A TOOLSET FOR SUPPORTING CONTINUOUS DECISION MAKING CASE: GRADE CHANGE OPTIMIZATION

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ABSTRACT

The production processes are becoming increasingly complex and the responsibilities of the operators and the engineers are widening. Tools to manage this complexity under dynamic conditions are needed. The dynamic optimization integrated to operator and engineer decision support has a high potential in everyday use. As a result of an EU Commission funded research project a toolset for supporting continuous decision making has been developed. This paper presents a case study, where this toolset is used to reduce grade change time on a paper machine. *Copyright © 2005 IFAC*

KEY WORDS: decision support system, simulation, optimization

1. INTRODUCTION

The main objective of the paper machine staff is to maintain acceptable machine runnability. In practice this means high utilization degree and machine speed as well as meeting high quality requirements. The paper is usually produced on order, and thus frequent grade changes are inevitable. The time spent in grade changes must be minimized in order to maximize the production time and minimize the costs. An important constraint for the grade change operation is to avoid web breaks due to fluctuations in key variables during the grade change.

The minimization of the grade change time while avoiding web breaks forms a challenging optimization problem. In this paper the objective function for optimization is formulated, and evaluated through running dynamic simulation. As the optimizer may need hundreds or thousands of iterations to reach the optimal solution, the simulation time in practical applications has to be as short as possible.

The optimization is done with the toolset developed in an EU Commission funded research project "DOTS" (G1RD – CT – 2002 – 00755). The present implementation of toolset is within Matlab which is easy to bring to mill environments either as a full system, or as embedded in other systems, e.g. the process analysis system KCL-WEDGE (KCL, 2004). The DOTS toolset offers inbuilt stochastic optimization methods and utilizes Tomlab environment (Holmström, 2004) as an external optimizer. In this paper we present the test the Sequential Quadratic Programming (SQP) method provided by the Matlab Optimization Toolbox in comparison with the stochastic methods offered by the DOTS Toolset. The objective functions are kept unaltered so that the results shown are comparable.

In this paper the first two chapters describe the case, the simulation model and the set up of the optimization. The third chapter presents the results of the optimization and the final chapter summarizes the experiences and the results.

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2. THE SIMULATION MODEL

When the model is driven by the optimizer, the response time of the simulation is essential. All extra features like displays and irrelevant outputs are removed. The model is parsimonious in that it captures only the features relevant for a realistic grade change, and nothing else. The parameterization of the model must be done so that the optimizer can run the model. The problem formulation sets requirements for the simulation model (Pulkkinen, et al., 2004). The inputs and outputs must be chosen and communicated correctly to get the information the optimizer requires.

The paper machine simulator developed is a combination of blocks based on the basic elements of a paper machine: tanks, valves and controllers (Pulkkinen, et al., 2003). The basic idea of the simulation has been to formulate a simplified model of what happens in a paper machine when a grade change is made. The main attention has been focused on the examination of the quality variables of the end product.

Figure 1 presents the simulation model. The simulator can be divided in three main elements: short circulation including the wire section, the press section and the drier section. In real life the optimal operation of the short circulation including wet end chemistry has been ranked to be one of the hardest challenges of the papermaking process. In the simulator the simplified short circulation model consists of the machine tank, wire section and the white water tank. The accuracy of parameters required is not high because of the nature of simulator use.

The flow of material has been divided into four categories in the simulator: the flow components are water, filler and both short and long fibers. The retention at wire section is taken into account by applying component-specific, yet constant in time, retention coefficients. The main emphasis is put on the fiber, filler and water flow after each block of the simulator.

The basic tank dynamics is that of ideally mixed one. Therefore the dynamics is added to the model as first order transfer functions. The dynamics of the stock feeding is expressed with the transfer function $G_1 = (1 + 20s)^{-1}e^{-20s}$. Transfer function $G_2 = (1 + 120s)^{-1}$ is used to express wire pit dynamics. The two transfer functions form the model of the dynamics of the short circulation.

A PI-controller has been used to control the filler content and the basis weight. It is well known that these variables are dependent on each other and this statically decoupled in the controller.

The press and drier blocks only increase the dry content. The delay caused by the dryer section can be calculated knowing the machine speed and the web length. The dynamics of the drier section is modeled with simplified thermodynamics of the heating cylinders.

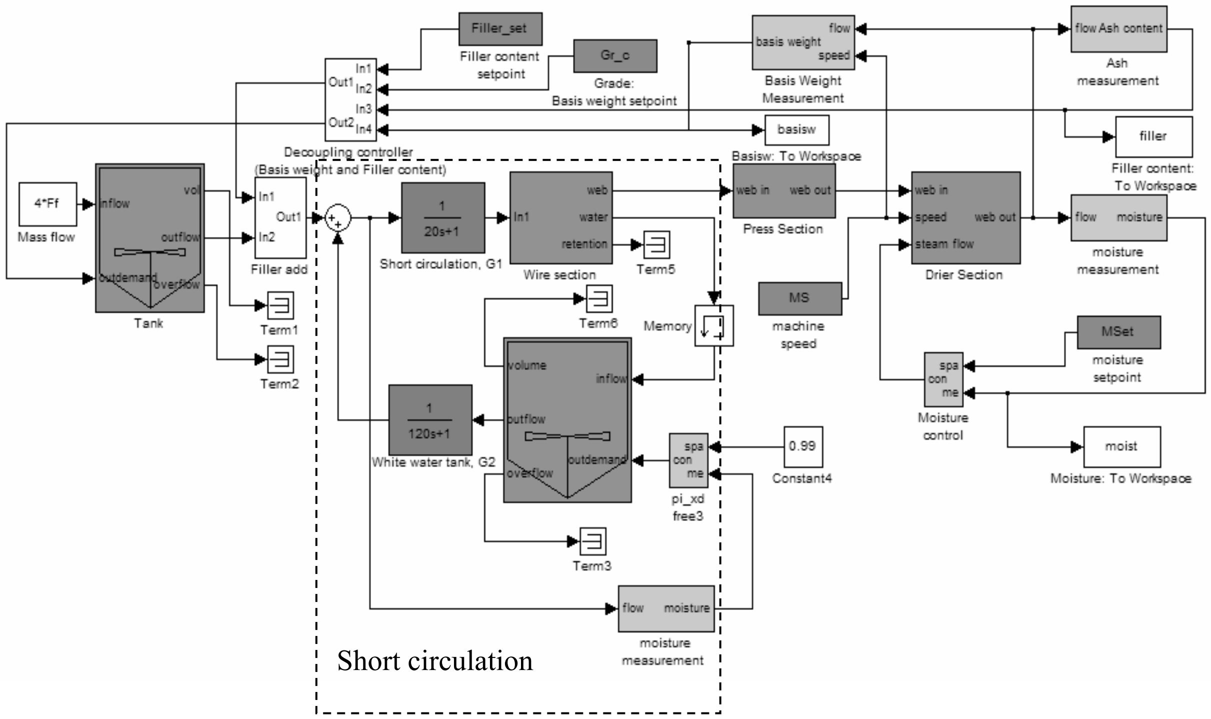

Fig. 1. The Simulink model for the paper machine.

3. COST FUNCTION AND PARAMETRIZATION OF SETPOINT TRAJECTORIES

When changing to a grade with higher basis weight the moisture of the paper produced increases if no action is made on the dryer section. Even with moisture control on at constant setpoint, there is a momentary increase in moisture, as the heating of the dryers is slower than the dynamics of fiber retention. An opposite variation happens during a change to a grade with smaller basis weight. The former case is used as an example in this paper. The idea of the optimization of the grade change is to minimize the fluctuation of the moisture as well as the fluctuations of basis weight and filler content.

The combination of control actions that results in smallest cost value is the answer to our optimization problem. The total cost in this case is a sum of the costs calculated for each key variable: moisture content, basis weight and filler content. Here the cost is calculated by squaring the variation from the grade-specific setpoint and integrating over the duration of the grade change. In practice the variance is minimized while the expected values are changed. This approach has been used in the following examples due to the better success in optimization.

The overall cost can be expressed as

$$C = M \cdot \text{cost}_{moist} + B \cdot \text{cost}_{bw} + F \cdot \text{cost}_{filler}, \tag{1}$$

where M, B and C are weighing factors with a relation 1:1.7:0.08. The cost caused by the variations in each quality variable is quadratic

$$\text{cost}_{\text{variable}} = \sum_{i=n_1}^{n_2} \left[x_i - x_{target_i} \right]^2, \tag{2}$$

where x is trajectory of the variable and x_{target} is the grade-dependent target for the variable. n_1 and n_2 represent the selected start and end times of the cost calculation.

An alternative approach of cost calculation is as follows. The cost is zero when the quality is within grade-specific quality requirements and a positive constant when the quality is not within the specifications ("quality pipe"). Hence the minimum cost is reached when the time that quality variables are outside the quality pipe is minimized.

In order to find a minimum cost we are seeking optimal setpoint trajectories. This leaves us with infinite choices: the trajectories as functions of time. It is however justified to simplify the optimization task by parametrizing the trajectories appropriately.

In practice, a step down and up again is parameterized into the moisture set point time series. The optimization algorithm is used for finding the optimum for the three parameters: the two timing parameters and the step size.

The timing of the grade change is fixed, so the trajectory can be formed knowing one constant parameter. The last parameter needed is the one for filler content. The change in filler content is stepwise and its size fixed, again only the timing parameter is needed. The parameterization reduces the search space down to four dimensions.

The parameters that need to be evaluated are shown in Table 1. The initial values are given for each optimized variable and the timing of the grade change is a constant. The optimization algorithm then finds the combination of values of the variables that result in the least cost.

Table 1 The evaluated parameters of the simulator

Parameter	***Type***	***Range***
Grade change, timing (Gc) (= time of setpoint change of basis weight)	Fixed	Gc
Filler content, timing	Optimized	Gc +/- 100
Moisture setpoint, step size	Optimized	0.01-0.05
Moisture setpoint, 1st timing parameter (down)	Optimized	Gc +/- 100
Moisture setpoint, 2nd timing parameter (up)	Optimized	Gc +/- 100

4. OPTIMIZATION

DOTS toolset offers an easy-to-use configuration for the dynamic optimization problems. In this paper stochastic methods have been used from the portfolio of optimization methods in the toolset. The parameters of the problem and the algorithm are specified through a graphical user interface in Matlab environment.

It is known that the algorithm performance is case dependent. We will show that choosing an algorithm plays an important role in starting with a new optimization problem (Dhak, et al., 2004). The minimum of the smooth quadratic cost function can be found by almost any optimization algorithm, which is also shown in (Ihalainen and Ritala, 1996). In this case the cost function is more complicated and differences in performance can be shown.

The optimization process was repeated using the stochastic methods in the DOTS Toolset and the SQP in Matlab Optimization Toolbox while the objective was kept the same.

Perhaps the simplest way of optimizing is a **blind random search** of right parameters. The parameter combination with best found cost is then selected.

Genetic algorithms (Goldberg, 1989) consist of following steps:
1) [Start] A random population of *n* chromosomes is generated
2) [Fitness] the fitness of each chromosome in the population is evaluated
3) [New population] a new population is created by repeating following steps until the new population is complete
   a. [Selection] two parent chromosomes from a population are selected according to their fitness
   b. [Crossover] the parents are crossed over with a certain crossover probability to form new offspring
   c. [Mutation] new offspring is mutated with a certain mutation probability
   d. [Accepting] new offspring is placed in the new population
4) [Replace] generated population is used for a further run of the algorithm
5) [Test] If the end condition is satisfied, the optimization is topped, otherwise the loop continues from the step 2

The idea of the **simulated annealing algorithm** (Otten and van Ginneken, 1989) is described with following steps:
1) a feasible set of movements is generated randomly
2) the standard deviation of the cost function values in the feasible set is estimated and the estimate as a starting temperature T is chosen
3) steps 3-6 are iterated *n* times
4) a feasible new point according to the previous procedure is chosen
5) the new point is accepted as a current point certainly if $\Delta C<0$ and with probability of: $\exp(-\Delta C / T)$ if $\Delta C>0$, where ΔC is the difference of cost function values beteen the new point and previous point
6) If the new point is the overall best found so far, the best point is updated
7) the temperature is reduced by $0.01*T^2 / \sigma$, where σ is the estimate of the standard deviation over the previous iteration path
8) If the best score has not improved during the last 50 iteration paths, the optimization is stopped; otherwise continued from the step 3

Tabu Search is also an iterative stochastic procedure designed for solving optimization problems. Tabu Search keeps a list of previously found solutions so that re-finding solutions in subsequent iterations is prevented. **SQP,** the sequential quadratic programming method, is a smooth nonlinear optimization method. It is a generalization of Newton's method for unconstrained optimization in that it finds a step away from the current point by minimizing a quadratic model of the problem. In its purest form, the SQP algorithm replaces the objective function with the quadratic approximation and replaces the constraint functions by linear approximations.

The simulation results with the initial values for parameters to be optimized are shown in Figure 2. It can be seen that the grade change actually results in a large peak in the moisture. When the set point of the moisture is not manipulated and the filler content is changed at the same time as the basis weight set point is changed, the cost caused by the grade change is 373.2 units (costs after optimization range from 31 to 35). This figure can be used as a comparison with the results in the optimization process.

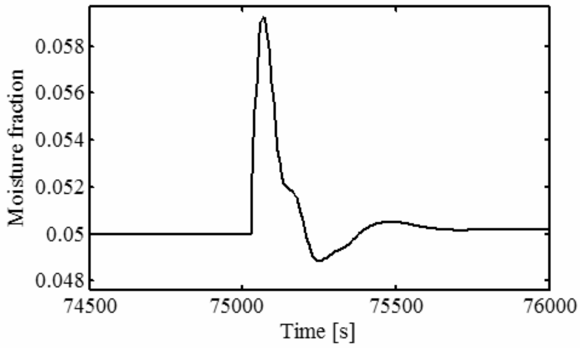

Fig. 2. Moisture of the end product before the optimization. Basis weight and moisture setpoint changes at 75000, no change in moisture setpoint.

It is obvious that with a step in the moisture set point we can stabilize part of the effect of grade change on the moisture of the final product. The three moisture set point parameters determine how the stabilization is done. The filler content change time is chosen so that the all the quality variables behave optimally.

Different methods of the toolset have been used in this optimization task. The simulator and functions used with DOTS Toolset have also been used with an SQP function in the Optimization Toolbox. It should be noted that the SQP algorithm gives local minima and the result depends on the initial values given for the function/algorithm. The results of each method used are shown in Table 2. Table 2 shows that the best result is achieved with genetic algorithm.

Table 2 The optimization results

Method / Variable	*Tabu Search*	*Simulated annealing*	*Blind Random*	*Genetic algorithm*	*SQP*
Grade change	75000	75000	75000	75000	75000
Filler content, tim.	75015	74980	74985	74990	75005
Moisture sp, tim. 1	74965	74965	74975	74980	74975
Moisture sp, tim. 2	75070	75055	75055	75050	75050
Moisture sp, step	0.05→ 0.038	0.05→ 0.036	0.05→ 0.034	0.05→ 0.032	0.05→ 0.032
Cost	33.57	33.90	31.57	31.32	34.34

Noticeable in the table is also the good result of the blind random search. This indicates, that the search space is rather flat, which gives no grip for the more advanced methods. However, as the Figure 3 shows, the optimization reduces the fluctuation effectively. Similar effect can also be seen in the behavior of basis weight and filler content. Reduced variance improves the stability of the process and speeds up the grade change.

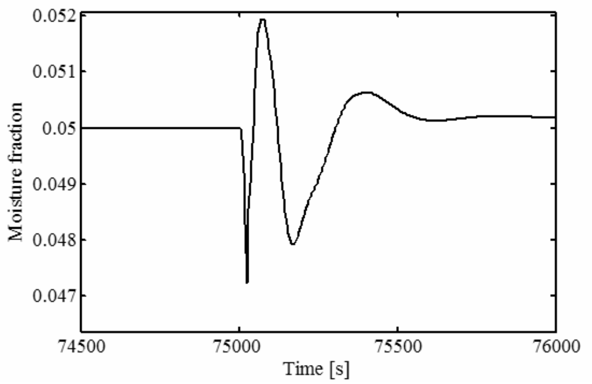

Fig. 3. Moisture of the end product after the optimization. The grade change starts at 75000.

An example of the behavior of the key variables and the set point trajectories in the optimized grade change situation are shown in Figure 4. It must be remembered that the results depend on the parameters given for the algorithm, and the comparison between the algorithms was carried out with default values.

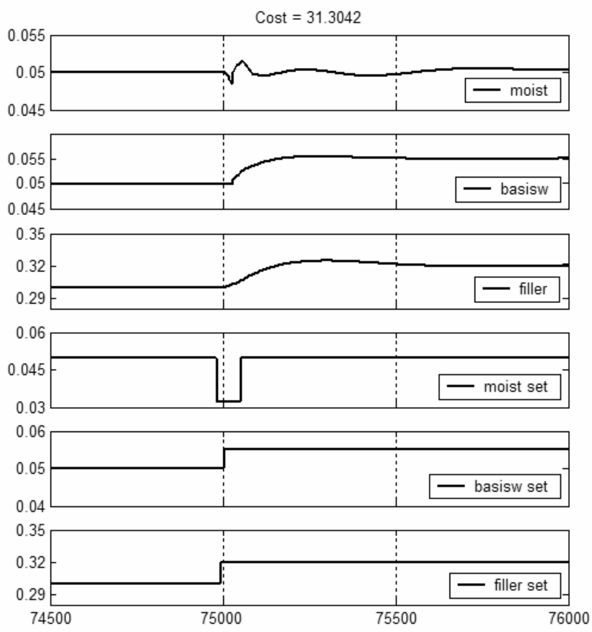

Fig. 4. Example of an optimization result. The behavior of the key variables and their set points are shown in the following order: moisture, basis weight and filler content. The grade change starts at 75500.

Figures 5 and 6 show the cost function as a function of two optimized parameters. The optimum combination of the variables is marked with a dot. The observation of the cost function plots from different angles reveals that the optimum is actually achieved.

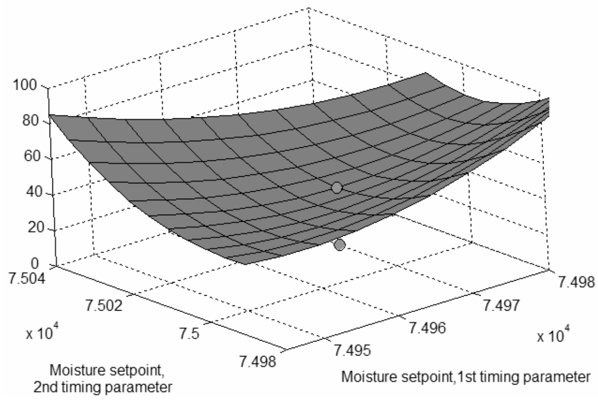

Fig. 5. Observing the cost value near the optimum with the moisture step timing parameters

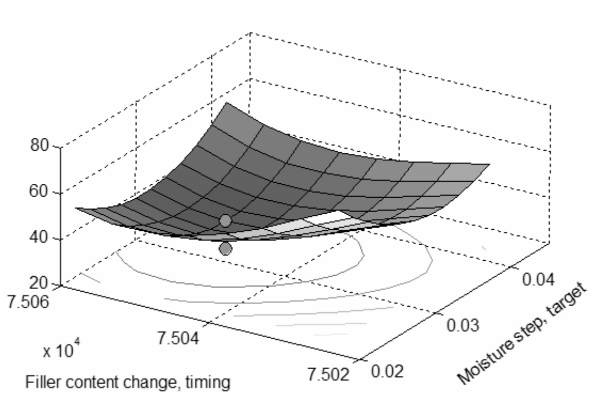

Fig. 6. Observing the cost value near the optimum with the following parameters: Filler content change timing and Moisture step timing

Figure 7 presents a comparison of methods as a function of convergence time. SQP is not involved, because it was not run from the DOTS toolset. Genetic algorithm finds a good result relatively fast and manages to reduce the cost when the others already fail. The similar trends reveal also the stochastic relation of the methods.

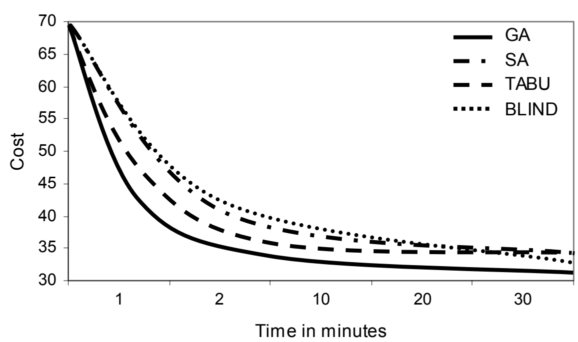

Fig. 7. A comparison of the optimization methods

5. CONCLUSIONS

By observing the cost values achieved for solutions with each method we conclude that the best result in this grade change optimization is achieved by using genetic algorithm. The genetic algorithm provides best results also for the "quality pipe" cost function. Despite the fact that the methods give results close to each other, the genetic algorithm with proper parameters should be preferred because of better optimized cost and lower number of iterations. However, the performance of the methods depends on the cost function used and the parameters of the algorithms. The algorithms have been applied with default parameters, if the parameters were tuned, the results could be somewhat different.

Compared with the functions in Optimization Toolbox, DOTS Toolset offers an easy way of solving an optimization problem. The graphical user interface makes the toolset somewhat more desirable tool to use.

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