Process Optimization and Model Based Control in Pulp and Paper Industry

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Abstract:

In this paper we discuss the usage of physical models for diagnostics and process optimization in pulp and paper applications. Specially diagnostics with respect to hang ups and channeling in digesters is described, and how a rigorous model can be used for this, but also for the purpose of MPC, Model predictive control. An example of optimization of a complete pulp mill with respect to mill balances is also presented. An example with respect to optimization of a paper mill with respect to both quality and mill balance is also presented briefly.

Introduction:

50 years ago paper machines had very little instrumentation and automated control, as computers did not exist yet. The paper machine speed was low and the paper width normal not very wide, just a few meters. On the other hand the manual control made use of a lot of operators, who normally new their part of the process very well.

Today we have a situation where the paper machines run faster and faster, up to more than 1800 m/min, and the width may be up to 11 meters, like the ones at Dagang in China. At the same time we see fewer operators running the production. Instead we have got much more automated control.

In the pulp mill we see similar developments, as a fiber-line can have a capacity of 3000 tpd today compared to much less than 1000 tpd 50 years ago typically.

In the next step we can see a trend towards even more diagnostics, decision support and process optimization.

The process optimization will be from on-line control using Model Predictive Control to dynamic optimization for next hours to days and weeks. To perform these optimizations and controls we need to have a good knowledge over the status in the plant with respect to instruments, performance of equipment and service and maintenance actions needed. This is needed as well as good information on orders and priorities.

Process Optimization and control:

In this paper we will focus much on the use of adaptive physical models for both on-line control and production planning the next 24 hours. In reality the boarders between statistical models and physical models may not be that clear. If we introduce a number of parameters into a physical model and these have to be tuned by plant data, it is in reality a combined physical and statistical model. The advantage is that we get the robustness of the physical model, but can make use of the statistics really relating to the actual process. In(Wisnewski P.A, Doyle F.J and Kayihan F 1997) we have a good example of a physical model of a digester while in (Aguiar H.C and Filho R.M 1998) we have an example of a neural net model, which is representing a statistical model.

Detailed physical model of digester

The digester is the major process in the pulp mill. There are two major types of digester: Batch cooking and continuous cooking. This paper will handle the continuous digester and specially the hydraulic digester. There are two types of continuous digesters: hydraulic- and vapor phase. The main difference is that the hydraulic digester is full of fluids while the vapor phase digester has a vapor cushion in the top. .

In a continuous digester, the wood chips are cooked in an aqueous solution of sodium hydroxide and sodium sulfide called white liquor at elevated temperature and pressure. The objective is to degrade and dissolve away the lignin and leave behind most of the cellulose and hemi-cellulose in the form of intact fibers. In practice, the chemical pulping method is successful in removing most of the lignin but unfortunately we also will get a degradation and dissolution of a certain amount of the hemi-cellulose and cellulose.

We have a digester model built on the same principle as the so called Purdue model (Bhartiya et al, 2002). The model contains two volume fractions, the volume occupied by the chips with the entrapped liquor, and the volume occupied by the free liquor. This can be divided into two regions: wood and free liquor in each digester section.

For digester operations we have been working with physical modeling of the digester in 2-D, including pressure drops inside the digester. The reason for this has been to account for both the aspects detection of channeling and hang ups as well as making use of the model for multi variable control, or Model Predictive Control, MPC.

A physical model over a digester has been made taking into consideration the pressure drop inside the digester due to the channels between the wood chips. When there are mostly large chips, the channels between the chips are large, with low pressure drop for fluid flowing in-between. When there are a major amount of fine pins etc, the channels will decrease, and the pressure drop increase. This is what happens in reality if we have different chip size distribution or different packing in the digester. One reason for this may be that the chip size distribution is inhomogeneous or the chip screw in the stack may not feed in a constant way. When it moves up and down the density may be different as it is to switch direction. When we have a lot of flakes these may adhere to the screens and cause hang ups. Aside of causing an increased pressure drop in the screens, also the chips will get different residence times and contact with liquors of different concentration of both chemicals and dissolved organics. This may cause a significant variation in kappa number of the final fibers. By identifying pressure drops, residual concentration of chemicals in the liquors, temperatures and flows and compare actual results to those predicted by the model, we can tune the model to match reality. This is under assumption first of good process performance.

Multipurpose use of the model

MPC (production optimization on-line)

3dMPC controller is intended for multivariable feedback control and optimization of an industrial process that has many input and output signals. Inputs are sensor measurements of manipulated variables affecting actuators, and outputs are process variable set points. For processes like pulp production with strong interaction between different signals this technique can offer substantial performance improvement compared with traditional singel-input singel-output control strategies. By using MPC instead of traditional PID to control a bark boiler a pulp mill decreased the NOx from a bark boiler by 50% (Dahlquist et al.2001)

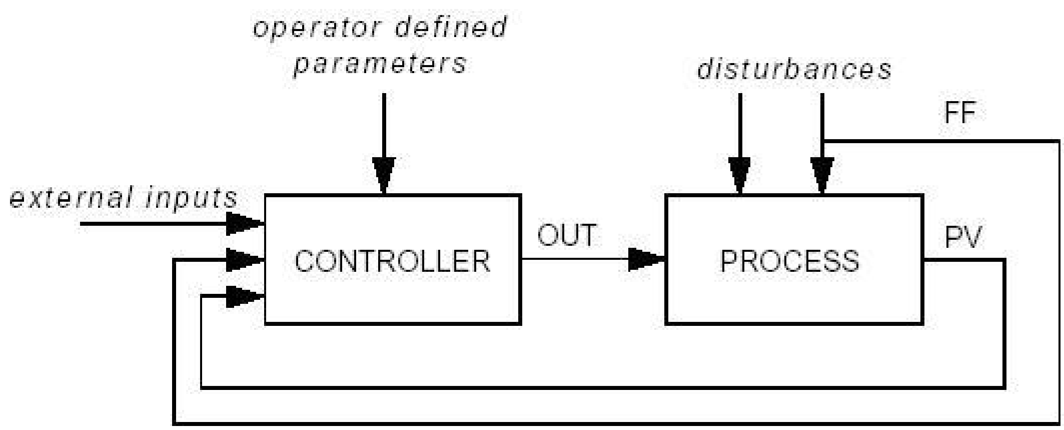

Figure 1 Feedback control system.

The controller determines the manipulated outputs, OUT, based on actual measurement of process variables, PV, and feed forward signals, FF, and of operator defined parameters, and external inputs. The process variables can be assigned set-points that the target for the feedback control law. The feed forward signals are measurable disturbances acting on the process that can be used for feed forward.
It is to prefer a model of lower order, because a system with many inputs and outputs can easily end up with hundreds or even thousands of state variables (Morari et al , 2000). To avoid this we have made some assumptions

- Chips are well-steamed (it means that there are no extractives in addition to lignin and carbohydrate) and fully penetrated with the white liquor before entering the digester;
- Both chips and liquor in the digester move as plug flow;
- The volume of the individual chips remains unchanged during the digestion;
- The digester is adiabatic;
- The wood chip is isothermal;
- The free liquor is homogenous;

- Radial gradients in temperature and concentration within phases can be ignored;
- Chip pressure and flow resistance are isotropic;
- Inertial forces can be neglected.

It is important that you do not simplify the models too much. The model must be so close to the real process as possible but still a useful model for control and optimization must calculate fast and give values with a reasonable accuracy. The result of the cook in the digester is measured by the kappa number. The kappa number is controlled by the temperature, residence time and the concentration of the cooking chemicals. The equations that are used in the digester section model are in principle the same that are used and described in (Wisnewski et al 1997) with respect to the chemical reaction, although we have complemented the hydraulics taking into account also pressure flow aspects. The Kappa number is the most important quality variable and is described by:

$$Kappa = \frac{Z_{c,I_{lig1}}^{out} + Z_{c,I_{lig2}}^{out}}{0.00153 \sum_{i=1}^{n_w} Z_{c,i}^{out}}$$

The most important variables that control the kappa number is the residence time, reaction rate and diffusion rate. The residence time is controlled by the production rate. The reaction rate and the diffusion rate are controlled by temperature and concentration of chemicals in the wood chip entrained liquor (e.g. Aguiar et al 1998, Dahlquist, Shuman et al 2001) and is described by:

$$R_i = -(A_i e^{-\frac{E_i}{RT_c^{out}}} Z_{c,I_{OH}}^{out} + A_{n_w+i} e^{-\frac{E_{n_w+i}}{RT_c^{out}}} Z_{c,I_{OH}}^{out\,\frac{1}{2}} Z_{c,I_{HS}}^{out\,\frac{1}{2}})(Z_{c,i}^{out} - Z_{w,i}^{0}) \frac{\rho_c{}^2 V_c}{\varepsilon}$$

$$i = 1, \cdots, n_w$$

$$R_D = \lambda_m \sqrt{T_c^{out}}\, e^{-\frac{4870}{RT_c^{out}}} V_{el}$$

From the physical model and an optimization algorithm set points for the different circulation and control loops are determined, and implemented. So far we have tested this in a simulation environment, but hope to get a real application to test on soon as well. Still, we have used real digester data for the tuning of the model parameters and verification of the digester performance.

Diagnostics (hang ups and channeling)

In this example we have simulated a clogging in the lower heater screen. The simulation has been scheduled in the following way: after one hour the open screen area will start to decrease in size. The area is decreasing slowly during five hours. After five hours the open area will jump back to the original open area (back flushing cleans the screen). The extraction flow out of the screen is described by:

$$0 = v_l - \frac{\phi F_l^{out}}{(1-\eta) A \rho_l}$$

The constrains are ($i = 1, \cdots, n_w$) Index, "R_D" Diffusion rate, "R_i" Reaction rate, "$Z_{w,i}^0$" Mass fraction, "λ_m"Mass transfer coefficient, "T" Temperature, "V" Volume, "ρ" is density, "ε" Porosity, "E" Holdup energy, "v_l" Velocity, "η" Compaction, "F" Flowrate, "ϕ" Flow direction.

When the open area is decreasing (see fig2), the extraction flow through the screen will also decrease and give an increasing free liquor flow rate inside the digester (fig3). The changes in the circulation flow will influence the temperature profile inside the digester and is seen in fig4. The disturbance in the circulation will in the end have an effect on the quality seen as the kappa number in fig5 and yield changes as well in proportion to this.

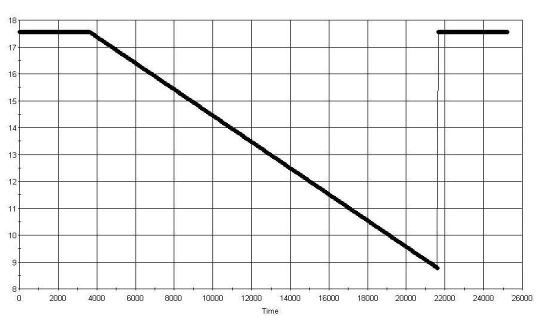

Figure 2: Open area in screen.

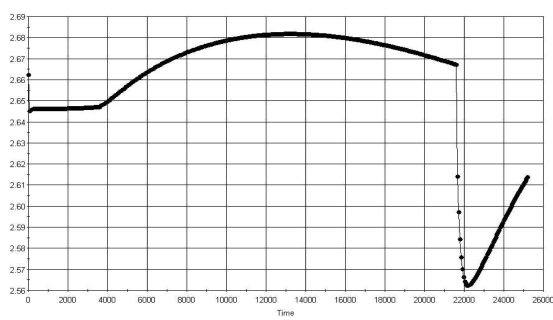

Figure 3: Inside free liquor flow.

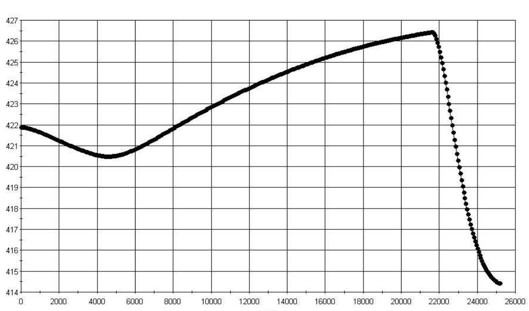

Figure 4: temperature profile.

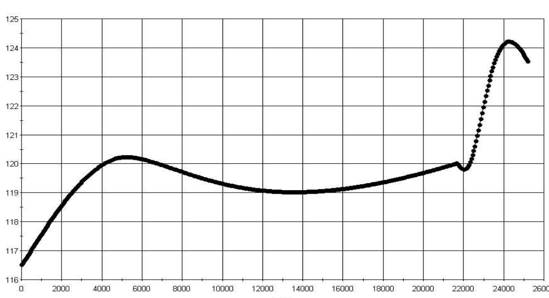

Figure 5: Kappa number.

The model then can be used later on both to optimize the performance of the digester by adjusting e.g. temperature and chemicals dosage, as well as back flushing screens to avoid hang ups before the problems become severe. There is also a potential of finding channeling to have a chance to go in and adjust, although this demands regularly measurements as well. The channeling is determined by adding the cross flow behavior in the digester model, going from 1-D to 2-D. The results from this will be presented later, but the results were not finalized when the paper was written, unfortunately. Still we have seen that channeling can be determined also by looking at the variation in kappa number if measured on-line. The standard deviation will increase when channeling occurs. By the model we hope to be able to quantify this as a tool to support the operator in his analysis. Also temperature, white liquor concentration and other factors will be varying, and together a useful tool can be achieved.

Scheduling and planning (what ifs)

The model can also be used for "what if scenario testing". This means that you can set a ramp or "event" at a certain time and then see what the result will be with respect to economy, quality etc for different input data sets. This can be a very good support for the operators. The tool can also be used to determine how different problems should show up in different measured variables. This information then can be used in a diagnostic system of more general character, as well as in a decision support system for the operators.

Mill optimization

Pulp mill balances

The next level of optimization is to control the chemical balance in a complex pulp mill. The first application is an example to control the Sulfur balance in an integrated Kraft and NSSC (Neutral Sulfite) pulp mill. It is important to adjust the dosage of sulfur, so that there is enough but not too much, and to keep the balance between different parts of the plant.(Persson U., et al 2003). The goals are to minimize variation in:

- sulfidity
- cost of sodium hydroxide and sulfur usage
- production losses due to up and down stream disturbances
- variation in sodium stock
- variation of the distribution of sodium between white and black liquor

This has been done by doing relatively simple physical models that have been combined to form a model. The main process units are the tanks and vessels, where buffering can take place. Between these units there are streams with a total flow as well as the composition of the streams with respect to concentration of fiber, dissolved organic solids, hydroxide, sulfide, carbonate, sulfate and sulfur.

The production units contain an expression between inflow (F_{in}) and outflow (F_{out}), as well as the time delay. For the tanks this is described by:

$dM/dt = F_{in} - F_{out}$

and

$dC_{out}/dt = F_{in}/M\ (C_{in} - C_{out})$

Here M is total Mass in the tank and C_{in} respectively C_{out} are the concentrations of the streams going in respectively out of the tank.

The coupling between the process model and the measurements is done by connecting with a sensor model. The measurement observations y(t) to the state x(t) is modeled as

$Y(t) = G[x(t),t] + \upsilon(t)$

Where measurement uncertainty is captured in $\upsilon(t)$ and $G[x(t),t]$ is the predicted sensor reading. The equations are discretized before used both for state estimation and optimization of the future operations. For the state estimation the moving horizon estimation (MHE) is used. By this method inequality constraints and non-linear dynamics can be included relatively simple.

The production planning problem is formulated as principally a MPC problem (Model Predictive Control). It is solved after transferring into the following problem:

$$\mathrm{Min}\Big[\sum_{K=1}^{N} \Big(q_{a,k}\,(y_k - y_{k,sp})^2 + q_{b,k}\,(x_k - x_{k,sp})^2 + q_{b,k}\,(u_k - u_{k,sp})^2 + \delta_k\,(u_{k+1} - u_k)^2$$
$$+ r_k x_k + p\Big(\sum_{j=1}^{J} V_j \rho_j x_{j,k} - M_{k,sp}\Big)^2 \Big) + s\Big(M_{sp} - \sum_{k=1}^{N} x_k\Big)^2 \Big]$$

The constraints are (k= 1,…,N). Index “sp” denotes set point. “x” denotes state variables, “u” manipulated variables, “y” sensor values. “ρ” is density, “V” volume, “M” the mass in the tank. The constraints are given as:

$F[x_{k+1}, x_k, u_k, k] = 0$	(process model)
$y_k = g[x_k, k]$	(sensor model)
$a_k <= x_k <= b_k$	(upper and lower bounds on state variables)
$c_k <= u_k <= d_k$	(upper and lower bounds on manipulated variables)
$y_{min} <= y_k <= y_{max}$	(maximum and minimum sensor values)
$e_k <= u_k - u_{k-1} <= h_k$	(upper and lower bounds on gradients of manipulated variables)
$x_0 = X_0$	(initial state value from state estimation)
$u_0 = U_0$	(initial manipulated value from state estimation)

A network with all units and stream is generated to form the model. This model is then used together with a commercial solver, to make a production plan for keeping the sulfur balance at it´s optimum. Set-points for each time step is calculated.

In parallel to the optimization a simulation is performed with the state estimates together with running at the current planning strategy. The time until a “crash” indicates how good the strategy is, and for how long it is possible to run with these old set points.

Implementation is being done right now at a mill in Sweden (Billerud at Grums). The software was started up at the end of June. The model is tuned with real plant data. The model is now being validated, and the goals that were set seem to be fulfilled.

Example of paper mill optimization

There are also other alternatives to dynamic optimization of production. What was mentioned above is a way of integrating the process model in the optimization objective function and the constraint.

In another example (Dhak J. et al 2004) the max and min levels in the tanks were handled directly as constraints instead.

Another alternative is to have a simplified optimization model, which is used for keeping control over storage volumes, what number of refiners to run at a certain time step etc, but to test the plan in a simulator before implementing. The interaction between the optimizer and the simulator will make it possible to determine if the optimization schedule is possible to implement in reality, as it contains all necessary information for all tanks, reactors etc, which may be far outside what can be handled by the optimization solver. This we can call an implicit dynamic optimization.

Examples of this dynamic optimization can be keeping control of a storage tank feeding a paper machine, and how to start and shut down refiners feeding this. Another example can be to control the water balance of a paper mill, or quality parameters like sizing, paper strength etc.

Conclusions:

There are many possibilities to use physical models directly or in combination with statistical models for multipurpose use. Applications can be for diagnostics, like detection of hang ups and channeling in digesters, and for optimization, MPC and as decision support to operators.

Examples have been shown and verifications done towards real process data.

In the future physical models can be expected to be used in these applications, to increase the production volume and quality.

References:

Aguiar H.C and Filho R.M : Modeling and optimization of pulp and paper processes using neural networks. Computers chem. Engineering Vol 22,suppl. Pp S981-S984, 1998.

Bhartiya , Dufour and Doyle (2001) : Thermal- Hydraulic modeling of a continuous pulp digester, in proceedings from Conference on Digester modeling in Annapolis, June, 2001.

Dahlquist E. ,Lindberg T., Karlsson C, Weidl G, Bigaran C and Davey A: Integrated process control, fault diagnostics, process optimization and production planning – Industrial IT,Paper for 4th IFAC Workshop on ON_LINE FAULT DETECTION AND SUPERVISION IN THE CHEMICAL PROCESS INDUSTRIES, June 8-9, 2001, Seoul, Korea

Dahlquist E., Shuman L,Horton R, Hagelqvist L : Economic Benefits of Advanced Digester Control.. Paper presented at Digester Modeling workshop in Annapolis,US, June 28, 2001

Dhak J., Dahlquist E., Holmström K., Ruiz J., Belle J.: Developing a Generic Method for Paper Mill Optimization. Paper submitted for Control Systems 2004 in Quebec City, June 14-17.

Morari M.,Lee J. and Garcia C: Model Predictive Control, Book at Prentice Hall, Englewoods Cliffs, (2000)

Persson U., Ledung L., Lindberg T., Pettersson J., Sahlin P-O and Lindberg Å: "On-line Optimization of Pulp & Paper Production", in proceedings from TAPPI conference in Atlanta, 2003.

Wisnewski P.A, Doyle F.J and Kayihan F.: Fundamental continuous pulp digester model for simulation and control. AIChE Journal Vol 43, no 12, dec 1997, pp 3175-3192.