Identification Tool for Cross-Directional Processes

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***Abstract*— This paper considers an industrial identification tool for cross-directional (CD) process of continuous web manufacturing such as papermaking. A special focus is on identification of the mapping between CD actuators and measured profiles of the web properties from input-output process data. The developed algorithms are based on nonlinear parametric models of the CD response shape and mapping and minimize a model fit error for a two dimensional array of data. The algorithms are deployed as a part of an automated process control support tool and have been successfully used over a period of time on many paper mills with various types of the CD actuators. The paper is illustrated by identification results from a real-life paper mill.**

***Index Terms*— distributed system, control, identification, optimization, paper process**

I. Introduction

CROSS-DIRECTIONAL (CD) control of continuous web manufacturing, in particular of paper manufacturing, is arguably the most established industrial application where large arrays of actuators are used to control spatial distributions of physical variables. In a paper machine, CD actuators can influence various properties of a continuously manufactured paper web, such as areal weight, moisture, thickness, gloss, etc. These properties must be maintained at target across the paper web, which is several meters wide and is traveling through the paper machine at speeds of up to 100 km per hour. The physical processes influenced by CD actuators and the actuator principle of action vary broadly. The actuators might locally modify high-speed sheet flow of the liquid pulp stock to influence cellulose fiber deposition on the moving 'wire' mesh, locally apply hot steam to enhance initial drying of the paper or locally deform steel rollers that squeeze the paper to the desired thickness (caliper). Many other principles of CD actuation exist.

In CD systems, the profiles of paper properties are measured downstream from the actuators with scanning gauges or array sensors and fed back to control system employing the actuators. CD control systems have been used in industry for more than two decades and technical approaches to their design, engineering, and support are well established. Typically, CD systems are maintained and supported by technician-level field personnel and the accepted technical approaches tend to be the simplest possible that would allow sustained operation. It is only recently that deployment of more sophisticated control-theoretic techniques in the industrial systems has been enabled by new computing technology. The advanced algorithms deployed in industrial plants have to be packaged as automated software applications that can be used by field personnel with little or no control theory background. Advanced model based control requires setting up and maintaining adequate process models. Identification is, thus, a necessary and important part of a CD process control package. As a premier vendor of advanced CD control systems, Honeywell recognized the identification importance and sponsored the development described in this paper.

This paper describes an integrated industrial tool for paper machine CD control identification. The tool dubbed IntelliMap is a result of several years of development effort. Presently, it has been installed in a few hundred of paper mills around the world and is being used for on-going identification of several CD processes on each paper machine. This is a significant responsibility because an identification error could easily detune control system to the extent of producing substandard paper or even interrupting the paper machine operation. The losses might be large since a paper machine makes a few hundred dollars worth of paper per minute. The tool is used to update a CD response model on a regular basis as a part of the on-going support of a CD control system. Several years of the deployment have validated reliability of its identification algorithms.

One of the most critical issues in the CD control is mapping between the measurements and the actuators. Practitioners of CD control know well that even moderate errors in defining the mapping in a CD control system might lead to control instability. In paper machine processes, the CD actuator mapping is influenced by a number of factors including: 1) geometric alignment of the CD actuators and measurement device; 2) position of the individual actuators within the CD actuator array; 3) wandering of the paper web; 4) paper shrinkage characteristics through the drying process; 5) flow pattern of the extruded liquid paper stock on the initial stage of the papermaking process (paper machine wire). While the first two factors, in principle, could be determined from an accurate measurement of geometrical parameters of a paper machine, the last three might change with the time, paper grade, and process equipment settings. In particular, the paper shrinkage is recognized to be a complicated, non-linear phenomenon depending on the paper furnish, drying process and many other factors, e.g., see [17], [22], [23]. The importance of accurate identification of paper shrinkage increased with the introduction of the CD actuators with very narrow spacing. With the number of CD actuators exceeding 300 on some modern systems, even a 1% increase of the shrinkage towards the paper web edges can result in the response center displacements exceeding an actuator zone width compared to the case of uniform shrinkage.

In addition to the mapping, the parametric model being identified includes CD response shape and time dynamics of the process response. Knowing these parameters is necessary for tuning the CD controller as discussed in [19], [18], [20].

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The prior work in CD control identification includes the papers [15], [4], [14], [24] considering applications of modern time-series analysis methods in CD process identification. These methods tend to use large number of free parameters to describe the identification models. They require relatively long time series rarely available in practice. The volume of computations associated with processing time series data for each of the thousands databoxes can be enormous. Significant amount of process noise present in the data, short time series, and computation performance requirements point at identification of simple parametric models as an attractive alternative.

The algorithms in this paper were chosen over those found in other technical papers on the subject mostly because of the practical application requirements. Section 2 discusses these requirements in more detail. This paper is a first one to present technical detail of the approaches outlined in the earlier journal papers [9], [11], [12]. Another part of this paper value is as a case study presentation on the algorithms successfully productized in the form of an integrated identification tool. The early versions of the tool have been briefly described in [12], [10]. This paper is the first archival publication that describes the entire set of the algorithms used in the tool and the accumulated deployment experience. Section 3 explains the main identification algorithm based on alternating identification of CD and time-dynamics model. The convergence of this algorithm was proven in [9] assuming that the CD identification sub-problem is solved somehow but not discussing the solution. Section 4 of this paper describes the CD identification in some detail. Most of technical material in Section 4 is new and was never published in a journal paper. Many of the application results in Section 5 are also novel, in particular the material on the 'multivariate' CD identification.

The developed algorithms can be used in CD control of other flat sheet manufacturing processes, in particular, plastic film manufacturing. Physics of these processes, actuation, and sensing are very different from the papermaking. Yet, the structure of the system models and data used for the identification are essentially the same. For all CD control processes, the time dynamics of actuation and sensing are much slower than process response, while spatial responses are largely shift-invariant. This yields "separable" system models where spatio-temporal system response is a cascade combination of purely dynamical and spatial response. It is believed that the identification algorithms discussed in this paper can be also applied in other, emerging, applications of spatially distributed control. The algorithms can be extended to spatially invariant distributed systems where the time dynamics of actuation and sensing are much slower than the time response of the system.

II. Application requirements

This section presents application requirements followed in designing the CD identification algorithms. Much of technical literature on identification considers mathematical problem statements requiring algorithms to be optimal and/or possess 'nice' asymptotic properties. Most of the practical engineering requirements below cannot be reduced to a simple mathematical problem statement.

First, consider requirements to the overall identification logic. An industry practice of identifying a CD process, in particular a CD mapping, is to step (bump) selected actuators and observe the process response. An arrangement of such 'bump test' experiment is shown in Figure 1. The collected data include actuator positions and process measurements with time stamps. It is an industrial practice to perform a bump test in order to verify the paper alignment in a CD control system. To facilitate acceptance of the developed identification tool by paper mill personnel, the tool uses a bump test-like excitation.

The main advantage of the bump test arrangement is that an operator can find out whether the process response to the 'bumps' is perceptible on the noise background and abort the test early if this is not the case. This is important because each test takes much time and interferes with the product quality. Other types of excitation were proposed for identification of CD processes in [5], [2], [4] and defended by various optimality arguments. When collecting bump test data, a pulse in space and step in time provide a good broadband excitation. Excitation of that type is commonly used in the process control identification. In particular, step responses of the process provide primary models in many industrial Model Predictive Control packages.

The setup of the bump test excitation is a part of the identification tool functionality. In order to perform a bump test, the control system is taken off the 'cascade' (closed-loop feedback) control and put into an 'automatic' mode of maintaining desired setpoints. In a CD process, the disturbances that are being compensated by the feedback control are slow. A paper machine can operate in an open loop for some time while making on-spec product provided the actuator setpoints are maintained the same as just prior to breaking the control loop. The described arrangement leads to the following two major constraints on the data collection. First, the duration of the bump test has to be limited to less than an hour (less than 100 measurement scans coming with a 15 sec interval). Otherwise, the open-loop process might drift into an off-spec condition resulting in production loss. Second,

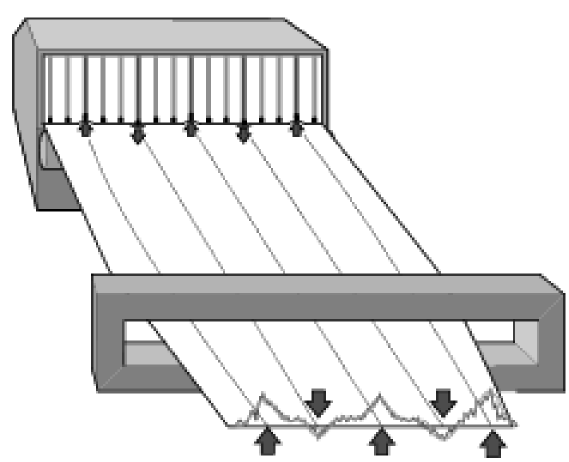

Fig. 1. Arrangement for experimental identification of the mapping for a paper machine

the applied bumps may not increase the naturally occurring process variation by much, lest the identification application is accused by process personnel in degrading the product quality.

Except for the bump test and data collection functions, the identification tool software shall run outside of and in parallel with the control logic. Its interaction with the controller includes acquiring model parameters currently used in the controller for comparison with the newly identified parameters. The tool also should allow an operator to upload a new model into the controller, as well as store and upload data sets for past tests.

The identification should be very robust and reliable while achieving a reasonable accuracy. In particular, an accurate identification of CD mapping is important, while CD response shape and time response identification could tolerate much larger relative error. Being completely automated, the identification algorithms should always produce some result or warn of impossibility of identifying a model reliably from a particular data set. For user to maintain confidence in the algorithms, a reasonable result should be produced for each data set where the process response is visible to a trained operator.

The most important requirement to the identification tool is operator usability. It should produce the result automatically, without a need for an operator to set up any parameters or initial conditions for a broad range of the CD processes. The computational delay for the identification should be reasonable, within one–two minutes, such that a user does not loose patience waiting for the results. This should be achieved for two-dimensional data sets with 100 to 2000 measurement databoxes and 20 to 300 actuator commands collected over 10 to 200 scans. The algorithms should work reliably for short data sequences with the response to the actuator excitation barely visible in the noisy data. The CD responses might be as narrow as a couple of actuator zones (4-5cm for 300 actuators in a 7 m wide machine) to a quarter of the paper width (a couple of meters). For narrow responses and many actuators identification of nonlinear shrinkage, it is important to achieve accurate modeling of the CD mapping. For wide responses, the nonlinear shrinkage identification is impossible and not needed.

Finally, consider the requirements to the CD process model used in the identification. This model should be simple and include just a few free parameters. It should be easy to explain to someone with the process knowledge but little control background. It should closely follow established practices of describing the CD processes. Using a model with a few free parameters makes it possible to identify these parameters reliably from noisy data. The two-dimensional arrays of data used for CD process identification contain many thousand data points and allow for significant statistical averaging when only a few model parameters are estimated.

The requirements brought up in this section were taken into account and satisfied in the design of the CD identification tool and its mathematical algorithms described in the following sections of this paper.

III. Overall identification approach

The CD process measurements are characterized by a profile of the process data sampled at regular intervals across the web. The profiles are obtained from a scanning device and are available on a periodic basis. We will describe the profile at scan t by vector $p(t) \in \Re^m$. The manipulated variables of the process are setpoints of the CD actuators influencing the process. These actuators are usually placed at regular intervals across the web. The actuator moves are synchronized with the scanning and are defined by the actuator profile $u(t) \in \Re^n$.

Consider the following control-oriented model of the CD process relating the manipulated variables and the obtained profiles.

$$p(t) = \gamma G g(z^{-1}) u(t), \tag{1}$$

where z^{-1} is a unit delay operator, $G \in \Re^{m,n}$ is a CD interaction matrix, and $g(z^{-1})$ is a SISO transfer function. The scalar parameter γ defines the overall gain of the process. The model (1) is *separable*. It assumes that the process response is obtained as a cascade connection of the dynamical response $g(z^{-1})$, which is the same across the web, and a spatial response G. Separable models of the form (1) are commonly used in the industry. They have been studied in many papers on CD process control and identification, e.g., see [1], [2], [4], [13], [24].

In what follows, parametric models of the transfer function in (1) are assumed in the form

$$g(z^{-1}) = g(z^{-1}; \theta_T), \tag{2}$$

$$G = G(\theta_{CD}), \tag{3}$$

where θ_T and θ_{CD} are the model parameter vectors.

In a bump test identification experiment the selected actuators are moved (bumped) simultaneously as follows

$$u(t) = U a(t), \quad U \in \Re^n, \;\; a(t) \in \Re, \tag{4}$$

where U is the bump profile and $a(t)$ is the amplitude of the bump. Typically, $a(t)$ would take one of the values $\{-1, 0, 1\}$. The model parameters are identified from the CD profiles collected in the bump test

$$P = [p(1) \; \ldots \; p(N)] \;\; \in \Re^{m,N}. \tag{5}$$

The identification problem is to find the vector of the model parameters in (2)–(4)

$$\theta = [\gamma \;\; \theta_T^T \;\; \theta_{CD}^T]^T \tag{6}$$

that provides the least square fit of the process output data set P (5)

$$\theta_* = \text{arg min} \|P - \hat{P}(\theta)\|_F^2, \tag{7}$$

where $\hat{P}(\theta)$ is the model based prediction of the system output obtained by feeding the input signal (4) through the model (1)–(3)and the subscript F denotes the Frobenius norm.

As discussed in [9], the loss index in the r.h.s. of (7) can be presented in the form

$$\|P - \hat{P}(\theta)\|_F^2 = \|P\|_F^2 + \gamma^2 \|h(\theta_T)\|^2 \|p_u(\theta_{CD})\|^2 - 2\gamma p_u(\theta_{CD})^T P h(\theta_T), \tag{8}$$

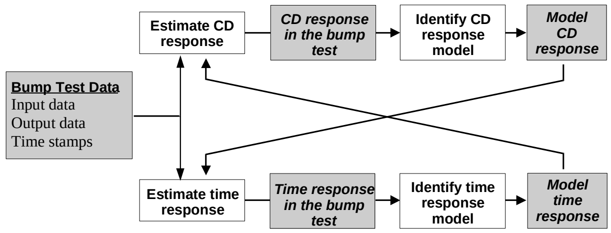

Fig. 2. Schematics of the iterative identification algorithm.

where the profile p_u defines a spatial response to the actuator excitation profile U in (4), the vector $h(\theta_T)$ with components $h(t;\theta_T)$ defines time-response of the process to the excitation sequence $a(t)$

$$\begin{aligned} p_u(\theta_{CD}) &= G(\theta_{CD})U, && (9)\\ h(\theta_T) &= [h(1;\theta_T)\ \dots\ h(N;\theta_T)]^T, \\ h(t;\theta_T) &= g(z^{-1};\theta_T)a(t). && (10) \end{aligned}$$

Without loss of generality, it can be assumed that $\|h(\theta_T)\| = 1$ and $\|p_u(\theta_{CD})\| = 1$. This is because the scaling or the gains in G and g is taken care of by the parameter γ in (6). In accordance with (8), the least square estimate of γ can be found as

$$\gamma = p_u^T(\theta_{CD})Ph(\theta_T). \qquad (11)$$

Assume now that the CD model parameter vector θ_{CD} is known (CD response $p_u^T(\theta_{CD})$ is known). By computing γ in (8) using (11), the least square optimal conditional estimate of the time-response model parameters θ_T can be found as

$$\theta_{T*} = \text{arg min}\|h(\theta_T) - \hat{h}\|^2, \qquad \hat{h} = P^T p_u(\theta_{CD})/\gamma, \qquad (12)$$

where $\hat{h}$ is an estimate of the process time response obtained by cross- correlating the collected CD profiles $p(t)$ with the predicted CD response shape p_u. The problem (12) is a standard single-input, single- output identification problem that can be readily solved by one of the standard identification methods. In the deployed algorithms, a first order with deadtime model is used for the process dynamics. Thus, the vector θ_T has two components: process time-constant and process deadtime. A combination of a global grid search and a Levenberg-Marquardt iterative minimization over the two parameters is used to solve the problem (12) and find an estimate θ_T.

Finally, assume that the time-response parameter vector θ_T is given and the time-response $h(t;\theta_T)$ is known. Then the least square optimal conditional estimate of the cross-directional model parameters θ_{CD} can be found as

$$\theta_{CD*} = \text{arg min}\|p_u(\theta_{CD}) - \hat{p}\|^2, \qquad \hat{p} = Ph(\theta_T)/\gamma, \qquad (13)$$

where $\hat{p}$ is an estimate of the process CD response obtained by correlating the time history for each databox with the single predicted time-response $h(t;\theta_T)$. The problem (13) deals with identification of the CD response parameters θ_{CD} for a single CD response profile and it is a much simpler problem compared to the original identification problem (5). The algorithms for solving the CD identification problem (13) are discussed in the next section of this paper.

An iterative algorithm that is used for solving the overall least-square identification problem (7) is described in [9]. This algorithms starts from assuming initial estimates of the parameters θ_T and θ_{CD} and proceeds with in turn solving the problems (12) and (13). The algorithm logic flow is graphically illustrated in Figure 2. Theoretical justification of the algorithm convergence is presented in [9]. The experiments in applying the proposed algorithm to various real-life data sets show that it converges rapidly, after 2-3 iterations. The algorithm is very efficient computationally, as it reduces the two-dimensional identification problem (7) to a series of one-dimensional identification problems.

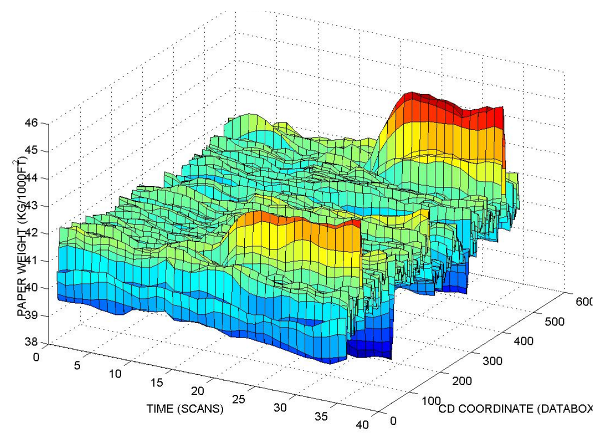

Fig. 3. Example of CD profile data obtained in a bump test data and used for identification

Figure 3 illustrates a set of bump test data used for identification. The results of applying the described algorithms to the data are illustrated in Figure 6 where the time-responses $h(\theta_T)$ and $\hat{h}$ as well as CD responses $p_u(\theta_{CD})$ and $\hat{p}$ extracted from the two-dimensional data set are shown in the lower two plots.

IV. CD MODEL IDENTIFICATION

This section considers the problem of identifying the CD response (13) in more detail. Unlike the time-response identification problem (12), the CD response identification (13) is a nonstandard problem. Though the high-level problem statements (12) and (13) look similar, the parameters appear in the fitted function in a very different way. After formulating the CD response model, this section discusses identification of response for single actuator. This simplified problem illustrates main ideas and builds justification for dividing the CD response identification problem into CD response shape identification and CD mapping identification. The identification algorithms described in this section include two stages. First, rough, approximate identification of the model is performed. Then the model is fine-tuned by iterative nonlinear optimization of a loss index.

A. CD response model

The assumed CD response model is that the process responses for each actuator have the same shape. This assumption is commonly made in practice and is satisfied for most CD processes with a reasonable accuracy. The entries of matrix G in (3) are

$$G_k^j \quad = \quad b(d_s k - c_j; \theta_S), \tag{14}$$

where $b(x;\theta_S)$ is a continuous function of the CD coordinate x, d_s is a spatial distance between the measurement samples (databox width), c_j is a coordinate of the response center for the actuator j, and θ_S is a parameter vector describing the model of the CD response shape. A mapping model complements (14) by describing how the coordinate c_j of the spatial response center depends on the CD coordinate position x_j of the respective actuator. The mapping model has the form

$$c_j \quad = \quad f(x_j; \theta_M), \tag{15}$$

where θ_M is a vector of the mapping model parameters. In accordance with (14) and (15), the overall CD response parameter vector in (3) is

$$\theta_{CD} \quad = \quad [\theta_S^T \ \ \theta_M^T]^T. \tag{16}$$

Based on extensive experience with paper machine processes, the CD response shape model (14) was assumed in the form

$$b(x;\theta_S) \quad = \quad \frac{g}{2}\left[r\left(\frac{x+\delta}{w}\right) + r\left(\frac{x-\delta}{w}\right)\right], \tag{17}$$

$$r(x) \quad = \quad \mathrm{e}^{-ax^2}\cos\pi x,$$

$$\theta_S \quad = \quad [w \ \ a \ \ \delta]^T. \tag{18}$$

In (17) g is a normalization parameter, the response gain is handled through the parameter γ in (6). The three components of the parameter vector θ_S define the response shape. The parameter w defines "width" of the actuator CD response. The "attenuation" parameter a defines the size of the response negative lobes. For large a these lobes are practically absent, for smaller a they are more profound. The "divergence" parameter δ defines the presence of two maximums in the response and the distance between these two maximums. In papermaking, bi-modal responses can result from diverging waves or wakes propagating on the surface of liquid paper stock on the wire mesh in production of heavy weight papers.

The CD mapping model (15) describes how the coordinate c_j of the CD response center depends on the CD position x_j of the j-th actuator. In industrial CD control, the mapping model (15) is the most important part of the CD process model. A parametric model of mapping used herein is introduced through a fuzzy logic model of the shrinkage profile and described in [7], [8], [11]. The model reflects that the paper typically shrinks more towards the edges of the web and has the form

$$c_j \quad = \quad c_0 + \left(x_j - \frac{1}{2}x_*\right)(1-s_0) + s_{low}l_{low}\sigma\left(1 - \frac{x_j}{l_{low}}\right)$$
$$-s_{high}l_{high}\sigma\left(1 - \frac{x_* - x_j}{l_{high}}\right), \tag{19}$$

where x_* is the total width of the CD actuator array and c_0 is a constant offset. The first two terms in (19) describe the shift and a uniform shrinkage s_0 of the paper, the last two summands describe shrinkage change towards the sheet edges. The parameters s_{low} and s_{high} have the meaning of the CD shrinkage increase towards the web edges. The two parameters l_{low} and l_{high}, as well as the function $\sigma(x) : \sigma(0) = 0, \sigma(1) = 1$ describe the shape of the nonlinear shrinkage profile. In accordance with [7], [8], [11] this function is assumed as

$$\sigma(x) = 2(x - \mathrm{atan}(x)) \tag{20}$$

The mapping model (19), (20) is fully defined by the parameter vector θ_M (15) of the form

$$\theta_M \quad = \quad [c_0 \ \ s_0 \ \ s_{low} \ \ s_{high} \ \ l_{low} \ \ l_{high}]^T. \tag{21}$$

In what follows, as a first stage in identifying the "detailed" CD response model (19)–(21) a "simplified" model is used, where some of the parameters in (21) are set to the fixed values

$$\theta_M \quad = \quad [c_0 \ \ s_0 \ \ 0 \ \ 0 \ \ x_*/4 \ \ x_*/4]^T, \tag{22}$$

$$\theta_S \quad = \quad [w \ \ 7 \ \ 0]^T \tag{23}$$

The simplified model (22)–(23) contains only three free parameters that need to be identified: w, c_0 and s_0. As a result, this identification can be done much faster and with better robustness than identification of the detailed model. The simplified model describes the practically observed CD responses qualitatively well. In what follows, identification of the simplified model is used as a starting point for the detailed model identification. In the implemented algorithms, using the simplified model allows to find a vicinity of the global minimum for the loss index. The detailed model identification then improves this initial guess of the global minimum.

B. Identifying CD response for a single actuator

An insight into the CD identification problem (22)–(23) can be gained by identifying CD response for a single actuator. In accordance with (14) the response (9) to a single actuator bump has the form

$$p_u(c,\theta_S) = u[b(d_s - c;\theta_S) \ \ \ldots \ \ b(md_s - c;\theta_S)]^T \in \Re^m, \tag{24}$$

where u is the scalar amplitude of the actuator move and c is the response center.

The response center c can be estimated by minimizing a quadratic loss index of the form (13) with respect to the assumed response center position c. Numerical experiments indicate that identification of c is very robust with respect to the response shape parameters [8]. Though minimal achievable error of the fit varies widely depending on the assumed shape parameters θ_S the location of the minimum coincides with the bump response center for a broad range of θ_S. This fact indicates that an accurate identification of the CD mapping is possible even with very rough knowledge of the CD response shape. A theoretical justification of this fact is suggested below.

Let us analyze the loss index in r.h.s. of (13) in more detail. By using (24) and denoting $\hat{p}_k$ the components of the vector $\hat{p}$ in (13), this loss index can be presented in the form

$$J \quad = \quad \sum_{k=1}^{m} |ub(d_s k - c, \theta_S) - \hat{p}_k|^2. \tag{25}$$

In the rest of this section, we assume that components $\hat{p}_k$ of the response profile vector $\hat{p}$ in (25) are the sampled values of a twice continuously differentiable function $\hat{p}(x)$, where x is the CD coordinate, so that $\hat{p}_k = \hat{p}(d_s k)$.

The sum in the r.h.s. of (25) closely approximates an integral of a continuous function over the CD coordinate. If the databox width d_s is small compared to the width of the CD response, which is usually the case in practice, the sampled-data loss index (25) can be replaced by the following continuos loss index with an accuracy $O(d_s)$

$$J_c(c) = \int |p_u(x-c) - \hat{p}(x)|^2 dx, \qquad (26)$$

where $p_u(x-c) = ub(x-c;\theta_S)$ is the modeled CD response of the process.

The following proposition shows the reason for the observed robustness of the CD response center identification to the response shape change

Proposition 1: Let us consider two symmetric, twice continuously differentiable functions $p_u(x-c)$, $\hat{p}(x)$, $\Re \mapsto \Re$, zero outside a finite support interval $x \leq x_0$. Then, for a loss index of the form (26) the following holds: (1) $c = 0$ is a stationary point of $J_c(c)$ (2) $c = 0$ is a local minimum provided that $\int p'_u(x)\hat{p}'(x)dx > 0$, where prime denotes differentiation.

Proof. Simple calculations show that

$$\begin{aligned} \frac{\partial J_c(c)}{\partial c} &= -2\frac{\partial}{\partial c}\int p_u(x-c)\hat{p}(x)dx \qquad (27) \\ &= 2\int p'_u(x-c)\hat{p}(x)dx - 2\int p_u(x-c)\hat{p}'(x)dx, \end{aligned}$$

where we used the fact that $p_u(x-c)$ has finite support interval and, thus, $\int |p_u(x-c)|^2 dx$ does not depend on c. Thus, $\frac{\partial J_c(c)}{\partial c}|_{c=0} = 0$ as an integral of an antisymmetric function - a product of symmetric and antisymmetric functions. In a similar way

$$\begin{aligned} \frac{\partial^2 J_c(c)}{\partial c^2} &= 2\int \hat{p}(x)p''_u(x-c)dx \\ &= -2\int \hat{p}'(x)p'_u(x-c)dx. \qquad (28) \end{aligned}$$

Computing $\frac{\partial^2 J_c(c)}{\partial c^2}|_{c=0}$ in accordance with (28) proves the second claim of the Proposition. QED

Proposition 1 shows that in the absence of the noise, the identified response center c effectively does not depend on the CD response shape. This center can be accurately determined by using a broad class of the CD response shape models that satisfy very mild requirements of Proposition 1 as to their similarity to the real CD shape. It can be theoretically demonstrated that a response center position obtained by minimizing the sampled loss index (25) differs from the position obtained from the continuos index (26) by an error of the order d_s^{-2}. Thus, the proposed method is very accurate if the databox width d_s is much less than the CD response width. The latter condition holds in most practical cases.

Proposition 1 assumes that the averaged process response $\hat{p}(x)$ is free of noise. Assume now that the response is in fact $\hat{p}(x) + \xi(x)$, where $\xi(x)$ is the noise and $p_u(x)$, $\hat{p}(x)$ satisfy the condition of Proposition 1. Denote by $J_e = \int |p_u(x-c) - \xi(x) - \hat{p}(x)|^2 dx$ the loss index for the noisy data. Substituting $\hat{p}(x) + \xi(x)$ instead of $\hat{p}(x)$ in (27) to compute the derivative of J_e and using (27), (28), yields in the vicinity of the correct center position estimate $c = 0$

$$\frac{\partial J_e(c)}{\partial c} = e(c) + c\left.\frac{\partial^2 J_c(c)}{\partial c^2}\right|_{c=0} + o(c^2), \qquad (29)$$

$$e(c) = -\int \xi(x)p'_u(x)dx, \qquad (30)$$

where $\left.\frac{\partial^2 J_c(c)}{\partial c^2}\right|_{c=0} > 0$ is as in (28). The error of the response center position identification can be estimated from (29) as

$$\Delta c \approx e(c)\cdot\left(\left.\frac{\partial^2 J_c(c)}{\partial c^2}\right|_{c=0}\right)^{-1}, \qquad (31)$$

By computing a Fourier transform of the convolution integral in (30), we obtain

$$|e(c)| \leq \frac{1}{2\pi}\int |\tilde{\xi}(i\omega)|\cdot|\tilde{p'_u}(i\omega)|d\omega, \qquad (32)$$

where tilde denotes a Fourier transform of the respective function. In many practical cases, the measurement noise $\xi(x)$ is concentrated on high frequency. At the same time, the differentiated model response $p'_u(x)$ computed in accordance with (4) exhibits low-pass characteristics. In this cases, the noise influence on the response center identification accuracy is minimal.

C. Finding the initial guess of the CD response parameters

Consider now the problem of obtaining initial estimates of the response shape and mapping parameters. The problem (5), (25), (13) with the parametric model of the process CD response (17), (22) is highly nonlinear and nonconvex in the parameters θ_S and θ_M. The loss index (13) can have multiple local minimums over these parameters. A search through a broad range of these parameters is necessary to ensure that a vicinity of the global minimum for the loss index is selected over one of the local minimums.

Consider the identification of CD response for a single actuator within the framework of the simplified model (22)–(23). When used for identification of a single actuator response, this model has two free parameters: response width w and center coordinate c. In accordance with (17), (23) the problem of minimizing the loss index (25) can be presented in the form

$$J = \sum_k \left| g\,u\,r\left(\frac{d_s k - c}{w}\right) - \hat{p}(d_s k)\right|^2 \to \min_{w,c}. \qquad (33)$$

The minimum of the loss index (33) is achieved if the CD response $\hat{p}(x)$ and the model response shape $r(\frac{x-c}{w})$ are in maximum correlation with each other. This follows from the normalization condition $\|p_u(\theta_{CD})\| = 1$, which for (33) takes the form $\sum_k \left|g\,u\,r\left(\frac{d_s k - c}{w}\right)\right|^2 = 1$. Similarly to the transition from (25) to (26), the problem of minimizing (33) can be approximately represented in the form

$$\psi(w,c) = C\int r\left(\frac{x-c}{w}\right)\hat{p}(x)dx \to \max_{w,c}, \qquad (34)$$

where C is a normalization constant. The expression (34) can be considered as a continuous wavelet transform of the process response $p_u(x)$ with the mother wavelet function $r(x)$. The minimization of the loss index (6) is equivalent to finding a maximum of the wavelet transform $\psi(w, c)$ (34). By evaluating the wavelet transform (34) on a relatively sparse grid of the parameters w and c and finding the maximum on the grid, the initial guesses for w and c can be found.

The use of the wavelet transforms for the CD mapping identification, though motivated differently, has been discussed in [6], [16].

Consider now identification of the simplified model (22)–(23) from the response data for multiple actuators (13). Since $\|p_u(\theta_{CD})\| = 1$ in (13), the loss index is minimized if and only if the response $\hat{p}$ and the model response $p_u(\theta_{CD})$ are in maximum correlation with each other. Similar to (33), (34) this problem of maximizing the correlation can be presented in the form

$$J = \sum_j U_j \psi(w, c_j) \to \max_{w, \theta_M}, \quad (35)$$
$$c_j = f(x_j; \theta_M), \ (j = 1, ..., n),$$

where $f(x_j; \theta_M)$ is the mapping function given by (19), (22).

The loss index approximation (35) suggests the following computationally efficient strategy for the simplified model identification. As a first step, compute and tabulate the wavelet transform $\psi(w, c)$ (34) on a grid of c and w values. Then, for any given w the loss index J in (35) can be quickly estimated as a linear combination of the tabulated wavelet transform values for $c = c_j$. The computations at the second step are very fast, therefore, it can be repeated for many different combinations of w and θ_M enabling a direct search for the global minimum of (35). This very efficient algorithm was successfully implemented in the developed tool.

D. Improving the CD model

Once an initial estimate of the global minimum for the loss index (13) has been obtained by using the simplified model (22)–(23), the estimate of the parameter vector θ_{CD} can be further improved by using an iterative optimization method. Minimization of the loss index (13) is a standard *Nonlinear Least Square* problem. Iterative numerical solution of such a problem can be performed by the *Levenberg–Marquardt* method [3]. Other well known methods such as Gauss–Newton or Gradient Descent could be considered as special cases of the Levenberg–Marquardt scheme obtained for special values of the scheme parameters.

The Levenberg–Marquardt update requires computing the gradient of the loss index (13) with respect to the parameters θ_{CD} (16). This, in turn, requires computing the Jacobian $\frac{\partial p_u(\theta_{CD})}{\partial \theta_{CD}}$. By using the closed form expressions for the modeled CD response $p_u(\theta_{CD})$ given by (9), (14), (17), (19), a closed-form expression for this derivative can be calculated analytically, see [7], [8] for more detail.

Unfortunately, the loss index minimization problem is ill conditioned, nonlinear, and nonconvex. Therefore, problem-specific modifications of the optimization method were implemented to obtain robust and reliable estimates of the nine model parameters with limited number of iterations. They include variable scaling, Rosenbrock method steps to deal with ill-conditioned Jacobians, and conditional switching between iterative minimization and grid search. The implemented combination of these methods contributes to the industrial-level quality and reliability of the identification algorithms.

The overall logic of the CD response identifications is based on splitting of the overall identification problem into a series of simpler problems, simular to how the identification of the time-response and CD response are separated in the previous Section. The CD response identification logic subproblems are as follows

- First, the simplified model (22)–(23) is identified as described in the previous subsection.
- Once the simplified model identification is completed, the identification of the CD mapping parameters θ_M is performed independently of CD response shape parameters θ_S. This means the performance index is minimized with respect to θ_M while θ_S is fixed and vice versa. The optimization of θ_S involves three parameters only and can be completed in a straightforward and reliable way for fixed θ_M.
- In identification of the CD mapping model, initially only first two components of the vector θ_M (21) are optimized yielding a model for the alignment and the average shrinkage. For many processes this simple model of the CD mapping is sufficient, in particular for processes with wide CD responses and with relatively small number of the CD actuators. This is the default option for CD mapping identification.
- Optionally, the six parameters θ_M (21) of the CD mapping model with nonlinear shrinkage are identified by using Rosenbrock method steps [3].

The described mixed logic of the identification proved very successful and reliable in practice for a broad range of CD processes.

V. Implementation results

The above described algorithms have been implemented in a software application tool named IntelliMap. The tool has been deployed in hundreds of paper mills and applied to practically all types of existing CD processes. The integrated tool architecture and the identification result examples are discussed below.

A. Integrated tool

Figure 4 which shows the system-level design of the application. The application consists of two independent parts: the main computational and data collection application, and the user interface application. These two parts interact through a real-time networked database connected to other parts of process control, measurement, and information system.

Figure 5 shows the dataflow of the application. Two sets of key parameters are maintained for each actuator. One set is called System Data and includes data being used in the actual operation of the process control system, such as process gain or paper shrinkage. Another set contains identification data,

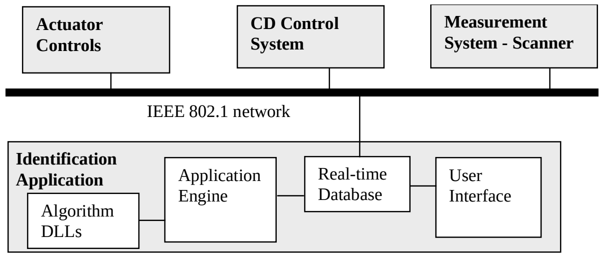

Fig. 4. System-level design of the identification tool

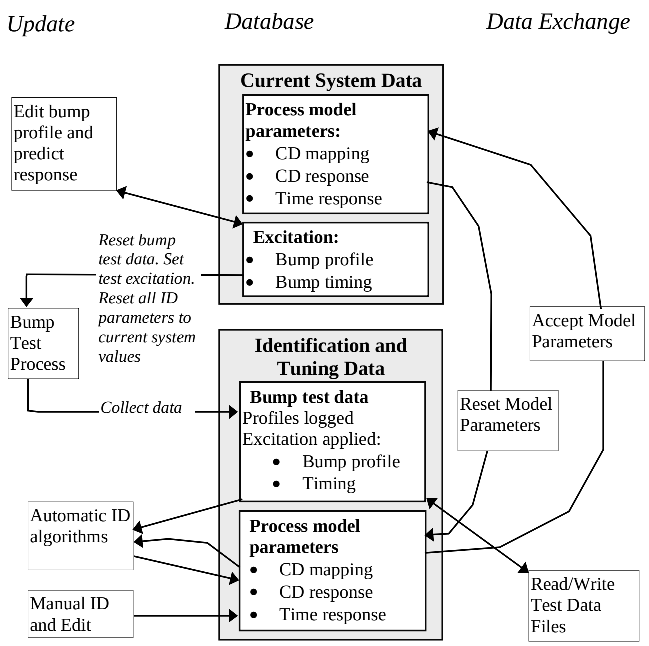

Fig. 5. Data flow and internal logic of the identification application

such as identified estimates of the process gain response shape or paper shrinkage. The user can evaluate the identification data, compare it to the current system data, and upload the new parameters into the CD control system. In the last case, the identification data is used to overwrite the system data.

As illustrated in Figure 5, different parts of the application work with the database, modifying and exchanging data between the two data sets and with external data. The supported data modification processes are as follows.

The bump test excitation setup in the tool supports dependence on the paper grade being manufactured. A specific excitation pattern is stored for each grade. When setting up a new grade or in some cases during operation, there is a need to edit the excitation pattern. The supported functionality includes modification of the positions and amplitudes of the bumps and modification of the time-sequence of the bumps.

The bump test process resets the identification model to the current System Data model. In the bump test, data such as high resolution profiles, actuator setpoints and sheet edges are collected from the CD control system and added to the tool database

By default, identification algorithms run automatically once the data collection in a bump test has been completed. The operator actions required to perform the identification are limited to initiating a bump test and approving the acceptance of the newly identified parameters as System Data. This degree of automation is very important in practice, very little learning effort is needed to successfully use the tool. The automated identification is supported by an intuitive user interface allowing the operator to initiate the test and examine the results before approving them.

At the same time, a more sophisticated user can have much more detailed control over the bump test setup and the identification process. For advanced users, the application allows for 'manual' identification by direct editing of the model data. This function is supported by displaying the fit of the process CD response $\hat{p}$ (13) and time response $\hat{h}$ (12) against the predictions $p_u(\theta_{CD})$ (9) and $h(\theta_T)$ (10) for the user-entered model parameters θ_{CD} and θ_T. The feature is helpful when understanding the process model parameters or dealing with extremely poor response data where an operator knowledge of the process needs to be taken into account in order to obtain meaningful estimates of the model parameters. As one more 'advanced' feature, the tool allows storing identification data in a disk file or uploading the data from a file.

B. Identification results

The developed CD identification tool was routinely used by hundreds of paper mills over a few years and proved to be robust, reliable, and convenient. It has consistently improved the quality of the CD control system operation. One screen of this identification tool with paper mill data is shown in Figure 6. The lower left plot in the screen shows the CD response identification results. The two displayed curves are the predicted model response p_u (9) (smooth curve), and the CD response $\hat{p}$ (13) (jagged curve) estimated from the two-dimensional array of the collected identification experiment data. The lower right plot shows the estimated $\hat{h}$ (12) and modeled $h(\theta_T)$ (10) time responses. This representation of the two-dimensional array of the identified data is highly intuitive. The upper left plot in Figure 6 shows the CD profile U (4) set up for the next identification experiment, the smaller upper right plot shows the time profile $a(t)$ of the excitation input (4).

The middle two plots in Figure 6 show current status of the CD process. The middle right plot shows the CD actuator setpoints. The middle left plot shows current measured profile error compared to the target. Another curve on the same plot is a prediction of how the process profile will be modified after the currently set bump profile (in the left top plot) is applied. The prediction is computed using the process model in the System Data and is very helpful for predicting what impact the bump test will have on quality of the continuously manufactured product.

The identification results in Figure 6 are obtained for paper weight process controlled with a slice lip actuator. A slice lip is a stainless steel bar mounted on the paper machine headbox and covering one side of the gap where the paper stock flows on the paper machine wire. The slice lip CD actuators are attached to different points of the lip and, by elastically deforming the lip, are capable of changing the extrusion gap,

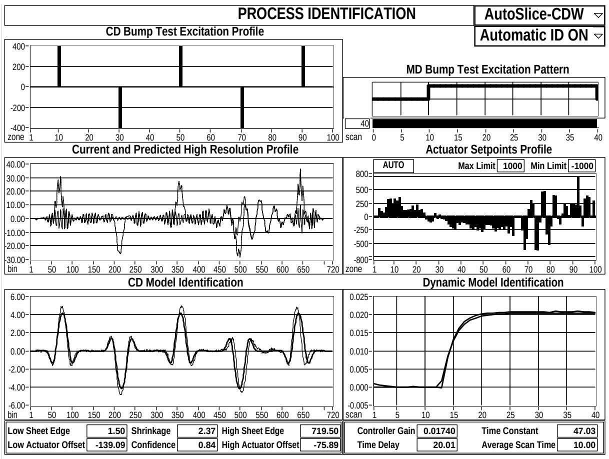

Fig. 6. Identification tool display

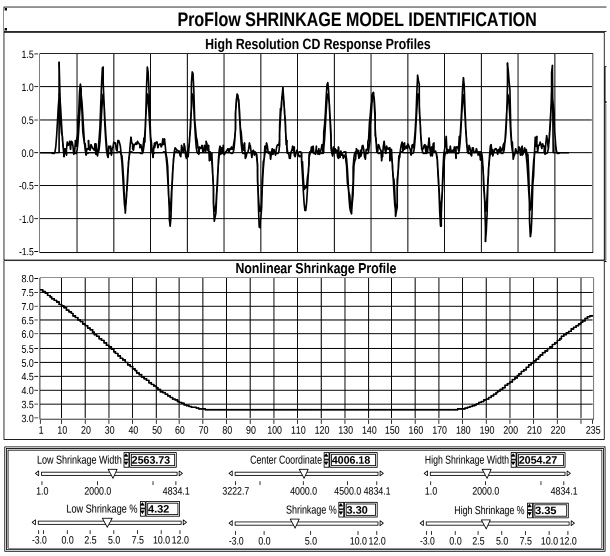

Fig. 7. CD mapping identification with nonlinear shrinkage

thus influencing locally the stock flow and ultimately the paper weight.

Figure 7 illustrates the screen of the developed tool controlling the nonlinear mapping function identification. The upper plot on the screen shows the fit of the identified CD response model against the estimated CD response in (13) . The lower plot shows the nonlinear shrinkage profile which corresponds to the identified nonlinear parametric mapping function (19). Finally, six sliders with indicators in the lower part of the screen correspond to the six components of the mapping parameter vector (21). Figure 7 shows identification results for a nonlinear shrinkage profile obtained on a fine paper machine with dilution weight actuators. The dilution actuators add water to the paper stock as it flows out of the machine headbox. This change in stock consistency reduces or increases the relative content of fiber in the stock and results in lighter or heavier weight paper being produced. The dilution water flow is regulated by motorized computer-controlled valve. There can be more than 300 dilution CD weight actuators across the machine, each changing the stock consistency locally. More

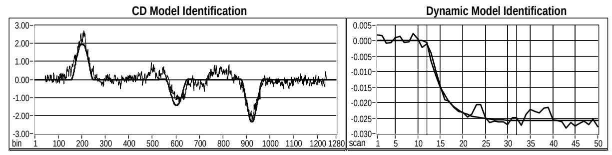

Fig. 8. Identification results for moisture profile response to a CD steambox

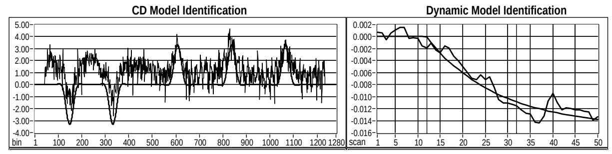

Fig. 9. Identification results for caliper profile response to an induction heating CD actuator

detail on the consistency profiling technology can be found in [21].

C. Multivariable identification example

Most of paper machines have multiple sets of CD actuators and paper properties are measured by multiple scanning gauges. Typically one CD actuator set is used to control one profile associated with it. The automated identification enables building 'multivariable' models of how each set of CD actuators is influencing each of the measured profiles.

An illustrative example of the multivariable CD identification is discussed below. A US paper machine with four CD actuator sets and three scanning gauges (on the same frame) was used in this study. The four CD actuator sets included in the study are: slice lip actuators for weight control (with 57 zones), steambox for moisture control (with 65 zones), water spay re-moisturisers (with 88 zones), and inductive heating caliper control (with 84 zones). There are three profiles of ready paper properties measured at the end of the paper machine: paper weight, moisture, and caliper (thickness). Each profile includes 1280 databoxes with 5.5mm width.

Figure 8 shows identification results for moisture profile response to a CD steambox actuator set. The CD actuator units influence the paper moisture by applying heat to localized areas of the paper surface. The data in Figure 8 is characterized by relatively weak response and high level of process variation.

Finally, Figure 9 shows results for identification of paper caliper (thickness) control using induction heating actuator. The paper caliper is adjusted near the end of the process by squeezing the paper between a stack of large steel rolls. The actuator set has 120 inductive heating elements each acting on a local area of one of the rolls. The localized thermal expansion of the roll reduces paper caliper in the area. Because the inductive heating has to overcome large thermal inertial of the roll, the inductive heating actuator has slow time-response.

The overall 'multivariable' identification results are summarized in Table I. For each pair of the CD actuators and the measurement, the table shows the parameters of the response shape model $\theta_S = [w\ a\ \delta]^T$ (18) , the process gain g, and the parameters θ_T of the dynamical process model (6). In the response shape model the response width w is shown in

	Measurement								
CD Actuator	**Dry weight**			**Moisture**			**Caliper**		
Slice lip	200	1.2	0.3	255	1.2	0	570	7	0
	15.3	30	0.65	22.2	30	0.50	147	0	0.55
Steambox	470	7	0	265	7	0.3	470	7	0
	37.5	30	0.26	53.5	30	-2.4	37.8	240	-0.45
Water spray	No interaction			250	7	0	130	7	0
				21.1	42	4.9	15.1	55.6	0.79
Inductive heating	No interaction			No interaction			250	7	0
							233	29.2	-1.8

TABLE I

MULTIVARIABLE MODEL IDENTIFICATION RESULTS.

The format of the displayed model is: $\frac{w}{T_c}\left|\frac{a}{T_d}\right|\frac{\delta}{g}$

millimeters. In the dynamical model, $\theta_T = [T_c \;\; T_d]^T$, where T_c is the process time constant (time constant of the first order lag model) and T_d is the process deadtime, both in seconds. The process gains are shown in relative units because of the proprietary nature of the data. The parameters θ_M of the CD mapping model (21) were identified for each actuator/sensor pair but are not displayed in Table I.

The results in Table I illustrate how automated CD identification can be used to improve understanding of complex interacting CD processes. Detailed explanation of the obtained model requires understanding of the papermaking process and is beyond the scope of this paper.

VI. CONCLUSIONS

This paper presented the design and core algorithms of a industrial identification tool for cross-directional (CD) processes. The tool has been successfully deployed for a few years in hundreds of paper mills around the world and proved to be very reliable in operation with many different types of CD processes. The acceptance of the tool by mill personnel is facilitated by following the established practices of CD process modeling and identification (bump tests). The tool uses a conceptually simple model of CD process and provides insight into the underlying physics of the process. Identification is performed by fitting a nonlinear parametric model to the bump test data. The overall problem is solved as a sequence of simpler sub-problems of identifying CD alignment, CD response shape, CD shrinkage profile, and process time-response. Estimation of two or three respective parameters in each sub-problem, as described in the paper, is very reliable and to large extent independent of other sub-problems.

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