Paper VII

Pajula, E., Ritala, R., Measurement uncertainty in integrated control and process design – a case study, *Chemical Engineering and Processing* 45(2006) 312-322.

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Chemical Engineering and Processing 45 (2006) 312–322
Chemical Engineering and Processing
www.elsevier.com/locate/cep

Measurement uncertainty in integrated control and process design—A case study

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Received 14 March 2005; received in revised form 16 June 2005; accepted 28 July 2005
Available online 8 November 2005

Abstract

Measurement uncertainty may be a decisive factor on the structure of process and control flow sheet design: e.g. whether a controller can achieve required level of disturbance attenuation or whether costly process equipment needs to be included. However, the effect of measurement uncertainty on the process performance is rarely if ever discussed. In this paper, we illustrate through a case study, how the control structure design is affected by measurement uncertainty and how the corresponding dynamic problem is defined and solved with rather regular tools. Our case is a conceptual and simplified paper machine short circulation control design, which involves defining a dynamic design optimization problem with scenarios on dynamic effects external to the process. With the case, we also want to illustrate that in practical design the choice of dynamic scenarios, their relative frequency of occurrence and even the objective function are far from being self-evident. These choices affect strongly the outcome of optimization. Therefore, scenarios and objective function should be understood more as advanced design tuning parameters rather than strictly given design requirements derived from business analysis.

Keywords: Measurement uncertainty; Short circulation; Process design; Control design; Dynamic optimization

1. Introduction

In process systems engineering, new fundamental and significant advances have become the state-of-the-art during the last 20 years [1]. The rather ad hoc analysis of flow sheets has been replaced by systematic numerical solution techniques on alternative process structures, widely implemented in computer modeling systems and simulation packages for both preliminary and detailed design. The development of process flow sheet structures has been raised to higher level of abstraction: intuitive development of process superstructures amongst which the best structure is to be chosen. These systematic synthesis methods employ conceptual insight and advanced optimization techniques.

It is widely recognized that the ability to manage and control a system with uncertainty and disturbances strongly depends on the process design [2]. In order to find economically optimal design, the interaction between process and control design should not be neglected. Today, unified frameworks including mixed integer dynamic optimization formulation have been proposed, e.g. the most recent approach by Bansal et al. [3], which provides a framework for studying and optimizing design problems involving dynamic phenomena. Although such methods are highly sophisticated and powerful, defining an accurate process model to be optimized remains a difficult task and involving uncertainties makes it even more difficult. However, it is possible to study to the dynamic process behavior to quite acceptable accuracy with commercial simulators and optimization software. In production plants, there may be readily available simulation models that can be utilized, and they may be integrated to work with external optimization software, which means that dynamic studies may not take too much effort when studying possible control and process alternatives.

A major additional difficulty of integrated process and control design is that as the dynamic behavior is optimized, the specifications must state the dynamic scenarios under which the process will be operated, and relative frequency of occurrence of these scenarios. Such information is not readily available from business considerations guiding the project, and only rarely from

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doi:10.1016/j.cep.2005.07.006

control or process engineers. As the scenario data will strongly affect the design, the robustness against uncertainty in scenarios should be verified, i.e. a "scenario analysis on scenarios" needs to be carried out (e.g. Suh and Lee [4]).

In pulp and paper industry, dynamic simulation has been applied in studies, e.g. on grade change dynamics [5] and on disturbance diagnostics for agitated pulp stock chests [6]. Optimization has also been applied to, e.g. paper trim loss minimization [7]. However, so far there have been very few publications that take into account uncertainty in realistic optimization problems in any process industries, the most notable example being the recent publication about multi-site capacity planning in the pharmaceutical industry by Levis and Papageorgiou [8].

This paper discusses how measurement uncertainty affects process performance and how it should be taken into account in the design of control and process structure. The issues are exemplified through a simplified case study of paper machine short circulation design.

2. Defining the problem

2.1. The problem and the role of measurement uncertainty

The general dynamic design problem consists of:

- Objective function defining what we want to minimize; this includes selection of design optimization search space:
  - continuous design variables;
  - discrete/binary design variables.
- The dynamic scenarios.
- Probabilities of scenarios.
- Process model as the equality constraints (system of differential, respectively, algebraic equations); this includes selection of:
  - differential state variables;
  - algebraic state variables;
  - dynamic control variables;
  - initial conditions (vector).
- Dynamic equality and inequality constraints.
- Design equality and inequality constraints.

The process model is typically implemented as dynamic process simulator serving external optimization software that manipulates the design variables. The mathematical framework [9] and how it has been applied in the case study is given in Appendix A.

2.2. Objective function and constraints

The choice of the objective function is a multifaceted: investment and operation costs form the basis but often other process performance aspects need to be included directly in a comparable way into the cost function. The process performance has many attributes; the production rate may be subject to be maximized, the amount of off specification production to be minimized or their ratio to be considered. Costs and constraints due to safety and environmental regulations must be considered in the objective.

2.3. Scenarios—taking uncertainties into account

In the integrated design problem, the iteration between control and process design is avoided because the dynamic analysis is included in the simultaneous control and design optimization. However, this means that external disturbances and changes of operation point become a part of the problem formulation.

Defining realistic scenarios for disturbances and changes in operation point, and, in particular, their frequency of occurrence is a most challenging task. The knowledge gained from earlier experiences with the same or similar processes is highly valuable in design. For instance, information about control loop performance can often be obtained from equipment suppliers' other installations. The co-existence of disturbances and their frequencies need to be carefully studied in order to include all relevant process specific interactions in the scenarios. Whenever disturbances are measurable, the design superstructure should include these measurements and the control structure based on the measurements. The disturbances during transients, such as changes of operation point, shutdowns and startups, are often known to differ from those in stationary operation. The design superstructure should allow controllers to be tuned differently in these cases. Obviously, this results in a search space of increased complexity. The scenario data greatly affects the optimization results, and therefore the scenario analysis should be carried out systematically with business management and operating personnel.

2.4. Practical aspects

Process model is from optimization point of view a set of equality constraints. All equations are implemented as a dynamic simulator model that is easy to maintain for later use in training and operational optimization. All real world phenomena can never be included, and therefore state variables need to be dynamically constrained to guarantee safe operation. However, the more safety margins applied the poorer is the optimum.

Simulation model needs to be validated with process data. For a process being designed such data is not always available, and the validation must be based on pilot studies and physicochemical principles. The uncertainty in the simulation model and the sensitivity of the optimal solution to model parameters must be known.

When defining the process/control superstructure the controlled and manipulated variables must be selected and paired. Hard questions, such as "should all possible combinations be considered or should we restrict the alternatives based on general process knowledge" or "how upper and lower bounds for tuning parameters should be defined", need to be addressed.

Optimization of controllers introduces complex continuous and discrete variables into the search space. Model based controllers actually have an internal dynamic model as a "tuning parameter". Furthermore, as they dynamically optimizing controllers, the parameters of their objective functions – such as weighing of the temporal instantaneous objective and time horizon – are potential design search space variables. The actuators, e.g. valves, have varying response times and stick-slip hysteresis that are related to device costs. Thus, optimal control design of a rather simple process may turn out to be high-dimensional. In practice, some process knowledge must be applied to reduce the problem. If some part of the potential discrete or continuous search space is ruled out on the basis of process knowledge, can we safely assume that the optimal solution is not lost amongst them?

When solving the general design problem the main difficulty in finding the optimal parameter tuning and process structure selection is that the optimization methods due to severe non-linearity of the problem can never guarantee global optimality. Thus, additional constraints and reasonable tolerances based on process knowledge are needed to speed up the optimization procedure and to avoid results locally optimal but far from globally optimal.

3. Case: paper machine basis weight control

This section outlines the case process and its potential controller structures. As a part of the controller superstructure there is a measurement – consistency before wire section – that would provide a fast control response but is rather uncertain and therefore not used in present controllers. The goal of this study is to analyze, how the uncertainty of the consistency measurement affects the optimal control structure. The corresponding objective, constraints and scenarios are specified and the optimization problem is solved. We show that there is a critical value of consistency measurement uncertainty below which the optimal control structure involves the consistency measurement whereas above consistency measurement should not be used. This can also be viewed as a development target for consistency measurement: should there be a consistency sensor with uncertainty below the threshold, it would be commercially justified and would return economic benefit for the owner of the process.

3.1. Case process

Paper comprises of wood fibers, mineral fillers and chemicals. Papermaking process consists of mixing, dilution and separation stages with rather little chemical action. In this analysis, the role of chemicals is neglected and the process is thus described as purely physical system. The subprocesses of papermaking process are (see also Fig. 1):

- Pulp preparation, mixing of water and fibers. We model these subsystems as two ideally mixed tanks in series, the blend and the machine chest. Also broke (waste paper recycled within the production line) is added to the mixture. Broke typically contains fillers.
- Dilution, web forming and water removal. Pulp is first diluted in a pipeline with white water, the diluted pulp is then spread on the wire to form a web structure, and large portion of the water is removed through the wire as white water to be circulated back for dilution stage through a wire pit. The web runs at speeds of 20–30 m/s and is 6–10 m wide. The wire pit is modeled as an ideally mixed tank, the dilution as direct mixing and the wire as a separation process characterized by individual retention values for fiber, filler and water. As the name suggests, retention determines how large a portion of material applied on the wire is retained in the product, and thus also how much the fibers and fillers the white water contains. In real process, there are a number of cleaning stages between dilution and web forming. These are simply modeled as an

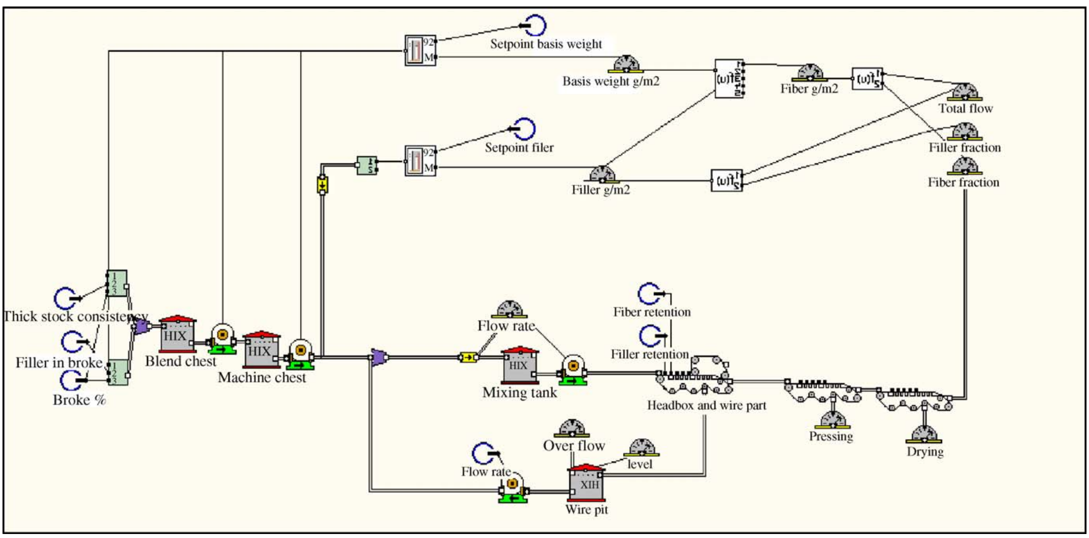

Fig. 1. Simulation model with two PI controllers. The control loops are one for filler content and one for basis weight.

ideal mixing volume corresponding to leading time constant of this section.
- Pressing and drying sections remove the remaining water. These sections are modeled as simple delays in our case study. The delay is rather long, typically 30–90 s.

The essential measurements of the process are:

- Fiber and filler consistency before wire section and in the wire pit. These give the portion of the fibers, respectively, fillers, in the slurry. Typical values are 0.1–1%.
- Basis weight and filler content of the ready-made paper. Basis weight describes the amount of material per unit area. Multiplied by web speed and width of the web it gives the production rate (kg/s). Filler content describes how large a portion of the production is due to mineral fillers in the web. These properties are measured with a scanning gauge traversing across the web in 20–40 s. This way of measuring adds to delay, as the common practice is to represent the measured quantity as a scan average. The sampling rate is one reading per scan, which is very slow compared to the web speed.

To actuate the process there are two manipulatable variables:

- Thick stock valve after the mixing chest. This determines the amount of undiluted main fiber flow to dilution point. The main flow may have fillers too, due to circulated broke.
- Filler valve. This determines the fresh filler dosage at the dilution point.

Two potential control structures exist:

- direct control based on basis weight and filler content measurements after drying section or;
- cascaded control where the inner loop regulates consistency before wire section and outer loop gives setpoints to consistency measurements based on basis weight and filler content measurements after the drying section.

In both of the structures, a proportional–integral (PI), Dahlin and Model-Predictive Control algorithm, each in univariate or bivariate form can be applied. The current best practice on paper machines is the direct control with bivariate MPC. Cascaded control is hampered by the high uncertainty in the measurement.

The basis weight and filler content control are the most important quality control loops in paper machines. These control loops are coupled, because the filler contributes to the basis weight. The dynamics of fiber and filler also differ due to vast difference in retention on wire.

The process was modeled for fiber and filler dynamics. Fig. 1 shows the simulation model with two PI controllers (for basis weight and filler content). The machine parameters are: nominal fiber retention 0.8, nominal filler retention 0.5, blend chest volume 100 m^3, machine chest volume 100 m^3, wire pit volume 171 m^3, web width 9 m, web speed 25 m/s, delay in pressure and dryer part 50 s, initial broke % = 40%. Design variables to be optimized are control structure, controller tuning and the volumes of blend chest and mixing chest. The tuning optimization can be viewed as a subtask from main optimization.

3.2. Measurement uncertainty in consistency measurement of fibers and fillers

Consistency (actually, concentration, but referred commonly as consistency) of fibers and fillers is measured at the headbox from which the fiber–filler suspension is spread out on the wire to form a web-like structure, and in the water that has flown through the wire, on its way to wire pit. The measurements are based on combinations of deflection of polarization angle of light through the flow, light transmittance and flow density [10].

The consistency measurements have a rather high level of uncertainty due to that they are indirect measurements and most commercial devices sample the flow before measuring. The common practice is to filter the measurement signal over, say 30–120 s. Thus, the rapid response of cascaded control is lost, and direct control is favored currently at the mills. Consistency sensors are today used only for controlling chemical dosage to the process, in particular the retention aid chemical affecting the flocculation of fibers and fillers.

In our analysis, we shall consider the measurement uncertainty in consistency, σ, as a design variable. This amounts to saying that we may choose any uncertainty, at a given cost—or, we want to analyze which is the allowed development and implementation cost of a sensor such that cascaded control outperforms direct control in economic terms. All the other measurements about the process are assumed to have a negligible uncertainty.

3.3. Potential control solutions

This section describes briefly and motivates the control structure and algorithms studied [11,12]. Valves are assumed to have ideal transfer functions. The control strategies included in control superstructure are PI-controllers, dead time compensated Dahlin algorithm (with decoupling of fiber and filler dynamics), model predictive control (MPC) and cascaded PI control.

3.3.1. PI controllers

Process industry has traditionally relied on linear models and regulators; approximately 85% of industrial controllers are of PI type. In our case, one control strategy is to manipulate the thick stock valve based on the basis weight measured after the drying section, and the filler valve based on the filler content after the drying section (Fig. 1).

3.3.2. Cascade controller

In feedback controllers, the disturbance needs to propagate through the system. For example, a disturbance in blend chest cannot be observed until the disturbance has propagated through machine chest, dilution, headbox, wire section and drying section to the basis weight measurement. Such disturbance can be counteracted faster with the cascade control having control of

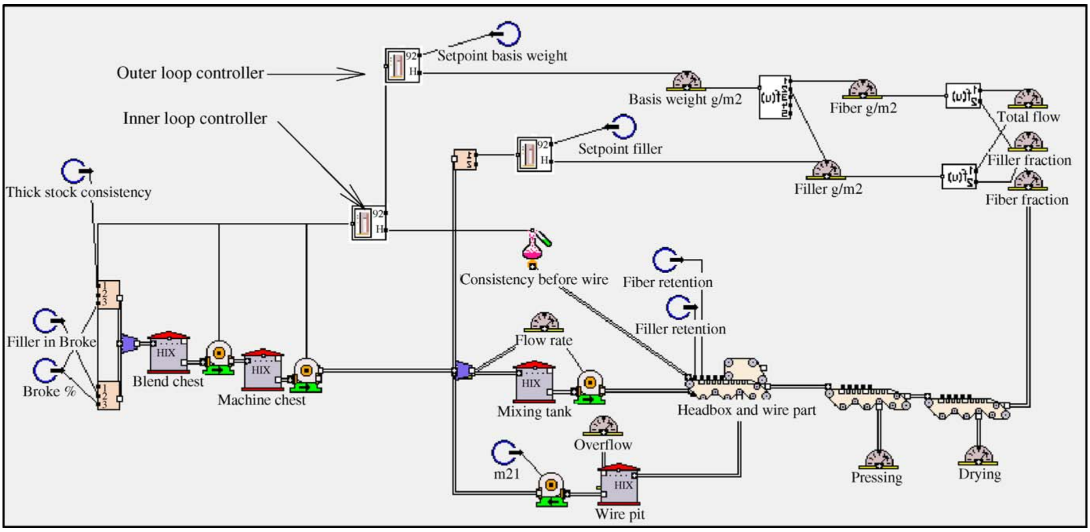

Fig. 2. Simulation model for cascade control structure.

consistency before wire section as inner loop (Fig. 2). The consistency before wire section is measured and controlled by a PI controller (inner loop or slave controller). The setpoint to the inner loop consistency controller is given by the outer loop or master PI controller of basis weight. The inner loop is tuned faster than the outer loop with better response to load disturbances. The effect the measurement uncertainty of consistency on controller performance is studied and the control structure optimized assuming a fictive and uncertainty-dependent price of the sensor.

3.3.3. Process model for model based controllers

Within MPC and dead time compensated controllers the short circulation was approximated with the simplified feedback/mixing/delay structure presented in Fig. 3 [13]. The parameters were fitted to the simulation model. The transfer function and parameters in this model – models for filler and fiber differing only through retention parameter – are

$$G(s) = \frac{b_1 s + b_2}{a_1 s^2 + a_2 s + a_3}\,\mathrm{e}^{-T_\mathrm{d} s} \qquad (1)$$

where s is the Laplace transform variable; τ_1 and τ_2 are the mixing time constants; T_d is the dead time; $a_1 = \tau_1\tau_2$; $a_2 = \tau_1 + \tau_2$; $a_3 = R$; $b_1 = R\tau_2$; $b_2 = R$; R is the retention.

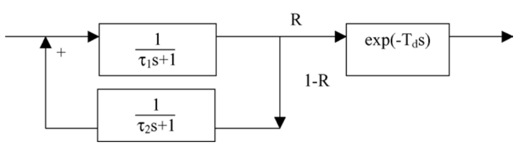

Fig. 3. Process model for MPC and Dahlin controllers.

3.3.4. Dahlin algorithm

One of the simplest and most widely used dead time compensation methods is Dahlin algorithm. Dahlin algorithm is particularly useful when the dead time is larger than the dominant process time constant. The method requires a reliable estimate of the process dead time, which usually can be obtained for paper machines. In the simulation model, the process time constants are 5 and 28 s and dead time is 50 s. In short circulation case, second-order plus dead time transfer function estimate (see Eq. (1)) can be used for fiber and filler.

3.3.5. Multivariate model predictive controller

Model predictive control is based on two principles:

- process output is forecasted with a process model;
- optimal control actions are determined through minimizing an objective function, subject to given constraints on process variables and actions.

The objective function is a weighted average of squared deviations from setpoints over the prediction horizon and squared amplitudes of actions. In the basis weight and filler content control, the process model for MPC controller was defined as bivariate step response model. The constraints for the manipulated variables are constant in time.

The sampling time was selected as 1 s, the same as in other control approaches. Sampling time could also be considered as a design optimization parameter, provided that the control equipment allows choosing between sampling times. Prediction and control horizon lengths were first considered as tuning parameters, but the effect to controller performance was found less important than that of weighing between action vector changes and deviations from setpoints. Thus, control horizon was chosen to 10 and prediction horizon 100 steps based on simulation experiments. The tuning parameter needing careful consideration is the weighing between penalties due to control actions and to deviations from setpoints, which means a compromise between robustness and fast response. The weight of basis weight and filler content deviations is defined based on simulation experiments to be equal to 2 and 1, to take into account the scale difference (±1 g/m^2 in basis weight and ±0.5 g/m^2 in filler content). In the case study, the model is time-invariant and retention disturbance is one scenario for the control. The performance of MPC and Dahlin control structure is worse with time-invariant model compared with one updating the internal process model according to (1). However, we did not include such semi-adaptive controller to our control superstructure for it is also the current practice not to use retention measurement for direct model updating. This is partly because the retention measurement is based on two uncertain consistency measurements.

3.4. Objective function

In order to select the best process structure, the investment costs and process performance indices need to be made comparable. In our case study of control design, the following potential overall objectives were identified based on general process knowledge:

- Index 1: The ratio of off spec production to in spec production is minimized. No capital costs of controller or process structures are taken into account, and only process performance is considered.

$$J = \frac{m_{\text{offspec}}}{m_{\text{inspec}}} \tag{2}$$

- Index 2: The production value is maximized and the cost of off spec production is taken into account by maximizing the function.

$$J = (m_{\text{inspec}} * r - m_{\text{offspec}} * c) \tag{3}$$

where r is the revenue from the product and c is the cost of manufacturing.

- Index 3: The ratio of off spec production to in spec production is minimized taking into account capital costs.

$$J = \frac{m_{\text{production(offpec)}} C_{\text{offspec}}}{m_{\text{production(inspec)}}} + C_i + C_{\text{process equipment}} \tag{4}$$

where

$$C_i = C_{i,\text{controllers}} + C_{i,\text{instr.}} + C_{\text{auxiliary equipment}}$$

$$C_{\text{process equipment}} = C_{\text{machine chest}} + C_{\text{blend chest}}$$

However, this alternative was dominated very strongly by capital costs that it was omitted.

- Index 4: The profit is maximized taking into account capital costs.

$$J = (m_{\text{production(inspec)}} C_{\text{inspec}} - C_i - C_{\text{process equipment}} - m_{\text{production(offpec)}} C_{\text{offspec}}) \tag{5}$$

In the index 4a, only controller and instrumentation costs are taken into account, in the index 4b also the chest alternatives and their costs are included.

Optimization problem is defined including controller tuning, algorithm and structure as well as blend and machine chest volume selection. The other process variables are assumed to have constant cost and performance. Utility costs are assumed constant in all scenarios and process designs.

3.5. Setting the constraints

Papermaking is a mature industry, and therefore the pairing of controlled and manipulated variables was based on preexisting best practice. With the simulation model constraints were defined in Matlab® workspace only for the parameters to be optimized, i.e. the controller tuning parameters, and the chest volumes. The constraints on measurements, manipulated and controller tuning parameters are defined based on process knowledge and/or simulation experiments. For instance, for MPC controller:

Manipulated variables:

u_1 (kg thick stock/s)		
Min	0	No negative flows allowed
Max	675	Max basis weight 60 g/m^2, machine speed 25 m/s, machine width 9 m and consistency of 2%
Δu_1	5	Assumed maximum slew rate
u_2 (kg filler/s)		
Min	0	No negative flows allowed
Max	0.7	Max basis weight 3 g filler/m^2, machine speed 25 m/s, machine width 9 m and consistency 100%
Δu_2	0.001	Assumed maximum slew rate

Controlled (measured) variable, limits for measurement values

y_1 (basis weight g/m^2)		
Min	0	No negative flows allowed
Max	inf	Feasibility limit—no need due to limits for u
y_2 (g filler/m^2)		
Min	0	No negative flows allowed
Max	inf	Feasibility limit—no need due to limits for u

Controller tuning parameter (weight between setpoint offset and penalty for controller action) λ was defined to be selected among the values:

$$\lambda \in [\,0 \quad 10 \quad 100 \quad 10,000 \quad 100,000\,]$$

The machine speed and delay in pressure and dryer section are assumed to be constant for each grade (25 m/s and 50 s).

3.6. Scenarios

To take into account external factors, scenarios about the external future environment of the system need to be specified. Both the dynamic characteristics of disturbances and their probability must be specified.

Table 1
Scenario elements

Disturbance	Description
1	Retention chemical change, retention increases (filler 50 → 55%, fiber 80 → 85%)
2	Grade change (setpoints basis weight 45 → 50 g/m^2, filler 1 → 2 g/m^2), retentions change (filler 55 → 60%, fiber 85 → 93%)
3	Grade change (new setpoints basis weight 50 → 45 g/m^2, filler 2 → 2.5 g/m^2), retentions change (filler 60 → 55%, fiber 93 → 88%)
4	Broke filler consistency drops 0.07 → 0.017%
5	Broke % increases from 40 to 45 (broke % = mass of broke/mass of fresh pulp × 100)

3.6.1. *Selecting scenario elements*

The disturbance scenarios are strongly specific to paper grade and machine. In this case, we set the scenarios rather ad hoc on the basis of our process knowledge, in order to illustrate the importance of measurement uncertainty. For full-scale designs, there is rather little systematics on how to extract the user requirements from process operating personnel or business personnel, and this appears to us the weakest point in systematic dynamic process design. Scenario elements included in the study are shown in Table 1.

We first check whether all the disturbances can be controlled using by at least some of the potential control solution. This is useful especially if it is very time consuming to optimize the system for a scenario. The process performance indexes 1 and 4a are calculated for scenario elements in Table 2. The cost information is presented in Table 3.

We shall now analyze the results concerning indexes 1 and 4a from two points of view. First, we assume that the measurement uncertainty σ of consistency is 0.0001, i.e. 0.01%, which is an optimistic estimate of the capabilities of present commercial sensors. It is seen in Table 2 that all the other presented control algorithms perform better than cascade controller with $\sigma = 0.0001$ considering disturbance 1. The grade change disturbances 2 and 3 cause changes in both retention values due and basis weight and filler setpoint changes. When disturbance 2 is considered PI and Dahlin controllers perform better than cascade alternative. Cascade controller is able to compete with MPC with disturbance 2 and is optimal choice when the setpoints for filler and basis weight are changed opposite directions in disturbance 3, because the information, even though noisy, reaches the control loop before pressing and drying part and in this way the interaction between filler content and basis weight is taken in to account earlier. All the controller alternatives were able to compensate disturbances 4 and 5. The model based controllers' performance can be improved by including more accurate process model (inaccuracies in defining the process delay, updating the models for operation point and retention chemical changes which affect the process behavior, but modeling these dependencies was beyond the scope of the current case study), but with current models PI controllers' performance is better.

Secondly, let us consider all the levels of uncertainty. The optimum is found according to indexes 1 and 4a with PI and Dahlin controller for retention chemical change (disturbance 1), and for grade changes (disturbances 2 and 3) the optimum is found with cascade controller ($\sigma = 1e^{-6}$) according to index 1, but when the controller costs is taken into account (index 4a) the optimum is found with the less expensive cascade controller ($\sigma = 1e^{-5}$ and $5e^{-5}$). The effect of scenario lengths of scenarios 4 and 5 to optimal solution were studied. These two scenarios were singled out because the disturbances in the pulp preparation part propagate slowly due to large chest sizes. It can be seen that all the controller structures are able to compensate disturbances 4 and 5.

These calculations give some idea of process robustness, but the disturbance frequencies and interactions are neglected. Neither the global optimality is reached because the controller-tuning subproblem is solved considering for only one scenario element at each time. However, if the simulation steps with the

Table 2
Three cost indexes calculated for scenario elements

Controller	Disturbance									
	1		2		3		4		5	
	Index 1	Index 4a	Index 1	Index 4a	Index 1	Index 4a	Index 1	Index 4a	Index 1	Index 4a
PI	0.101	9.00E + 05	0.357	7.49E + 05	0.441	6.34E + 05	0	4.05E + 06	0	1.92E + 07
Cascade										
$\sigma = 0.000001$	0.122	8.51E + 05	0.273	7.96E + 05	0.258	7.35E + 05	0	4.02E + 06	0	1.92E + 07
$\sigma = 0.00001$	0.130	8.58E + 05	0.273	8.10E + 05	0.277	7.35E + 05	0	4.04E + 06	0	1.92E + 07
$\sigma = 0.00005$	0.149	8.41E + 05	0.314	7.77E + 05	0.268	7.41E + 05	0	4.04E + 06	0	1.92E + 07
$\sigma = 0.00007$	0.155	8.50E + 05	0.366	7.49E + 05	0.291	7.36E + 05	0	4.05E + 06	0	1.92E + 07
$\sigma = 0.0001$	0.162	8.44E + 05	0.576	6.11E + 05	0.296	7.37E + 05	0	4.05E + 06	0	1.92E + 07
Dahlin	0.101	8.98E + 05	0.363	7.41E + 05	0.633	5.31E + 05	0	4.05E + 06	0	1.92E + 07
MPC	0.123	8.65E + 05	0.580	5.88E + 05	0.473	5.96E + 05	0	4.04E + 06	0	1.92E + 07

Disturbance scenario descriptions: disturbance 1, retention chemical change scenario 500 steps; disturbance 2, grade change scenario 500 steps; disturbance 3, grade change scenario 500 steps; disturbance 4, broke consistency change scenario 2000 steps; disturbance 5, broke % change scenario 9500 steps.

Table 3
Initial conditions, disturbance scenario and costs used in the study

Initial conditions

Initial parameter	Value
Setpoint, basis weight (g/m^2)	45
Setpoint, filler (g/m^2)	1
Broke %	40
Broke fiber consistency	0.0193
Broke filler consistency	0.0007
Thick stock consistency	0.02
Fiber retention	0.8
Filler retention	0.5
Wire pit level (%)	100
Blend chest level (%)	100
Machine chest level (%)	100

Disturbance scenario

Time	Disturbance
150	Retention chemical change, retention increases 10% (now filler 55%, fiber 85%)
500	Grade change (new setpoints, basis weight 50 g/m^2, filler 2 g/m^2), retentions change (now filler 60%, fiber 93%)
1000	Grade change (new setpoints, basis weight 45 g/m^2, filler 2.5 g/m^2), retentions change (filler 55%, fiber 88%)
1500	Broke filler consistency starts to increase, thick stock consistency drops to 0.017%
2000	Broke % increases to 45, broke filler consistency reaches level 0.0014 stays there
2500	End of scenario

Costs used in the study

Controller scheme	Controller and instrumentation cost/duration of scenario	Chest volumes (m^3)	Cost = C_0(volume m^3/V_0)$^{0.7}$ [1] $C_0 = 50000$, $V_0 = 100$
Two PI controllers	100	0	0
Dahlin algorithm	1000	50	30779
Cascade control		100	50000
σ = multiplier for white noise (variance = 1)	150	66410	
$\sigma = 0.000001$	30000	200	81225
$\sigma = 0.00001$	15000		
$\sigma = 0.00005$	14000	Product	Cost/price
$\sigma = 0.00007$	10000	Paper	200 units/tonnes
$\sigma = 0.0001$	1000	Broke	50 units/tonnes
MPC	10000		

realistic scenarios are very time consuming and if the scenarios are difficult to define, this approach helps in understanding the dynamic process behavior before defining and optimizing the more complex scenarios. For instance, if disturbance 1 is 10 times as frequent as disturbance 3 the index 1 gives the value.

PI	$10 \times 0.101 + 0.441 = 1.451$
Cascade, $\sigma = 1e^{-6}$	$10 \times 0.122 + 0.258 = 1.478 \rightarrow$ PI controller is better

But if the disturbances are equally frequent

PI	$0.101 + 0.441 = 0.542$
Cascade, $\sigma = 1e^{-6}$	$0.122 + 0.258 = 0.380 \rightarrow$ cascade controller is better

3.6.2. Weighting of scenario elements and interactions

The disturbance interactions are taken into account by including them with realistic occurrence rates into the same scenario. In this way, also unexpected interactions can be found if the simulation model and scenarios are good enough.

In the short circulation case, the disturbances are all included in one scenario and it is assumed that their occurrence describes well their importance from the controller performance point of view. Thus, no weighting factors for separate scenarios or time intervals are needed. Also the interactions are assumed to be well described in the scenario. The scenario length is 2500 s, and the sampling time in all the controllers is assumed to be 1 s. The initial conditions and the disturbance scenario are presented in Table 3. Notice that measurement uncertainty is assumed to be negligible in all but consistency measurement utilized in cascade control scheme. The model in Dahlin and MPC strategies is not updated to compensate the change in retention caused by change in retention chemical dosage or paper grade (the higher the basis weight, the higher the retention). The measurement uncertainty in consistency measurement depends on actual sensor installed, and thus several variances of white noise were studied.

Table 4
Results

Control strategy	Index 1	Index 2×10^{-3}	Index $4a \times 10^{-3}$	Index $4b \times 10^{-3}$
Two PI controllers	0.221	3998	3997	4211
Dahlin algorithm	0.3096	3675	3674	4000
Cascade control				
$\sigma = 0.000001$	0.1461	4361	4331	4335
$\sigma = 0.00001$	0.144	4373	4358	4367
$\sigma = 0.00005$	0.1911	4149	4135	4226
$\sigma = 0.00007$	0.2368	3949	3939	4092
$\sigma = 0.0001$	0.3347	3580	3579	3804
MPC	0.2772	3767	3766	3897

4. Results

The main design problem was to find the level of uncertainty in consistency measurement where cascade controller becomes more attractive alternative than other controller structures. To answer this we solved separately for the optimal value of the cost function of each controller structure. Thus, in our approach we did not explicitly use the controller superstructure, but simply note that this can – and should for more complex cases – also be done.

Our results in Table 4 and Fig. 4 show that the cascade controller becomes optimal when the uncertainty in consistency measurement is below, roughly 0.00007. This is to be compared with the average measured value of 0.002. The cascade controller becomes optimal roughly at the same value of standard deviation independently on which of the performance indices are employed. The optimum with index 4b was found with one chest of $100\,\mathrm{m}^3$. The results depend on capital costs, price of end product, cost of off spec production and on scenarios. The optimal controller tuning in each case was optimized with the same cost function as the structures.

However, it is clear that when the consistency measurement uncertainty is above 0.00007, there is very little to be gained in basis weight and filler content control by implementing the sensors: they are worthless in this respect. However, when the measurement uncertainty falls below the threshold, considerable economic gain can be achieved. Taking into account the high added value per time in papermaking, almost any development costs of such a sensor would be justified, not to mention the implementation costs. Thus, we have established an important goal for sensor design that would unlock high efficiency improvement in papermaking.

It is also seen that PI controllers and in some cases also dead time compensated control (Dahlin) perform better than MPC in this case study. However, the MPC performance could be improved by modeling the known retention chances due to grade and retention chemical changes, and thus creating a more accurate process model for MPC algorithm. The performance of PI controllers could be improved by gain scheduling, for instance for setpoint changes. The improvements were beyond the scope of the current case study.

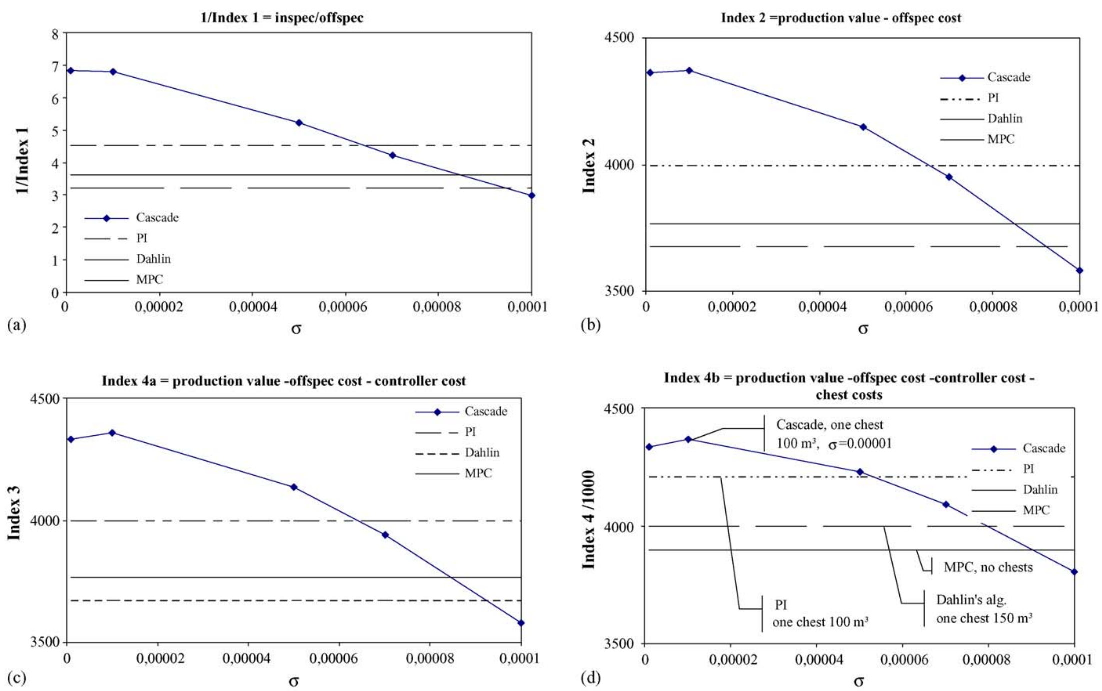

Fig. 4. Results of the short circulation case study.

The tools used in the case study were KCL-Propose dynamic simulator (proprietary simulator based on Matlab® Simulink), Matlab® including optimization and MPC Toolboxes. The DIRECT algorithm included in Tomlab optimization software was used for optimization. The time needed for minimizing one index and control alternative was a 2–4 h. The calculations were stopped when the increasing the calculation time did not have any more effect on the found best solution. Running the simulation was clearly the most time consuming step. The simulation model could be made faster, e.g. by writing it in C.

5. Conclusions

We have demonstrated that measurement uncertainty may play an essential role in optimal process design. The result of the optimization with respect to uncertainty can be formulated as a sensor development requirement: decreasing measurement uncertainty below a given threshold would unlock considerable economic potential through enabling cascade basis weight and filler content control. The case example derived the condition for cascade control employing additional but uncertain measurement becoming the optimal structure over direct PI, Dahlin or MPC. However, our analysis also clearly demonstrates the difficulties in defining rigorously the joint process and control design optimization problem. In particular, our findings depend strongly on scenario elements selected and their relative frequency of occurrence. It appears that there is no reliable or even educated source of information about dynamic scenarios.

In this article, methods for solving scenario based dynamic optimization problems were discussed and a simplified short circulation dynamic control and process design problem was solved. To apply this approach to industrial cases, more accurate process models, disturbance scenarios, cost information and control strategies are needed. The information needed for robust design with the presence of measurement uncertainties as well as unknown disturbances were discussed in detail. The problems in choosing dynamic scenarios and their relative frequency of occurrence, and objective function in practical design were exemplified and discussed.

Appendix A. General dynamic design problem

Mathematically, the general dynamic design problem can be presented by slightly expanding on [9]:

$$\begin{cases} J = \min\limits_{\mathbf{u}(t),\mathbf{d},\mathbf{y}} & \int \mathrm{d}Z(t) f(\{Z(t)\}_{t=t_0}^{t_f}) J(\mathbf{x_d}(t_f), \mathbf{x_a}(t_f), \mathbf{u}(t_f), \mathbf{d}, \mathbf{y}, t_f; \{Z(t)\}_{t=t_0}^{t_f}), & \\ \text{s.t.} & \mathbf{h_d}(\dot{\mathbf{x}}_\mathbf{d}(t), \mathbf{x_d}(t), \mathbf{x_a}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{y}, Z(t), t) = 0 & \forall t \in [t_0, t_f] \\ & \mathbf{h_a}(\mathbf{x_d}(t), \mathbf{x_a}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{y}, Z(t), t) = 0 & \forall t \in [t_0, t_f] \\ & \mathbf{h_0}(\dot{\mathbf{x}}_\mathbf{d}(t_0), \mathbf{x_d}(t_0), \mathbf{x_a}(t_0), \mathbf{u}(t_0), \mathbf{d}, \mathbf{y}, Z(t_0), t_0) = 0 & \\ & \mathbf{h_p}(\mathbf{x_d}(t_i), \mathbf{x_a}(t_i), \mathbf{u}(t_i), \mathbf{d}, \mathbf{y}, Z(t_i), t_i) = 0 & \forall t_i \in [t_0, t_f], \quad i = 1, \ldots N \\ & \mathbf{g_p}(\mathbf{x_d}(t_i), \mathbf{x_a}(t_i), \mathbf{u}(t_i), \mathbf{d}, \mathbf{y}, Z(t_i), t_i) \le 0 & \forall t_i \in [t_0, t_f], \quad i = 1, \ldots N \\ & \mathbf{h_q}(\mathbf{d}, \mathbf{y}) = 0 & \\ & \mathbf{g_q}(\mathbf{d}, \mathbf{y}) \le 0 & \end{cases} \tag{A.1}$$

where J is the objective (e.g. costs/tonnes paper produced), functional on scenarios; $Z(t)$ is the vector of time variant scenario parameters; $f(\{Z(t)\})$ is the probability of scenario $Z(t)$; $\mathbf{h_d} = 0$, $\mathbf{h_a} = 0$ are the process model; system of differential, respectively, algebraic equations (e.g. short circulation process model); $\mathbf{h_0} = 0$ is the initial conditions (e.g. feed of filler and thick stock, chest levels); $\mathbf{h_p} = 0$, $\mathbf{g_p} \le 0$ are the dynamic equality and inequality constraints; $\mathbf{h_q}$, $\mathbf{g_q}$ are the design equality and inequality constraints; $\mathbf{x_d}(t)$ is the vector of time-dependent differential state variables (e.g. concentration dynamics); $\mathbf{x_a}(t)$ is the vector of time-dependent algebraic state variables (e.g. mass flows in direct mixing); $\mathbf{u}(t)$ is the vector of time-dependent control variables (e.g. valve position); $\mathbf{d}$ is the vector of continuous design variables; $\mathbf{y}$ is the vector of discrete/binary design variables (e.g. process and control structure selection, selection between discrete equipment sizes).

The system is fitted to the simulation and optimization environment as follows: J is minimized in Matlab® (every function evaluation includes running the simulation); $Z(t)$ is defined within the simulator; $f(\{Z(t)\})$, the disturbances in our case are included into one scenario; $\mathbf{h_d} = 0$, $\mathbf{h_a} = 0$, short circulation model is defined in the simulator with readily available process models and their connections; $\mathbf{h_0} = 0$, the initial conditions are defined within the simulator; $\mathbf{h_p} = 0$, $\mathbf{g_p} \le 0$, not present at the current case; $\mathbf{h_q}$, $\mathbf{g_q}$, constraints for manipulated variables are defined for the optimization routine; $\mathbf{x_d}$, dynamics are defined within the simulator; $\mathbf{x_a}$, mass flows are calculated within the simulator at each time step; $\mathbf{u}(t)$, control variables calculated within the simulator at each time step; $\mathbf{d}$, e.g. controllers' tuning parameters are manipulated by the optimization algorithm $\mathbf{y}$ process and control structure selection, equipment sizes are manipulated by the optimization algorithm.

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