CONTROL-ORIENTED IDENTIFICATION AND UNCERTAINTY ESTIMATION FOR PAPER MACHINES

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ABSTRACT

A control-oriented identification and uncertainty estimation approach from input-output data is presented, for use in the design of control systems for paper machines. The application of this approach is demonstrated on a high fidelity simulator. An estimate of the process model along with the uncertainty bounds that describe the confidence limits of the model, consistent with the robust control theory, is obtained. These results can then used to design a multivariable controller based on loop-shaping principles and guided by the estimated uncertainty bounds. The simulations demonstrate the suitability of the approach and illustrate that the technique can be used to provide high bandwidth performance for both servo and regulatory control.

1. INTRODUCTION

Motivation for this work has been driven by the goal to improve the control of paper machines. Recently multivariable predictive controllers have been used for controlling paper machines. Although multivariable predictive control technology is relatively mature, it has not taken full advantage of the developments in the area of robust control theory. Success of robust loop shaping techniques such as those used in controlling temperatures in diffusion/CVD furnaces [1,2], motivated the authors to use these concepts for paper machine control. While this paper presents the application to a high fidelity paper machine simulator, a preliminary evaluation of the concepts with real plant data has produced similar results.

In a quick description, a paper machine process begins by spraying diluted paper pulp (~3% solids) onto a wire mesh. After evaporation of some of the water content, the paper is fed through a sequence of dryers, coated with latex (depending on the type of paper produced) and, eventually, collected on a reel (see Fig.1). Important parameters include machine speed, paper dry weight and paper dryness that are measured by sensors located at different points in the production line. Stock flow and dryer temperatures are among the variables used to control the process. While the actual set of control inputs and process outputs includes more variables, only the ones listed above are considered here. An existing paper machine simulator is used to validate the performance of the Loop Shaping controller. This simulator had been developed several years earlier, and has been used in the development and verification of other Honeywell paper machine control products. It is a full First Principles simulator, covering the process areas from the machine chest to the reel. It includes high fidelity models for the thick stock system, approach flow, head box, forming table, press and dryer sections. It also has a size press, speed/draw system, and a closed-loop white water system. Disturbances can be added at various points in the process, and the variations can be spectrally tailored to approximate real machine conditions. Over the course of many evaluations, it has been shown to be a faithful representation of an actual paper machine.

Paper machine control provides a particular challenge. Many of the process variables are interacting, so a combination of single loop controllers is not effective. For a multivariable approach, the situation is complicated by the wide range of process responses, which need to be solved simultaneously. For example, some relationships have long dead-times, but short settling times, (eg. Stock/Weight), some have short dead-times and long time constants, (Steam/Moisture) and others can have a minimal dead-time and fast dynamics, (Speed). Historically, forming a decoupled control strategy to solve this problem, and maintaining robust control in the presence of model errors, has been a difficult challenge.

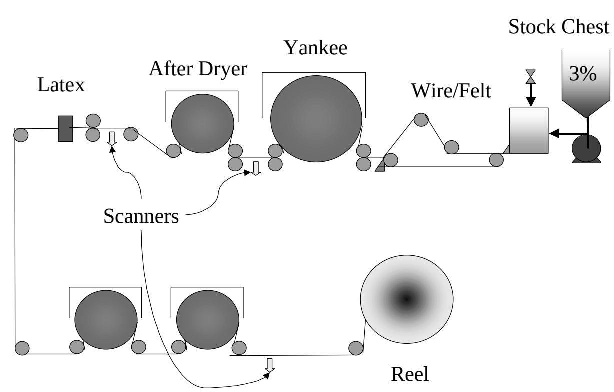

Figure 1. Paper Machine Schematic

There are two main objectives that the controller must address. The most common requirement is to minimize the long and medium term variability of the process. The control must thus be optimized for disturbance rejection. Bearing in mind the presence of some long transport delays, there is a practical limit on how fast a variation can be reduced, but by using a computationally

[#] on sabbatical leave with Honeywell HTC-Phoenix fast, robust, controller the bandwidth can be maximized. The other requirement is for the controller to allow smooth changes to its operating point. The system must therefore perform well at set-point tracking. Whilst some traditional controls could be optimized for either objective, but not both, the Loop Shaping approach allows for a complete control solution, making use of the available extensive insight and computational tools.

To solve this problem a multivariable controller is designed using a traditional implementation approach consisting of: step test, modeling and uncertainty estimation via system identification, controller design, and controller validation. The key design approach is to use an integrated and systematic method to obtain control models using input-output data and design a multivariable H_∞ controller to meet the desired objectives. Particular attention is focused on the computation of uncertainty estimates that limit the achievable controller performance. The success of implementation in terms of performance and expediency in implementation depends critically on the correct estimation of the limitations imposed by the model uncertainty.

2. MODELING VIA SYSTEM IDENTIFICATION

2.1 Parameter Estimation

The system identification relies on a least squares parameter estimation algorithm to obtain parameter estimates for a linear model that describes the process locally around an operating point. The main objectives of identification are to determine a system model that describes the input-output data and to estimate uncertainty bounds that describe the confidence in the model. The choices of system model structure and uncertainty description during identification are not unique. In this application, the approach follows that of [1,2].

To describe the dynamical system, a state-space model is used with the states and outputs given by:

$$\dot{x} = Ax + Bu; y = Cx + Du$$

For multiple-input, single-output (MISO) systems, under an observability assumption [3], the above model can be written as:

$$\dot{x} = Fx + \theta_1 u + \theta_2 y; y = qx + \theta_3 u$$

where *F* and *q* are selected a priori so that *F* is Hurwitz, *(F,q)* is a completely observable pair, and $\theta_1, \theta_2, \theta_3$ are adjustable parameters. The usefulness of this description is that it can be readily converted into a linear model form, which is convenient for parameter estimation, that is, $y=w^T\Theta$. Here Θ is a vector containing all the adjustable parameters (elements of $\theta_1, \theta_2, \theta_3$) as well as the initial conditions *x(0)*. The regressor vector *w* contains the signals $(sI-F^T)^{-1}q^T u$, $(sI-F^T)^{-1}q^T y$, *u*, and $(sI-F^T)^{-1}q^T$, where the last term corresponds to the unknown initial conditions. After generating the regressor vector, Θ can be determined in a least squares sense from:

$$\Theta = \arg\min \left\| y - w^{\mathrm{T}}\Theta \right\|_2^2 .$$

For systems with multiple outputs (MIMO), the above formulation is repeated for each output and the resulting state-space model is concatenated to produce the overall model of the system. Since this approach may result in a non-minimal model, it is followed by a model order reduction step.

A by-product of the above approach is that the minimized error corresponds to the contribution of coprime factor uncertainty [5]. For this, the above parametrization of the system can be written as:

$$y = M^{-1}\left[N(u) + e\right]$$

where *e* is the fitting error, and *M* and *N* are stable proper systems determined by F,q and $\theta_1, \theta_2, \theta_3$. The coprime factor uncertainty arises from attributing the error to the input and the output, i.e.,

$$e = \Delta_N[u] + \Delta_M[y]$$

Summarizing, the system identification procedure is described as follows: Generate an input excitation signal [4,9]. Compute the filtered signals and estimate the parameters of the linear models by solving the least squares problem. Compute the corresponding state-space representation of the identified system *[A,B,C,D]* and perform model order reduction, if necessary, [5]. Compute the uncertainty bounds for the identified system.

2.2 Uncertainty Estimation

The estimation of model uncertainty bounds (or confidence limits) is an important component in system identification. It is even more crucial in the context of feedback, since it imposes constraints on the achievable performance that enters as user selected parameters in the standard controller design techniques. Violation of such constraints may lead to poor control performance and possibly closed-loop instability.

It should be emphasized that the role and usefulness of feedback is to reduce the effects of certain forms of uncertainty and modeling errors. Feedback controllers can typically tolerate and attenuate low-frequency uncertainty but are more susceptible to modeling errors in the mid-frequency range (the separation is based on the closed-loop crossover frequency). The implications of this observation are twofold. On one hand, the identification procedure should emphasize the model accuracy in the frequency range around the crossover. This can be achieved by a proper selection of the excitation sequence and the identification design parameters (input signal, prefilters, etc. [4,9]). On the other hand, once a model becomes available, it is important to compute uncertainty estimates that are suitable for the controller design technique used. Furthermore, these estimates -although approximate - should be able to detect a possible infeasibility of the controller design problem with the given closed-loop performance objectives.

Concentrating on the last issue, and with H_∞ as our controller design technique, we express the uncertainty estimates as weights for the loop sensitivity ($S=[I+GK]^{-1}$) and complementary sensitivity ($T=GK[I+GK]^{-1}$) functions. This is compatible with standard software (MATLAB's Robust Control Toolbox, [6]). In this form, H_∞ design draws considerable insight from classical loop-shaping principles, while fundamental feedback limitations are easily observed (e.g., $S+T=I$).

Various model error structures have been used in control systems design for describing the uncertainty in a manner consistent with robust control theory [5]. In a typical uncertainty estimation approach from data, the model-data mismatch is described by a multiplicative uncertainty, say Δ such that $y = (I+\Delta)G[u]$, where G in the nominal (identified) model of the plant. To ensure closed-loop stability, the magnitude of Δ imposes a constraint on the magnitude of T in the frequency domain.

In this work, we adopt the coprime factor uncertainty approach of [1,2] which is defined as follows. Let $G = M^{-1}N$ *be a* coprime factorization of the nominal plant model. Then the coprime factor uncertainty is defined in terms of two stable operators Δ_N and Δ_M such that the actual plant is $y = (M+\Delta_M)^{-1}(N+\Delta_N)[u]$. This approach is well suited for the earlier described identification scheme since $\Delta_N[u]+\Delta_M[y]$ equals the estimation error which is the signal minimized during the parameter estimation. Its main advantages lie in its handling of low-frequency perturbations and perturbations that can change the number/location of unstable modes.

A difficulty with this formulation arises from the fact that the correlation between the plant input and output prohibits the estimation of separate bounds for the two uncertainty components from input-output data. To alleviate this problem, we adopt an unfalsification approach, similar to [7] but with the perturbation sources being both the plant input and output. That is "*we seek to find a bound for the most favorable uncertainty that is required to describe the residual error."* Of course, the interpretation of such bounds in the controller design is also modified. Instead of sufficient condition for stability, we now have the pseudo necessary conditions for instability. That is, loosely speaking, if the controller design violates the given bounds, then it is likely that the closed-loop system will be unstable. In this case, we should design the controller so that it maintains some distance from the estimated stability boundary (interpreted as a risk factor).

The key ideas for the computation of uncertainty bounds and the corresponding S and T weights for H_∞ design were introduced in [1,2]. These computations are fairly efficient for systems with similar channel bandwidths and "low" condition numbers and where the objective is channel matching (i.e., S and T are scalar-times-identity). Here, however, the same computation may lead to undesirably conservative results due to (possible) channel bandwidth separation and conditioning problems. Notice that in [1,2] the inputs and outputs had comparable magnitudes and frequency contents, while here the inputs and outputs represent physically different quantities, which can easily cause conditioning problems by a simple unit transformation. To avoid such problems and reduce the conservatism of the bounds, we use diagonal input and output scaling transformations and an error whitening filter, as shown in Fig. 2. The diagonal scales are computed so that all channels (input or output) contribute the same energy. The objective of these operations is to extract the obvious structural information from the uncertainty blocks so that a lumped estimate of their gain is not too conservative. For the above system, the application of the Small Gain Theorem [5] with "D-scale" optimization yields the following robust stability condition:

$$\bar{\sigma}[U_s KSM^{-1}W_e]\bar{\sigma}[\Delta_{\mathbf{N}}] + \bar{\sigma}[Y_s SM^{-1}W_e]\bar{\sigma}[\Delta_{\mathbf{M}}] < 1$$

where $\bar{\sigma}$ denotes the maximum singular value. For square systems, writing KS as $G^{-1}T$, the uncertainty bounds are then computed as in [1,2], by solving the following optimization problem:

$$\min_{\delta_1,\delta_2} \bar{\sigma}\lfloor U_s G^{-1}TM^{-1}W_e \rfloor \delta_1 + \bar{\sigma}\lfloor Y_s SM^{-1}W_e \rfloor \delta_2$$

$$s.t.: \begin{cases} \Delta_N[u_s] + \Delta_M[y_s] = e_w \\ \bar{\sigma}[\Delta_N] \le \delta_1; \bar{\sigma}[\Delta_M] \le \delta_2 \end{cases}$$

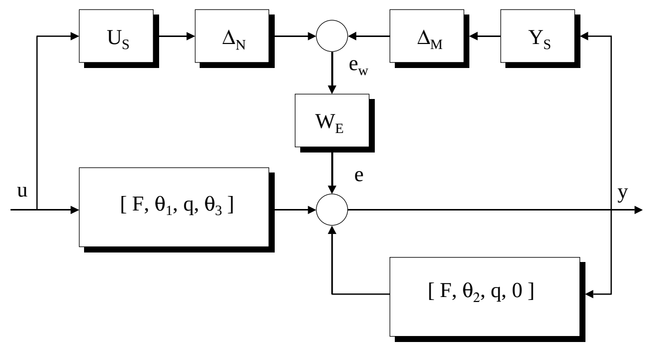

Figure 2. Structure of Identification Uncertainty

With T and S replaced by the respective target values, these uncertainty bounds are attractive as they depend only on the desired loop properties and not the controller itself. In addition, the various quantities have simple frequency domain definition and can be readily computed via FFT's. By defining T and S as diagonal transfer matrices, the design requirements can be specified to accommodate significant variations in the channel bandwidths (not the most general but covering most practical objectives). Notice that guidelines for the selection of the target loop sensitivities can be obtained from this expression by analyzing the per-channel contributions. It is also worthwhile to mention that there is no loss of information when the uncertainty is split. Simply the energy of the error is distributed to the two uncertainty blocks. Consequently, if the actual design does not match the target loop, the evaluation of the robust stability condition will simply be suboptimal and more conservative. Based on practical experience, there is rarely a need to iterate the uncertainty decomposition step as long as the designed closed-loop is "close" to the target. After the controller design is complete, the robust stability condition should be re-evaluated for the actual controller to obtain a more accurate estimate.

For plants with highly mismatched channels, better estimates could be obtained by using a formal μ-analysis (e.g., see [11]). Nevertheless, in our case, the simpler approach relying on error whitening and scaling has proven to be adequate.

While the above analysis provides only estimates of the uncertainty bounds and closed-loop stability is not strictly guaranteed, practical experience indicates that there is a very strong correlation between these bounds and successful controller designs.

3. CONTROLLER DESIGN AND IMPLEMENTATION

Using a (sensitivity) loop-shaping approach the uncertainty bounds obtained in the system identification step are used to define simple sensitivity and complementary sensitivity weights. The weights are chosen to maximize the disturbance attenuation properties without violating the constraints imposed by the uncertainty estimates. These together with the identified plant are then converted in the format required by the computational software [6]. An H_∞ approach was selected for the controller computations because it minimizes the weight selection iterations for achieving a target loop shape. (Of course, other controller design tools may be used as well, as long as the loop-shaping objectives are met.) This process may require a few iterations for a first-time design, especially when right-half plane zeros (or delays) appear close to the desired bandwidth. The entire process is quite fast; starting with raw data, it takes less than an hour (considerably less for second-time designs) to generate and validate the final controller. In our case, we performed an additional iteration for controller refinement by appending closed-loop step data to the original PRBS and repeating the identification and controller design.

Following this initial solution, the obtained controller is reduced and discretized and is augmented with an observer-based anti-windup scheme [8] to handle control input saturation. The final controller is also augmented with a plant observer to supply an estimated plant output in case of bad or missing sensor measurements. This augmentation helps to preserve the controller integrity, since the sensors (scanners) used in paper production, undergo frequent cleaning/resetting procedures and paper breaks are not uncommon.

The final controller was implemented in the TDC3000[1] at a sampling rate of 2 seconds. Step set-point changes showed excellent tracking performance and channel-decoupling along with smooth control activity. Subsequently, the closed-loop response to a large unmeasured disturbance (a change in consistency), the transition to a grade change under closed-loop control, and the closed-loop response to various set point changes at the new operating region were successfully evaluated. Due to space limitations, more details on the controller evaluation have been included in the second author's web page **http://enuxsa.eas.asu.edu/~tsakalis**.

4. CONCLUSIONS

The above "experimental" results demonstrate that the robust loop shaping control design is a sound methodology for designing controllers for paper machine applications. Similar results were obtained in a preliminary evaluation of the design approach with actual plant data. Moreover, the incorporation of the uncertainty bound in the controller design is intuitively appealing. The control performance was excellent. The user time requirement for the input-output data collection is in the order of 2 to 3 hours for a typical paper machine. The identification, controller design, and validation cycle can be completed within an hour. This leads to a significantly fast turnaround time. This technology utilizes traditional control design concepts whereby an extensive insight and computing tools available.

Even though, the above controller worked quite well at a different operating region, this may not be true for all possible regions of operation (e.g., making different grades of paper). For such cases, a non-linear or a gain-scheduled controller may be designed and, possibly, coupled with an outer loop optimizer. The details for this are left as a subject of future work, together with the evaluation of other anti-windup mechanisms [10].

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