments to the cooking temperature profile in the dual vessel digester shown in Fig. 1. The first location to adjust the temperature is in the transfer line between the impregnation vessel and the digester, which controls the temperature in the BC zone. The second is at the extraction screen through manipulation of the fresh liquor temperature added through the center pipe, which controls the MC zone temperature. The control as stated represents a single output multiple input process. To simplify the problem to a single input single output system (SISO), three potential single variable permutations for the control output were explored.

As stated earlier, the process was perturbed using a number of process tests to evaluate the process response. In these tests, both temperatures were manipulated independently, as well as in a coordinated fashion. Upon consultation with operations, for the coordinated approach, factors of 1 and 2.5 were applied to the perturbation of the BC and MC temperatures, respectively. **Figure 2** shows the trials over a seven-day period, where some tests were conducted multiple times.

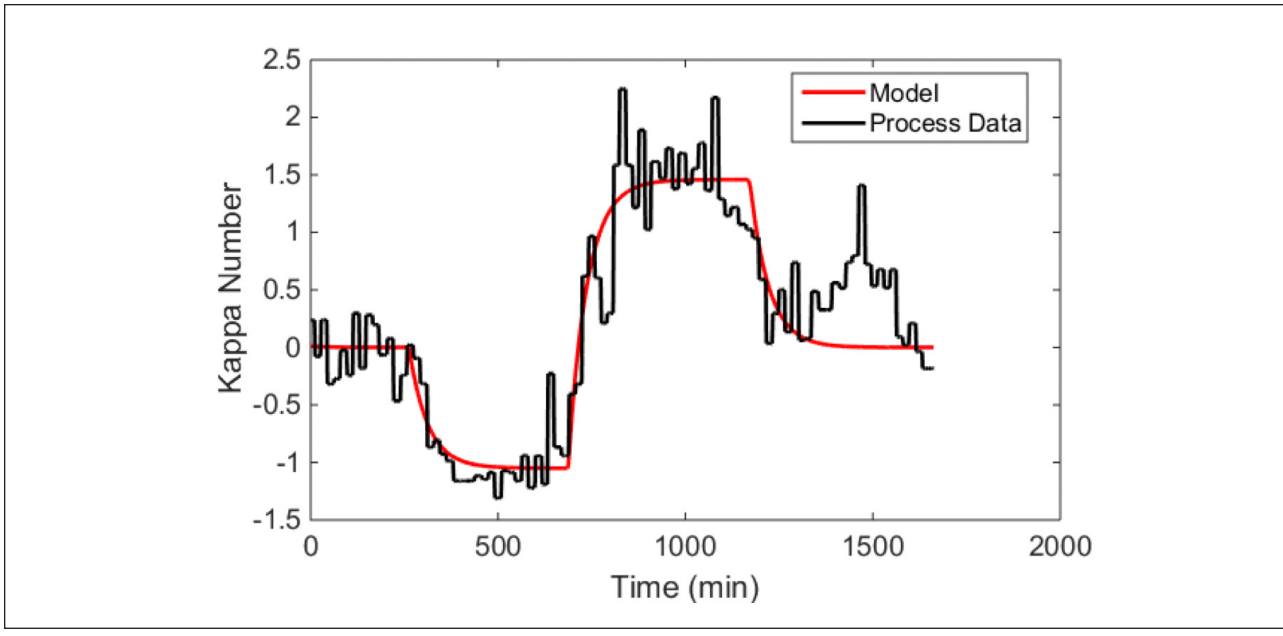
Each process test was designed to elicit a response in the kappa number sufficient for model identification without significant upset to downstream processes. The tests were conducted above and below a nominal production rate typical of normal operation for a duration that was sufficient to see the full dynamic response. The process was then returned to the initial operating conditions. In some cases, a nonlinear response was encountered at low kappa numbers. This nonlinearity appeared as a low limit on the outlet kappa number. Any tests that exhibited this nonlinear behavior were either redone or removed from the analysis.

The process data was then modeled using the system identification toolbox in MATLAB (Mathworks; Natick, MA, USA). The process was assumed to follow a simple first-order plus dead time (FOPDT) model:

$$Y(s) = \frac{k_p e^{-\theta s}}{\tau s + 1} U(s) \quad (1)$$

where k_p, τ, and θ are the process gain, time constant, and dead time, respectively. **Figure 3** shows the process and modeled responses for the coordinated temperature output. The identified parameters are listed in **Table I**.

The BC tests had a larger process gain when compared



3. Kappa number model identification for a coordinated change in cooking temperature: process (black) and model (red) response.

Process Test	k_p, kappa/°C	τ, min	θ, min
Bottom circulation	-0.3	20	350
Extraction	-0.2	4	230
Coordinated	-0.6	32	230

k_p: process gain; τ: time constant; θ: dead time.

I. Identified parameters for first-order plus dead time (FOPDT) models for different manipulated variables.

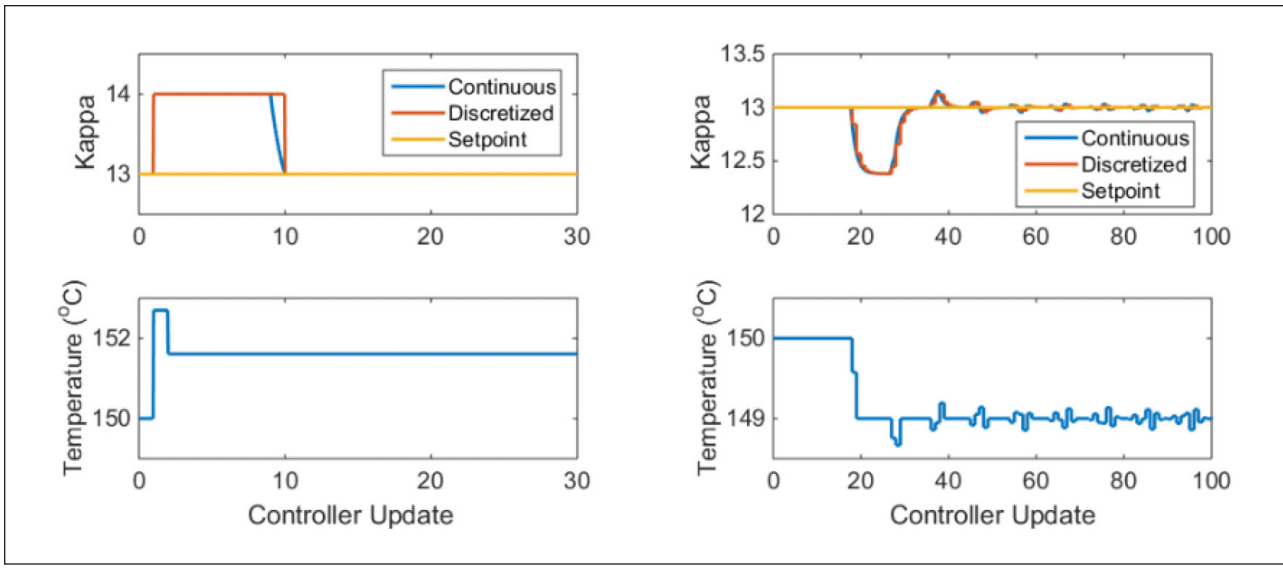
to the tests at the extraction screen. However, as expected, the dead time for the BC test was considerably longer. All tests suggest that the process has a pure dead time response, as the associated time constants are all relatively small. The coordinated approach had a larger process gain that appeared similar to the scaled sum of the individual gains. A similar result can be implied for the time constant. However, the dead time identified is identical to manipulating the extraction screen alone. The coordinated approach has the benefit of a larger gain, which translates to less actuation of the heaters, while having a similar dead time to manipulating the extraction screen and was therefore adopted as the manipulated variable.

The adopted model is a dead time-dominated process. The work of Ingimundarson and Hägglund studied the performance between proportional-integral (PI), PID, and dead time compensators (DTC) based on the ratio of the process time constant and dead time [14]. In their work, the DTC was found to outperform PI control for ratios below 4. However, PID was found to have similar performance to that of a DTC for ratios below 1. In this paper, the derivative term is neglected due to its sensitivity to high frequency process noise. Here, the time constant-to-dead time ratio of 0.14 suggests the performance benefits of the DTC warrant the application of GPC over PI.

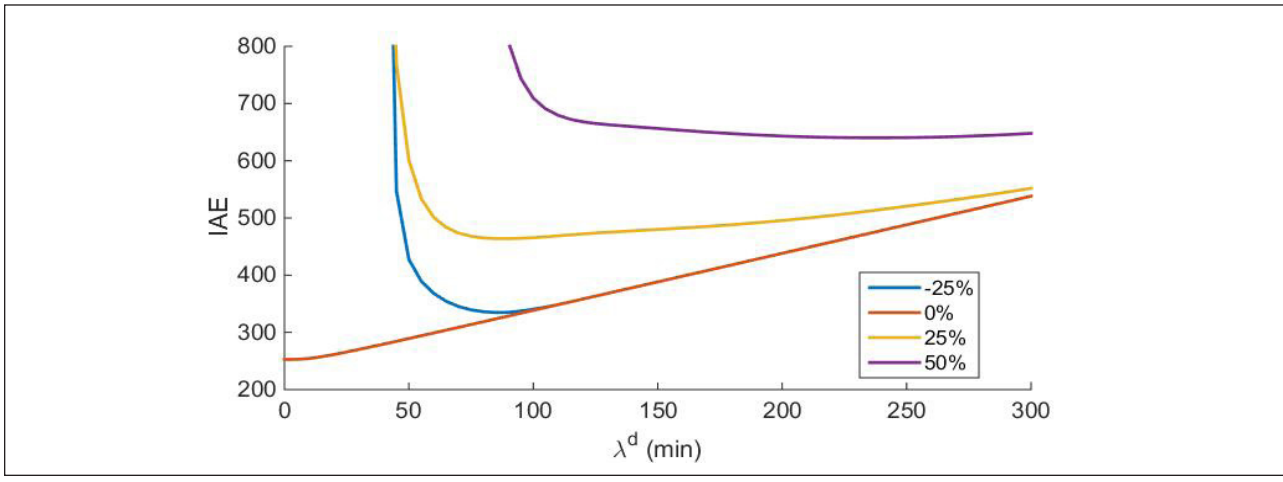
Simulation and training

To use the FOPDT models with GPC, they must first be discretized. Kappa number measurements occur on an irregular basis, however, at typically only once every 20 min. To ensure the controller is working on new information, a controller update rate of 30 min was chosen to prevent the control from acting on stale values. For control purposes, the model dead time was increased to be an integer multiple of the control rate to prevent the complication of fractional delay terms. This adjustment also compensates for the delay introduced due to the slow sampling. The GPC controller was then tuned to give a dead-beat response [15]. **Figure 4** (left side charts) shows the response for previously-described model when the model used in the controller is a perfect match to the process.

The dead-beat control response provides an idealized starting point that represents the best control possible, where the output returns to target one time step after the dead time. However, such an aggressive tuning approach is sensitive to process-model mismatch, and in general, feedback controllers are known to exhibit robustness issues for errors in the dead time [14,16]. Here, we study dead time mismatch between the process and controller for a unit step disturbance in the kappa number. Figure 4 (right side charts) shows that the dead-beat controller is already marginally unstable with a dead time mismatch



4. Inlet disturbance response: dead-beat GPC input/output response for matched case (left side charts), and dead-beat GPC response for 8.5% dead time mismatch (right side charts).



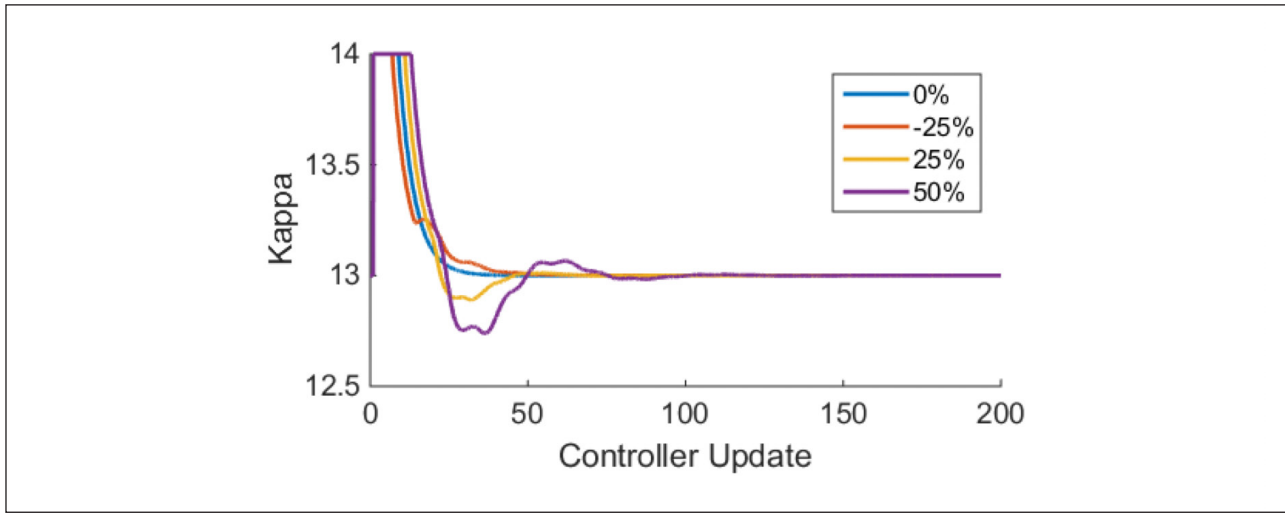
5. Integral of absolute error (IAE) response to changes in dead time mismatch and closed loop time constant ().

of only 8.5%, a stability margin considered too low for application. Furthermore, a robust design against production rate changes is sought, as mismatch is expected in the dead time, and to a lesser extent, in the process gain. The identified model parameters were fit during periods of maximum production rate and so it is of greater importance to study mismatched parameters associated with lower production rates (longer dead times).

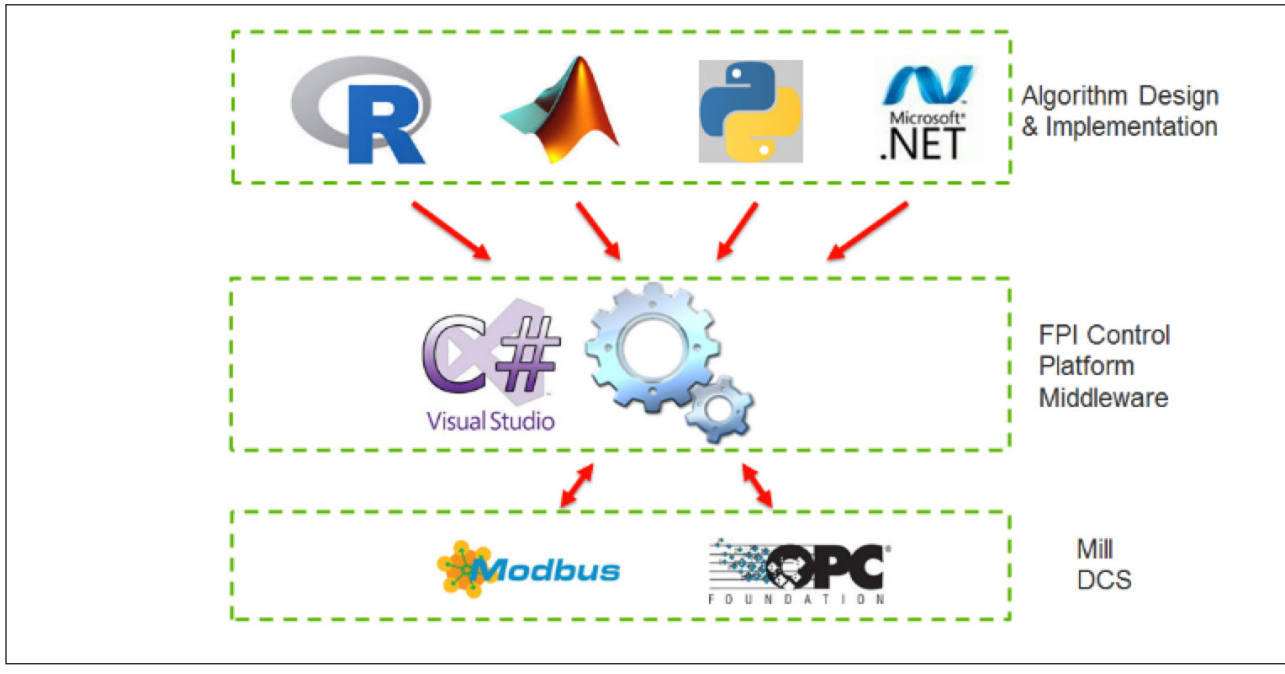
With MPC, it is possible to compensate for model mismatch through model adaptation, model scheduling, or robust tuning. Although model scheduling and adaption could achieve better performance in theory, they come at the cost of increased complexity of implementation. In this application, GPC was tuned based on robustness towards a worst-case dead time mismatch of 50%. **Figure 5** shows the effect of varying model mismatch and closed loop time constant (λ^d) on the integral of the absolute error (IAE). The closed loop time constant represents a single tuning parameter that reflects the aggressiveness of the controller response, where a larger λ^d results in slower control action (see Appendix).

In the nominal case, dead-beat control, λ^d, represents the minimum IAE attainable by the system with no model mismatch. As the model mismatch increases, so does the minimum IAE attainable. In the presence of model mismatch, the choice of λ^d, if too short, is shown to drive the system unstable as IAE grows unbounded. As mismatch grows, the location of instability shifts to the right. To ensure sufficient stability margin at 50% mismatch, a λ^d of 150 min was used for control. This represents an increase of 50% in the IAE with respect to the dead-beat IAE with no mismatch.

Figure 6 shows the final simulated responses of the controller for λ^d = 150 min. In most cases, the controller brings the simulated kappa number near the setpoint within 5–6 times the process dead time.



6. Disturbance response of λ^d = 150 min for different dead time mismatch.



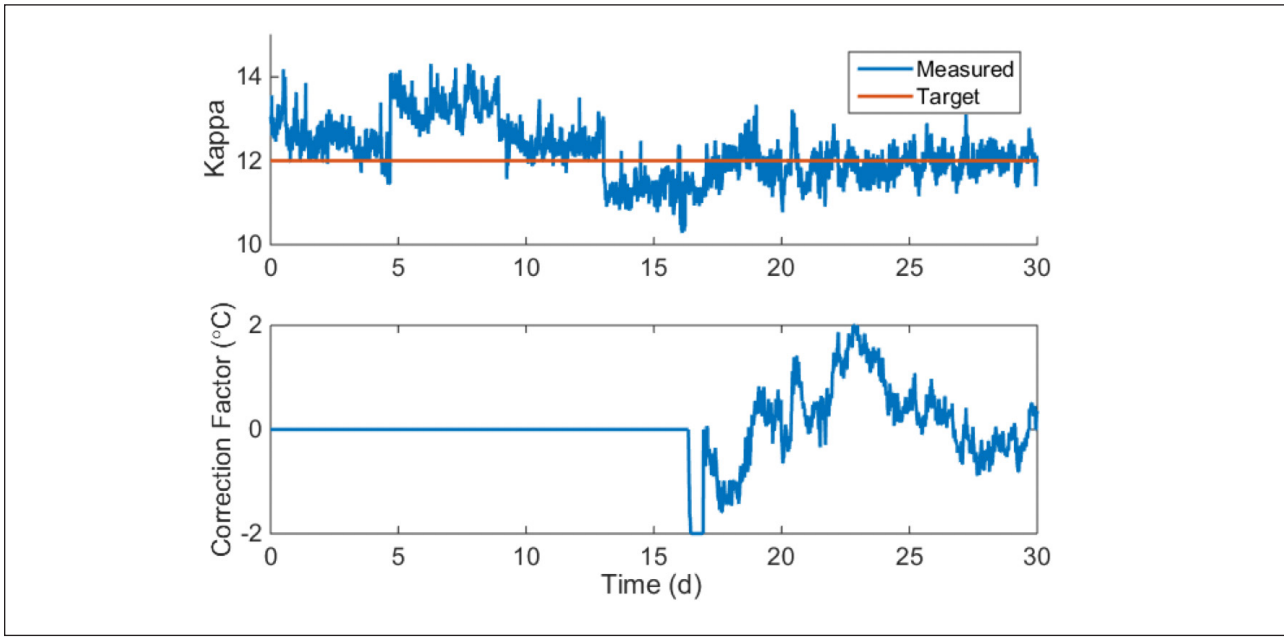
7. Middleware design for industrial control application.

APPLICATION AND RESULTS

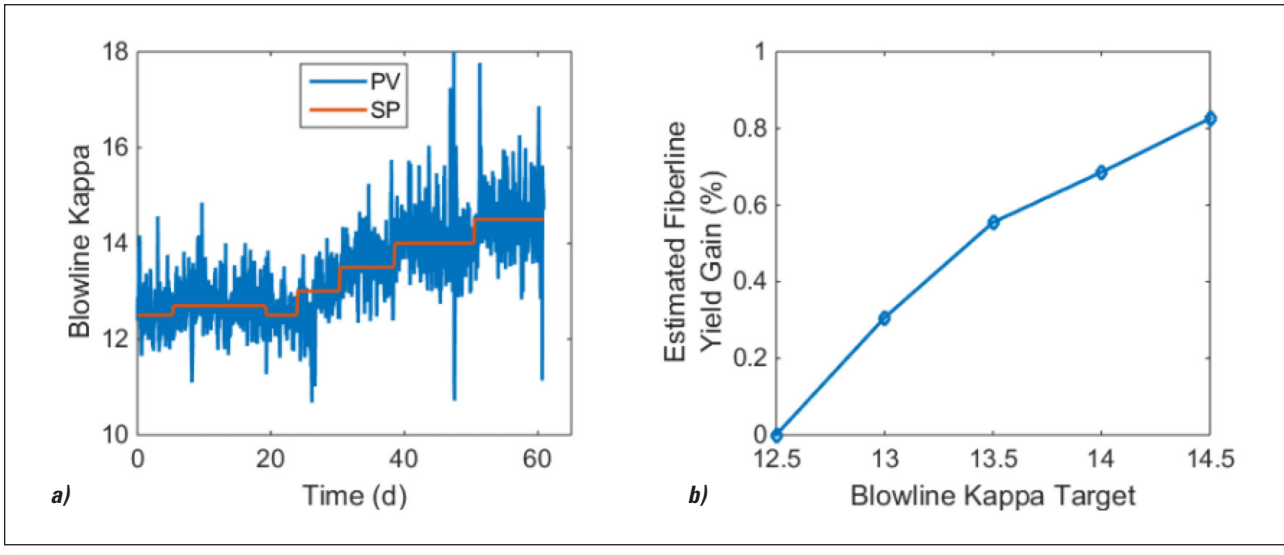
The MATLAB-based GPC algorithm was implemented in a Microsoft Windows service application. Windows service applications are maintained by the operating system and require no user interaction. The application itself is designed to act as a middleware that facilitates communications to the mill's distributed control system (DCS). The middleware is kept generic by using object-oriented programming techniques and is designed to wrap the control algorithm in its native language (**Fig. 7**).

The middleware then facilitates the industrial communication using standard protocols such as Open Platform Communications (OPC) and Modbus. The software supports the rapid deployment of advanced control techniques, such as GPC, alongside an industrial DCS. For long dead time processes, most of the commissioning effort lies in the identification of the models and tuning. The successful identification of the models requires that all instrumentation is maintained and in good working order. The remaining installation of software, DCS configuration, and industrial communications is completed in 1–2 days.

The GPC control adjustments to the temperature setpoints were applied as a correction to the existing targets to ensure the original temperature feedforward configurations were preserved. **Figure 8** shows the kappa number variability over a 30-day period. Before the control is implemented (days 0–16), the kappa number is regulated only via operator adjustment of the temperatures and drifts



8. Before and after kappa number control results.



9. (a) Kappa target trial results, and (b) estimated fiber line yield gains.

above and below the target. Upon application of GPC (days 16–30), the kappa number is regulated to the desired target, requiring the temperatures to be adjusted by roughly +/- 2°C. The benefits of the application are twofold. First, the closed-loop control ensures the mean value of the kappa number is held close to the target value. In this dataset, the mean value of the kappa number before and after implementation of GPC is 12.4 and 12.1, respectively. The standard deviation from the mean value is also reduced from 0.80 to 0.47 and represents a 40% reduction in variability.

A mill trial was then conducted to quantify the impact of kappa number target on the fiber line yield. The mass of wood into the fiber line was determined directly from online measurements [11]. Pulp mass flow was determined from the scales off the baler. Major tower inventories were also considered in the estimation. The average fiber line yield was evaluated for each of the different kappa targets, with runs ranging between 5 to 10 days. **Figure 9a** shows the results of the trial, and Fig. 9b shows the average fiber line yield for each period. The results show there is potential to increase the yield of the fiber line by increasing the kappa number out of the blow line. Here, a 1-point change in the kappa number target translated to approximately 0.3%–0.5% in fiber line yield gain.

While yield improvement increases the pulp production, the additional lignin in the pulp leaving the digester must be removed, resulting in increased downstream costs. For hardwood pulping, machine runnability may also act as an

upper limit, as additional yield comes from the retention of the hemicellulose component. Increased hemicellulose content negatively impacts pulp machine drainage, reducing the maximum machine production rate. As such, the optimal kappa number target is considered mill specific. Variability reduction is also important, as this allows operation closer to the mill specific optimal upper kappa number limit. The variability impacts profitability, as it translates to yield loss and high bleaching costs associated with low and high kappa number excursions, respectively.

CONCLUSIONS

Kappa number variability at the digester impacts pulp yield, physical strength properties, and lignin content for downstream delignification processing. Regulation of the digester kappa number is therefore of great importance to the pulp and paper industry. In this work, an industrial application of MPC, based on GPC, was developed for kappa number feedback control and applied to a dual vessel continuous digester located in Western Canada.

The problem was complicated by the need to apply heat at multiple locations in the cook. Here, the problem was reduced from a multiple to a single input system by identifying three potential single variable permutations for temperature adjustment. In the end, a coordinated approach to the BC and MC heaters was adopted. The process was perturbed and modeled as a simple FOPDT model and implemented in GPC. The GPC was then configured to be equivalent to Dahlin's controller, which reduced tuning parameterization to a single closed loop time constant. The controller was then tuned based on robustness towards a worst-case dead time mismatch of 50%.

The MATLAB-based GPC algorithm was implemented in a Microsoft Windows service application designed to simplify the communications to the DCS. The control held the mean value of the kappa number close to the setpoint, and a 40% reduction in the standard deviation of kappa numbers was achieved. Additionally, mill trials suggested that fiber line yield gains of 0.3%–0.5% were possible for each 1 kappa number target increase. The regulation of kappa number is therefore an important tool to help a pulp mill identify and maintain the optimal pulping rate in a continuous digester, although identification of the optimal kappa number target is expected to be mill specific. **TJ**

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APPENDIX

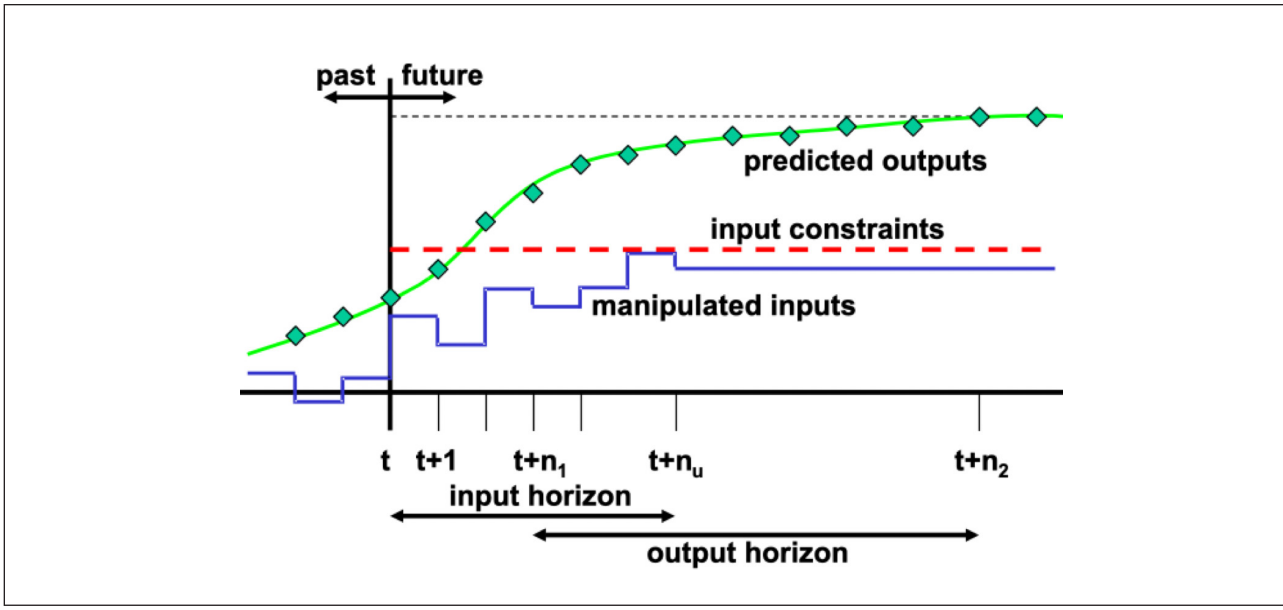
Generalized model prediction control

The MPC algorithm employed in this study is based on GPC [12,13]. Generalized predictive control is general enough to handle processes with any number of controlled outputs, manipulated inputs, and measured disturbances, including non-square systems. Most of the main ideas in GPC can be conveyed by considering the univariate (single-input, single-output) case.

The quadratic cost function to be minimized in univariate GPC is:

$$J = E\left\{\alpha \sum_{i=n_1}^{n_2}[w(t+i) - y(t+i)]^2 + \rho \sum_{i=1}^{n_u}[\nabla u(t+i-1)]^2\right\} \quad (2)$$

where w is the setpoint; y is the controlled variable (output); u is the manipulated variable (input); $\nabla = 1 - z^{-1}$ is the differencing operator (z^{-1}) is the backward shift operator, i.e., $z^{-}y(t) = y(t-1)$; and E is the expectation operator. In effect, GPC minimizes the predicted errors (setpoint minus output) over a future number of sampling instants,



A1. Diagram showing generalized predictive control (GPC) cost function optimization (t: current time; n_1, n_2: future sample instants and where controller tries to minimize error; n_u: future input moves representing number of controller moves allowed to bring measured value back to its setpoint).

called the output horizon, and defined by n_1 and n_2 (see **Fig. A1**). The independent variables in the minimization are n_u future input moves, called the input horizon. The weighting factors α and ρ are used to adjust the relative importance of predicted errors and control moves, respectively. Only the first (current) input move is implemented, and the optimization is resolved with new information at the next sampling instant.

The output predictions are made using a process model that, in the case of univariate GPC, is represented by the following controlled auto-regressive integrated moving-average (CARIMA) model:

$$A(z^{-1})y(t) = B(z^{-1})u(t-k) + T(z^{-1})v(t)/\nabla \quad (3)$$

where v is an independent normally distributed (white) noise with variance σ_v^2; A, B, and T are polynomials in the backward shift operator; and k is the dead time.

The tuning parameters in univariate GPC are n_1, n_2, n_u, α, and ρ. Consider the situation when the process may be represented by a first-order plus dead time model, which is very often the case in process industries. Now, consider the choice of tuning parameters $n_1 = n_2 = n_y$, $n_u = 1$, $\alpha = 1$, $\rho = 0$; and $T = A$. When a step change in setpoint or an output step disturbance occurs, this controller will calculate a single control action ($n_u = 1$) that will drive the output back to the setpoint at a point n_y sampling intervals into the future. Furthermore, the return to setpoint will occur in the minimum possible time when $n_y = k$ (recall that k is the dead time). This is called dead-beat control and may lack robustness or require excessive control actions. As shown in [17], robustness is improved and control action magnitude reduced by setting:

$$T(z^{-1}) = A(z^{-1})T^*(z^{-1}) \quad (4)$$

where $T^*(z^{-1}) = (1 - exp(-T_s/\lambda^d)z^{-1})$. Here, T_s is the sampling interval and is the closed-loop time constant for an output step disturbance. Since the choice of T does not affect the setpoint response in GPC, it is necessary to filter the setpoint:

$$w^f(t) = [exp(-T_s/\lambda^w)]w^f(t-1) + [1 - exp(-T_s/\lambda^w)]w(t) \quad (5)$$

and use $w_f(t)$ in place of $w(t)$ in the controller. Here, the designer is free to choose λ^W different from λ^d, yielding a two-degree-of-freedom design. When $\lambda^W = \lambda^d$, this GPC is exactly equivalent to Dahlin's controller [18], which is a dead time compensator widely used in the pulp and paper industry, particularly in paper machine control systems. Of course, GPC is more general than Dahlin's controller. For example, making $n_y > k$ detunes the controller, and in the limit as $n_y \to \infty$, GPC becomes a mean-level controller. Different choices for the other tuning parameters may be necessary when the process model is more complex than first-order plus dead time.

Unconstrained GPC control assumes that there is an infinite amount of control space for the manipulated variable. In practice, however, there are limits imposed by the actuator. In some applications, it is also desirable to impose limits on the output variable. As the cost function

in GPC is quadratic, quadratic programming (QP) techniques are well suited for solving the problem of constraints in the general case. Although a QP accounts for present and future constraints in an optimal way, the computational burden is large. To avoid the complexities of a QP, output constraints are not considered in this study, and input constraints are enforced by using the much simpler one-step optimal saturation correction algorithm proposed in [19].

ABOUT THIS PAPER

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About this journal

ABOUT THE AUTHORS



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We studied this topic because development of new measurements and control algorithms for continuous cooking, with a focus on stability and yield maximization, is my (Gilbert) area of specialty. Previous research has been around modeling and controlling continuous digesters. This study differs in that it focuses on one aspect of the wider goal.

The most difficult aspect of this study was implementation of generalized predictive control (GPC) in the mill's distributed control system (DCS). To overcome this problem, a software platform was created to help simplify the process.

We found that the challenges associated with controlling a long dead time process are not simple problems. Also, the links between kappa number target and fiber line yield were interesting. We were surprised that this successful study led to the mill adopting the controller.

For mills, kappa control can help reduce pulp quality variability coming out of the digester. Additionally, yield benefits may be realized, depending on the target chosen. Our next step is to study a unique twist to the mill's liquor controls.

Gilbert is manager of the Process Control Group, and Allison (retired) was lead researcher for the Process Control Group, at FPInnovations in Vancouver, BC, Canada. Email Gilbert at wesley.gilbert@fpinnovations.ca.