Paper VIII

Pajula, E., Tienari, M., Studying broke tank averaging level control with stochastic simulator, *Proceedings of the Control systems 2006 Conference*, ed. R. Ritala, Tampere University of Technology, Tampere 2006, pp. 43-48.

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STUDYING BROKE TANK AVERAGING LEVEL CONTROL WITH STOCHASTIC SIMULATOR

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ABSTRACT

Controlling broke tank level has strong effect on wet end stability at a paper machine. Nowadays the broke tank level is often controlled manually of by a single PI controller and the stochastic nature of the inflow disturbances are not taken into account. In this averaging level control problem the fluctuations in the outflow need to be minimized while keeping the tank level within acceptable limits. A stochastic simulator has been developed; the stochastic features are included as run time and break time distributions. In this paper non-linear P controller performance and its tuning are studied with stochastic simulator and compared to real mill data. The criteria defining the goodness of alternatives in the optimisation cost function were discussed; these criteria are case specific and strongly affected by the downstream processes.

1. INTRODUCTION

Currently with advanced machine speeds and printing technologies the uniform paper quality has become more and more important, therefore the stochastic disturbances caused by the broke tank inflow to paper machine wet end affecting the paper quality need to be carefully minimized. Nowadays the broke tank level is usually controlled manually by the operators or by single feed back controller that tries to keep the level at its setpoint. However, the inflow varies greatly. During breaks the flow may be over 20 times the normal flow, but the outflow from the broke tank should change as smoothly as possible in order to not disturb the wet end conditions while keeping the tank level within acceptable limits. Because the occurrence of single break is impossible to predict, statistical analysis is useful when comparing the process behaviour with different control schemes. Controlling this stochastic disturbance optimally requires process knowledge and careful tuning and selection of controller. So far broke tank level control problem has been widely studied, a recent review is found in /1/, but stochastic simulators have not been utilized in selecting the optimal control strategy, only for defining the hard constraints for broke tank outflow maximum value and maximum change /2/.

The controller selected to the case example was non-linear P controller. It was found interesting because the setpoint offset has minor importance compared to the outflow smoothness. This kind of approach has been studied by Kelly /3/ and Foley /4/ with PI controller and liquid surge drum level process.

The paper is organized as follows. First the data analysis creating the bases for stochastic simulations is described in detail and the factors affecting cost function selection are discussed. Next the NLP controller is described and finally a case study analysing the effect of different grade on the tuning is presented.

2 STOCHASTIC SIMULATOR

2.1 Background

Predicting exact occurrence and duration of a single break is impossible or extremely difficult. However, nowadays data from the process is collected and stored automatically to history databases. Statistical analysis can be made using this readily available data and include the stochastic features to a simulator. Another reason to use simulators is that they visualize the results well, and chances in process parameters can be made easily in the model, which increases the user acceptance at the mills. As mentioned by Ogawa /2/ the process time constant is very big compared to the valve operation etc., so they can be safely neglected and the problem simplified.

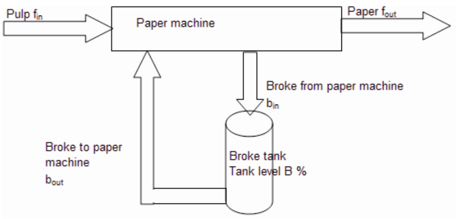

Figure 1. Case process

The data for the background study for the example application (Figure 1) was collected from a mill for a period of one year with the sampling rate of 1 minute. During this period seven different grades were produced, and the grades with at least 125 runs (machine running between breaks and grade changes) were included in the analysis. The number of runs analysed was 1350. The histograms of the run times and break durations for one grade are presented in Figure 2 and Figure 3.

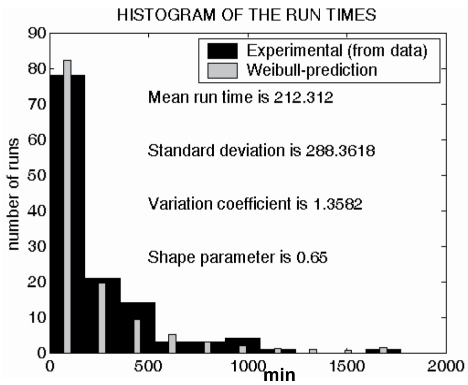

Figure 2. Histogram of run times

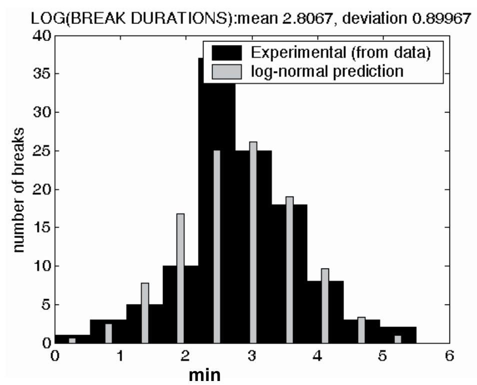

Figure 3. Histogram of break durations

2.2 Run time and break duration distributions

Different distributions were considered. In the literature exponential distributions were fitted for run time and break length distributions with varying degree of success (/2/, /5/). Based on our current data Weibull distribution fits for run time distribution surprisingly well with shape parameter less than 1 (Table 1). This supports the general opinion at the mills that the probability of breaks decreases when the machine has been running longer time without any breaks because the chemical equilibrium is not being disturbed by changes in broke flow to the process or other changes. The χ^2 tests, Table 1, show that different grades could be described using only few different parameter sets in the Weibull distribution.

For stochastic simulator, a suitable break length distribution is needed. In Ogawa's study /2/ break signal followed exponential distribution, but with our data none of the tested distributions (normal, Weibull and exponential distribution) passed the chi-squared test. Because for simulation purposes a break length distribution was needed and the log normal distribution visual fit was satisfactory, log normal distribution with grade independent parameters was included into the simulator, Table 2 and Figure 3 (see /7/ for the definition of the Weibull and log-normal distributions).

Table 1. Grade specific run time distributions and chi square test

Grade	Weibull parameters, 95% confidence intervals	Chi square test	Number of runs	Grade	Weibull parameters, 95% confidence intervals	Chi square test	Number of runs
1	$\eta = 0.600 \pm 0.073$ $\sigma = 195.803 \pm 32.342$	$\chi^2 =$ 9.9308 P = 0.1925	N=212	3	$\eta = 0.650 \pm 0.114$ $\sigma = 158.521 \pm 33.647$	$\chi2 =$ 12.1873 P = 0.0946	N=125
Grade 2	$\eta = 0.615 \pm 0.049$ $\sigma = 205.041 \pm 21.414$	$\chi^2 =$ 17.1465 P = 0.0165	N=491	4	$\eta = 0.705 \pm 0.056$ $\sigma = 282.080 \pm 25.856$	$\chi2 =$ 12.6388 P = 0.0814	N= 523

Table 2. Grade specific break length distributions

Grade	Average break length and standard deviation	Log normal parameters	Grade	Average break length and standard deviation	Log normal parameters
1	$\mu = 58.621$ $\sigma = 192.274$	$\mu = 2.882$ $\sigma = 1.161$	3	$\mu = 25.545$ $\sigma = 33.546$	$\mu = 2.807$ $\sigma = 0.900$
2	$\mu = 72.323$ $\sigma = 504.028$	$\mu = 2.901$ $\sigma = 1.084$	4	$\mu = 55.622$ $\sigma = 367.694$	$\mu = 2.861$ $\sigma = 1.073$

2.3 The stochastic simulator

Since run time signals for different grades follow the Weibull distribution with different parameters, it makes sense to build a stochastic simulator for the case process. This kind of simulator provides a platform that helps to find optimal control parameters for the broke feed for each grade. All the flows are calculated based on dry substance and maximum change in b_{out} is defined as 5 % of fiber flow to the process in an hour.

Mass balance of the simulated process is

$$\begin{cases} \frac{dB}{dt}\frac{cV}{100} = b_{in} - b_{out} \\ b_{in} = \begin{cases} f_{trim}, \text{machine is running} \\ f_{in}, \text{break is on} \end{cases} \\ f_{out} + b_{in} = f_{in} + b_{out} \\ b_{out} = F(B) \end{cases} \tag{1}$$

where

V = volume of the broke tank, m^3
c = broke tank consistency tn/m^3, constant
B = tank level %
b_{in} = flow to the broke tank tn/h
b_{out} = flow from the broke tank tn/h
f_{in} = fiber flow to the process tn/h
f_{out} = fiber flow from the process (paper) tn/h
f_{trim} = trim broke tn/h
F = the control strategy depending on the tank level and control parameters

The time axis is discretized and at each time point the status of the machine is updated (i.e. break or running) to make the run and break signals follow the specified distributions. The implementation utilizes the analytical form of the hazard function associated to Weibull distribution.

2.4 Cost factors

The task of broke tank is to prevent the stochastic changes in feed flow from disturbing the process conditions in the paper machine wet end. Therefore following the broke tank level set point is not alone useful criteria in the broke tank level control. The outflow from the broke tank should change as smoothly as possible so that the amount of fibres in the broke tank remains constant and no extra fluctuations are created. On the other hand the tank should be run rather empty during normal operation to avoid overflows when breaks occur. How smoothly the changes need to be made depends strongly on the downstream processes and their control, are they able to compensate some changes and how fast they react. The smoothness requirements can be included in the simulator by defining how often control actions can be made and how big changes are allowed in the outflow from the storage tank. On the other hand penalties for running the tank empty or overflow are also needed to.

The stochastic properties, e.g. standard deviation can be used in describing the smoothness. For instance, when the production plan has been defined the stochastic simulator can be run for thousand times and the standard deviation of the tank outflow and level can be calculated at each time point or for each simulation.

3. CASE STUDY: NON-LINEAR P CONTROLLER

In the simulator only dry mass flow has been calculated, the results have been calculated with assumed water content of 3%. The amount of trim break has been assumed to be 5 % of the total fibre flow. The grades used in our example are defined with Weibull parameters

Grade A: $\eta = 1$, $\sigma = 180$

Grade B: $\eta = 0.6$, $\sigma = 120$

With both grades the average run time is 3 hours and the parameters for log-normal break length distribution are $\mu = 2.35$ and $\sigma = 0.35$. These parameters give average break length 10 minutes which is realistic when shut-downs etc. are excluded from the mill data.

3.1 Non-linear P controller

The simulator uses nonlinear P controller where the controller gain depends on the operating point, so that the flow out from the broke tank is calculated as:

$$b_{out} = \left(b_{out}^{(\min)} + \frac{B - B^{(\min)}}{B^{(\max)} - B^{(\min)}} \left(b_{out}^{(\max)} - b_{out}^{(\min)} \right) \right) \frac{f_{in}}{100} \tag{3}$$

where

$b_{out}^{(\max)} \in [11\ 30]$ % of total fibers

$b_{out}^{(\min)} \in [1\ 10]$ % of total fibers

$B_{out}^{(\min)} = 20$ % tank level

$B_{out}^{(\max)} = 80$ % tank level

B = broke tank level, %

b_{out} = flow out from the broke tank (tn/h)

Because the actual tank level has minor importance as far as no overflows occur, it is obvious that bigger control actions can be allowed near upper and lower limits. The minimum and maximum values of $B_{out}^{(\min)}$ and $B_{out}^{(\max)}$ were defined a priori based on general process knowledge.

3.2 Tuning the NLP controller with stochastic simulator

To tune the control parameters $b_{out}^{(\min)}$ and $b_{out}^{(\max)}$, the stochastic simulator is run 10000 times with all allowed parameter combinations. Simulation time horizon was chosen to 1000 minutes for convenience. Since the initial tank level has strong effect on the probability of overflow, simulations with two different initial tank levels (20% and 80 %) are calculated. The aim is to minimize variation of the broke feed while keeping the joint probability of running empty or full under 1 % (i.e. 100 times of 10000).

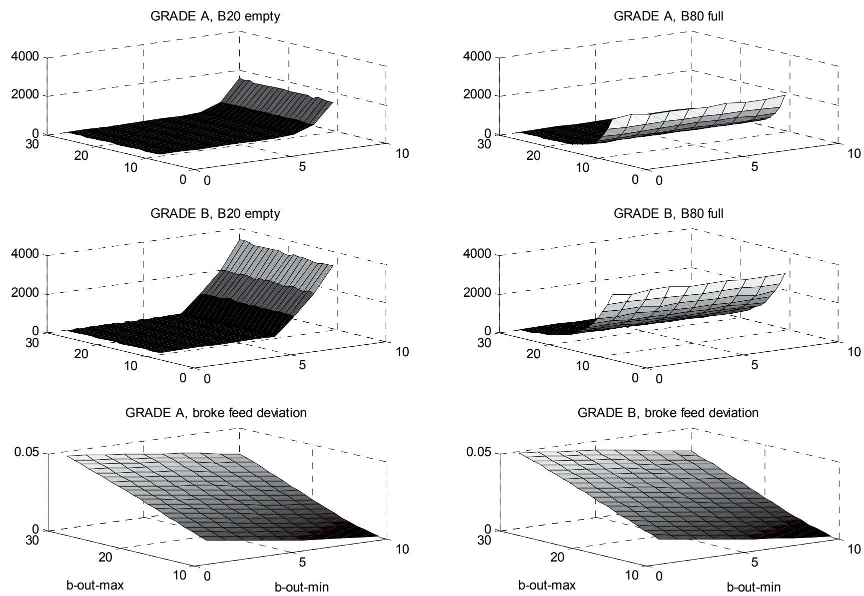

Figure 4. The number of simulation runs where tank constraints are violated and deviation of broke feed as function of control parameters $b_{out}^{(\min)}$ and $b_{out}^{(\max)}$**.** Total number of simulations was 10000.

In Figure 4 the effect of control parameters on probability of running the broke tank empty or full from initial tank levels 20% and 80% are demonstrated together with broke feed deviation. The optimum is found for grade A with $b_{out}^{(\min)} = 7$ and $b_{out}^{(\max)} = 18$ while for grade B with $b_{out}^{(\min)} = 7$ and $b_{out}^{(\max)} = 26$ %. This result is natural since grade B, having a lower shape factor, is more unstable in the beginning of a run. To overcome this, higher $b_{out}^{(\max)}$ is needed to decrease tank overflowing probability.

To compare the with real mill data, the simulator was run with real break signal and two sets of control parameters:

- the optimum $[b_{out}^{(\min)}, b_{out}^{(\max)}, B_{out}^{(\min)}, B_{out}^{(\max)}] = [7\ 18\ 20\ 80]$
- alternative control strategy $[b_{out}^{(\min)}, b_{out}^{(\max)}, B_{out}^{(\min)}, B_{out}^{(\max)}] = [5\ 10\ 10\ 90]$

The break signal, resulting broke tank level and broke feed are presented in Figure 5-6. The optimal control produces broke feed with less variation that in the mill data. Alternative control strategy produces even smoother broke feed but simulation reveals that the probability of tank overflow is 3% for grade A and 10% for grade B when initial tank volume is 50%.

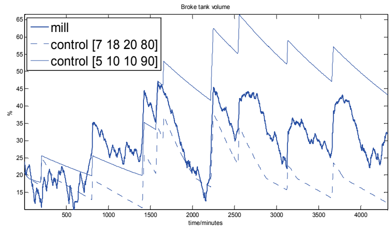

Figure 5. Broke tank volume, mill data

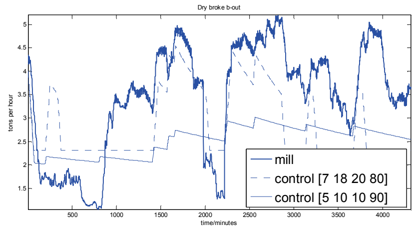

Figure 6. Broke flow to paper machine

4. CONCLUSIONS

In this work a realistic environment for comparing different control strategies when stochastic disturbances occur was created. Non-linear P control algorithm was tested and utilizable controller tuning was found. The effect of stochastic distributions fitted and selection of the distribution were also studied and it was found out that grade dependencies should not be neglected. The stochastic simulator using grade dependent Weibull distribution for run times and grade independent log normal distribution for break times was programmed with MATLAB. This approach made it possible to simulate realistic stochastic features of the process in reasonable time. The best choice is selected based on the downstream process requirements, and compared to the mill data optimal NLP control provided smoother control than current situation. The presented approach provides a platform for more rigorous control studies.

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