International Journal of Recent Engineering Research and Development (IJRERD)
ISSN: 2455-8761
www.ijrerd.com || Volume 09 – Issue 03 || May - Jun 2024 || PP. 59-65

Comparative Analysis of Different Models Used for Cross Directional Control

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Abstract: For many industrial applications such as sheet and film processes, the model-based controlleris of great importance. Model-based controllers, however, may suffer a large performance loss under such conditions due to the presence of model-plant mismatch (MPM), which can occur in many industrial processes over timeand may create performance degradation. For sheet and film processes like paper making process, we suggest acomparisonof different cross-directional models based onperformance evaluation, ease of implementation, and their respective advantages and limitations in different operating conditions.

1. Introduction:

The pulp and paper industry has been under intense pressure to enhance overall efficiency because of the stiff competition occurring on a worldwide scale to reduce energy usage with quality improvement.This can be done by using efficient models that describe the process behaviour and capture the necessary process dynamics. This work focuses on the different process models used for paper profile control applications. In the introductory part we describe the basic operation of the paper machine and the modelling challenges.

1.1 Paper machine operation:

Paper machines convert a slurry of water and wood cellulose fiber into sheets of paper.Fig 1 shows a diagram of a typical Fourdrinier paper machine. Four sections make up a paper machine: wet end section, press section, dryer section, and post-drying section. Diluted fiber (a mixture of water and fiber with a concentration of about 0.5% fiber) is pumped into the headbox. To vary the amount of pulp spread on the drainage belt, an array of actuators is used to control the slice lip opening at the headbox. With numerous suction devices underneath, the drainage belt runs at a high speed to remove most of the water in the fiber. The paper sheet is further dewatered in the press section using steam boxes and pressing rolls, which leaves the paper sheet with a final fiber concentration of about 40%. The water concentration in the fiber in the dryer section is further reduced to roughly 5-9% by a series of steam-heated cans[1]. Calendar stacks control the paper properties in the post-drying segment, such as paper sheet thickness (calliper) and surface properties (gloss), before the paper sheets are wrapped up on the reel at the end

Basis weight, moisture content, and thickness are the three most crucial paper properties. At the end of the paper machine, traversing scanners are used to measure these properties. To estimate the paper properties, these scanning sensors move back and forth over the paper sheet. Due to the movement of the paper sheet, the scannerfollows a zigzag path. The purpose of the paper machine control is to minimize the variations in the properties and to increase the bandwidth so that disturbances with frequencies below the bandwidth will be attenuated and the effect on paper properties caused by disturbances will be minimized. Paper machine control can be separated into two categories, one is referred to as the Machine Direction (MD) in which the paper sheet moves. The other direction, known as Cross Direction (CD), is perpendicular to the sheet travel.By manipulation of actuators, the main goal in controlling a paper machine is to bring the real paper qualities as close to the desired as possible.Controlling the average values of measurement points is the purpose of MD control, and MD processes are typically considered as single-input-single-output (SISO) systems. For example, the overall level of moisture is controlled bythe average steam flow rate control in the drying section.

CD control is a finer resolution control and a much more difficult task than MD control. One finer example of CD control is slice-lip control, The amount of pulp coming out from the slice lip can be controlled locally by adjusting the opening of each slice lip actuator, which changes the local basis weight of the fibers on the sheet. Several slice lip actuators are positioned after the headbox. Slice lip actuators can also affect the moisture content and calliper of the paper sheet. The steam box actuators are used in the press section for dewatering the paper sheet by spraying hot steam onto the paper sheet. To avoid over-drying, rewet showers spray water drops onto the paper sheet. Similarly, the calendar stacks, a collection of induction heating rolls, are employed to modify the paper sheet's thickness. Although there are significant interactions between various actuator and controlled variable (CV) arrays, in this study, for the cross direction, we primarily focus on the single-array CD process models

Due to the characteristics of the CD processes, CD control is significantly more difficult than MD control [2] First, an industrial paper machine can be up to 10 meters wide and have hundreds of actuators and measurement bins. The huge dimension will make the controller design a difficult task if modelled as a multivariable system [3]. Second, because most CD process models are often ill-conditioned due to their spatially distributed nature, a significant number of eigenvector directions with small eigenvalues are difficult to control. Third, it is challenging to attain robust stability because of model uncertainty, particularly the gain sign uncertainty linked to the uncontrollable eigenvector directions.[4]The majority of MD and CD controllers are based on models established a priori from experiments like bump tests.A common example of model-based control is model-predictive control (MPC). The effectiveness of the closed-loop performance in these traditional CD control techniques is greatly influenced by the quality of the CD process model.There are several reasons, including poor model quality, improper controller tuning, and disturbance changes, that might cause the control performance to degrade.In general, the quality of the process model may decline as the process operating conditions change, which would negatively impact the control performance [4]In this situation, a new model for the process must be identified.

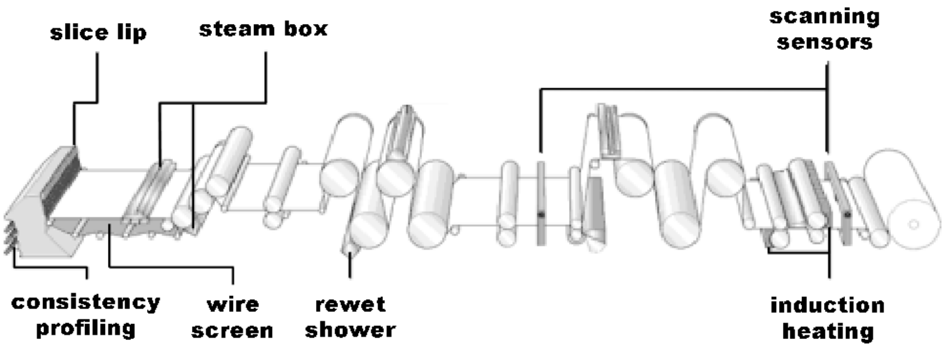

Figure 1. Wide view of the paper machine. (Artwork courtesy of Honeywell Industry Solutions.)

1.2 Model Identification:

The models in the paper industries are identified from input-output data. The schematic of the model is shown in Fig. 2. This data is captured by model identifier which can be a kindof formula or the algorithm and generates the model and this process for model generation is called Model Identification. Model identification can be done in two ways one is open-loop model identification which is commonly used in industries. In the open loop modelidentification, there is no correlationbetween noise and input signal but the drawback is that for this type of identification, the plant needs to be shut down resulting in economic loss.The closed-loop identification can be performed during the closed-loop operations but the limitation of the closed-loop identification is that there is a strong correlation between input and measurement noise that results in a biased estimate.

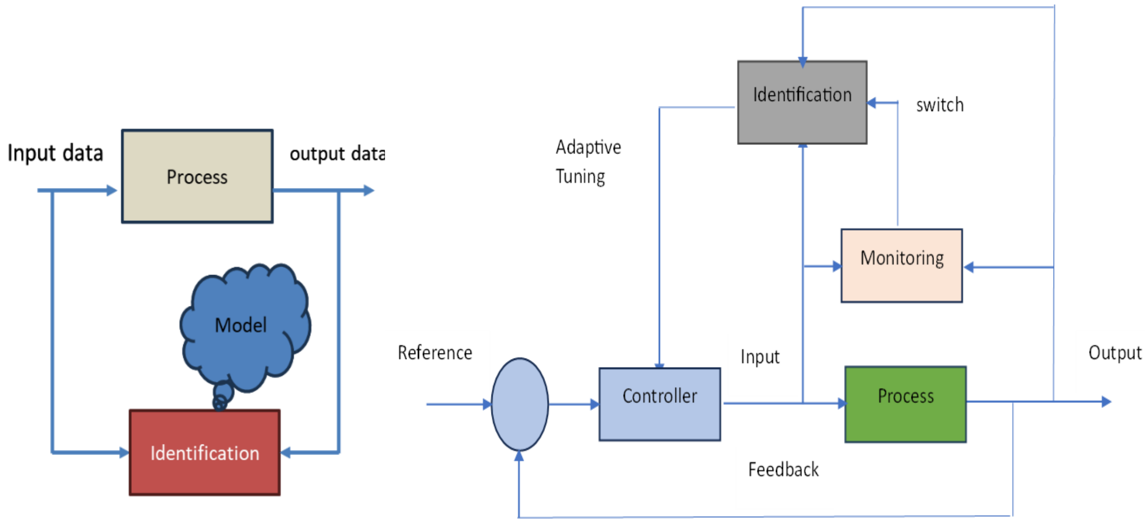

Figure 2. Model identification from input-output data

The following key contributionsto this work are:

- To describe the dynamics of different modelconcerning paper machine operations.
- To compare the different models based on their capabilities to explain the data

1.3 Basic Process model

We present typical process models for Cross Directional processes that are used in the industry. A typical basic process model, for instance, can be modelled as

$$y(t) = G(q)u(t) + H(q)e(t) \tag{1}$$

$G(q)$ is the first-order plus time delay model,$H(q)$ is the filter which is a monic, stable, and inversely stable transfer function through which the white Gaussian noise$e(t)$ passes and formsa filterednoise.$y(t)$ and $u(t)$ represents the output and input to the process respectively.

1.4 Controller PerformanceAssessment:

Most performance assessment techniques aim to find a benchmark theoretically perfect control performance. And compare it to the performance that is being evaluated. several reasons can hinder a controller from attaining optimal control performance in a typical control system. Performance limitations are restrictions on a controller's achievable performance, such as time constants, delays, etc[5]

1.5 Model-plant mismatch detection:

Several factors can affect control loop performance, such as model-plant mismatch (inadequate model), varying disturbance characteristics, and improper controller tuning. Since the model plant mismatch (MPM) has an impact on the control system's performance, it is important to monitor the model quality and see what are the key reasons for the performance degradation. The system must be reidentified only when there is considerable model degradation. MPM leads to poor control decisions, production loss, or even closed-loop instability[6].

2. Models used for cross-directional control:

The most commonmodels that are proposed for cross-directional (CD) control are

2.1 Toeplitz model (Conventional Model):

The Toeplitz model is named because of the Toeplitz structure of the spatial interaction matrix. This model is proposed by[7],[8],[9]

The CD process is a spatially distributed process that describes the relation between an actuator array and a controlled property. The CD process can bemodelled by

$$\boldsymbol{Y(z) = G(z)U(z) + D(z)} \tag{2}$$

The discrete-time deterministic multivariable process model is

$$\boldsymbol{G(z) = G_o T(z)} \tag{3}$$

Where $\boldsymbol{G_o}$is the spatial interaction matrix which is the Toeplitz matrix andgiven as

$$G_o(\boldsymbol{\bar{a}, n}) = \begin{bmatrix} a_1 & a_2 & \cdots & a_q & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ a_2 & a_1 & a_2 & \vdots & a_q & 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & a_2 & a_1 & a_2 & \vdots & a_q & \ddots & \ddots & \ddots & \vdots \\ a_q & \vdots & a_2 & a_1 & a_2 & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & a_q & \cdots & a_2 & \ddots & \ddots & \ddots & a_q & 0 & \vdots \\ \vdots & 0 & a_q & \ddots & \ddots & \ddots & a_2 & \ddots & a_q & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & a_2 & a_1 & a_2 & \ddots & a_q \\ \vdots & \ddots & \ddots & \ddots & a_q & \ddots & a_2 & a_1 & a_2 & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 & a_q & \cdots & a_2 & a_1 & a_2 \\ 0 & \cdots & \cdots & \cdots & \cdots & 0 & a_q & \cdots & a_2 & a_1 \end{bmatrix}$$

where

$$\boldsymbol{T(z)} = \frac{\boldsymbol{z^{-T_d(1-a)}}}{\boldsymbol{1-az^{-1}}} \qquad \textbf{(4)}$$

$\boldsymbol{Y(z)}$is the z transform of the measurement profile Y(t), $\boldsymbol{U(z)}$is the z transform of the actuator CD profile $U(t)$,$\boldsymbol{D(z)}$is the z transform of the disturbance profile $D(t)$
$\boldsymbol{m_y}$is the number of data boxed, $\boldsymbol{n_u}$are the actuators,$\boldsymbol{G_o}$ is the steady state spatial interaction matrix,$\boldsymbol{T(z)}$ is the discrete-time model,$\boldsymbol{T_d}$ is the dead time

The Toeplitz models capture the actual behaviour of the process where the response is truncated at the edges[10] but the model is quite complex for the controller design.

2.2 Circulant symmetric model:

To simplify the analysis to synthesize the controller the original Toeplitz matrix is transformed into a circulant symmetric matrix This makes the modeling and controller design simpler. The edge effect on the paper sheets is neglected or the boundary conditions are assumed to be periodic[8], [11]

The input-output model is given as

$$\boldsymbol{\hat{G}_o(\bar{a}, n)} = \begin{bmatrix} \boldsymbol{a_1} & \boldsymbol{a_2} & \cdots & \boldsymbol{a_q} & \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{a_q} & \cdots & \boldsymbol{a_2} \\ \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} & \cdots & \boldsymbol{a_q} & \boldsymbol{0} & \ddots & \ddots & \ddots & \vdots \\ \vdots & \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} & \vdots & \boldsymbol{a_q} & \ddots & \ddots & \ddots & \boldsymbol{a_q} \\ \boldsymbol{a_q} & \vdots & \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} & \ddots & \ddots & \ddots & \ddots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{a_q} & \cdots & \boldsymbol{a_2} & \ddots & \ddots & \ddots & \boldsymbol{a_q} & \boldsymbol{0} & \vdots \\ \vdots & \boldsymbol{0} & \boldsymbol{a_q} & \ddots & \ddots & \ddots & \boldsymbol{a_2} & \ddots & \boldsymbol{a_q} & \boldsymbol{0} \\ \boldsymbol{0} & \ddots & \ddots & \ddots & \ddots & \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} & \ddots & \boldsymbol{a_q} \\ \boldsymbol{a_q} & \ddots & \ddots & \ddots & \boldsymbol{a_q} & \ddots & \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} & \vdots \\ \vdots & \ddots & \ddots & \ddots & \boldsymbol{0} & \boldsymbol{a_q} & \cdots & \boldsymbol{a_2} & \boldsymbol{a_1} & \boldsymbol{a_2} \\ \boldsymbol{a_2} & \cdots & \cdots & \cdots & \cdots & \boldsymbol{0} & \boldsymbol{a_q} & \cdots & \boldsymbol{a_2} & \boldsymbol{a_1} \end{bmatrix}$$

$$Y(z) = \hat{G}(z)U(z) + D(z) \qquad (5)$$

Where

$$\hat{G}(z) = \hat{G}_o T(z) \qquad (6)$$

$\bar{a}$ is the actuator response vector, n being the order of the Toeplitz matrix and q represents the degrees of freedom

2.3 Two-dimensional (2D) Autoregressive moving average with exogenous input (ARMAX) model:

This model can be used in identifying the CD process and describe the linkage between the multi-variable model and two-dimensional systems [12]

$A(z,\lambda)y(m_t,n_c) = z^{-T_d}B(z,\lambda)u(m_t,n_c) + C(z,\lambda)e(m_t,n_c)$ (7)

Where $y(m_t,n_c)$ is the output, $u(m_t,n_c)$ is the input and $u(m_t,n_c)$ is the white noise with variance σ_e^2

$A(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} a_i\, z^{-j}\,\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} a_{-i}\, z^{-j}\,\lambda^{i}$

$B(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} b_i\, z^{-j}\,\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} b_{-i}\, z^{-j}\,\lambda^{i}$

$C(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} c_i\, z^{-j}\,\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} c_{-i}\, z^{-j}\,\lambda^{i}$

The backward shift operators z^{-1} and λ^{-1}' operate in the horizontal (MD) and vertical (CD) directions respectively.

The coordinates (m_t, n_c) represent the position in the plane concerning some arbitrary origin towards the bottom-left corner of the plane.

A, B, and C are all non-symmetric half-plane (NSHP) causal.

The term z^{-T_d} models the delay in the temporal domain. The local supports are assumed to be truncated at the edges to develop the appropriate prediction and control algorithms

2.4 Two- dimensional (2D) Autoregressive with exogenous input (ARX) model:

The model is described by [13][14] to estimate the basis weight. In refining process of the pulp and paper industry[15].This model comes fromEquation Error model family like the ARMAX model by taking$C(z,\lambda) = 1$ and the structure is given by

$$A(z,\lambda)y(m_t,n_c) = z^{-T_d}B(z,\lambda)u(m_t,n_c) + e(m_t,n_c) \quad (8)$$

The model cannot capture the true dynamics until the true process is ARX

2.5 Two-dimensional (2D) Output Error(OE) Model:

The model structure is given by

$$y(m_t,n_c) = z^{-T_d}\frac{B(z,\lambda)}{A(z,\lambda)}u(m_t,n_c) + e(m_t,n_c) \quad (9)$$

The model uses a nonlinear least square estimator and having the excellent abilityto capture the dynamics of the true model. The OE model is proposed by [13] with the hybrid approachto estimate paper profile parameters.

2.6 Spatial FIR model:

The spatial Finite Impulse Response(FIR) model can be represented by a two-sided λ transform that decays after n samples from both sides[12]

$$G_{FIR}(\lambda,\lambda^{-1}) = g_n\lambda^n + \cdots +. g_1\lambda^1. + g_0 + g_1\lambda^{-1} + \cdots + g_n\lambda^{-n} \quad (10)$$

λ^{-1} is the spatial left shift transform operator.
n is the model order for the FIR representing the causal spatial response Employing the separability assumption, the CD process is modeled by a noncausal spatial FIR cascaded by a temporal transfer function giving the following two-dimensional system.

$y(z,\ \lambda) = G_{FIR}(\lambda,\lambda^{-1})T(z)u(z,\lambda) + d(z,\lambda)$(11)

$T(z)$ is the actuator dynamics,

2.7 Box-Jinkins (BJ) model*:*

The structure of the model is given

$y(m_t,n_c) = z^{-T_d}\frac{B(z,\lambda)}{F(z,\lambda)}u(m_t,n_c) + \frac{C(z,\lambda)}{D(z,\lambda)}e(m_t,n_c)$ (12)

The BJ model is the most efficient model to identify the true process behaviour but highly complex due to many parameters.This model uses a nonlinear least square approach for parameter estimationThis model is proposed by [16] for forecasting of import and exports of paper products.

The polynomials for this model are given by

$B(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} b_i\, z^{-j}\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} b_{-i}\, z^{-j}\lambda^{i}$

$C(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} c_i\, z^{-j}\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} c_{-i}\, z^{-j}\lambda^{i}$

$D(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} d_i\, z^{-j}\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} d_{-i}\, z^{-j}\lambda^{i}$

$F(z,\lambda) = \sum_{j=0}^{M_x}\sum_{i=0}^{M_t} f_i\, z^{-j}\lambda^{-i} + \sum_{j=1}^{M_x}\sum_{i=1}^{M_t} f_{-i}\, z^{-j}\lambda^{i}$

Table 1 illustrates the comparative analysis of different models

Table 1: Comparison between different models

Model	Property
FIR (Finite Impulse Response)	Advantage • Linear least square approach for estimation • No need to build the stochastic model Limitations: • Just provide the prior information not explain the entire dynamics of the process
ARX (Auto-Regressive with exogenous input)	Advantage: • Linear least square approach for estimation Limitations • Joint parameterization (noise and process model share the same dynamics) • Not realistic model

	• Inability to reach the true model
ARMAX (Auto-Regressive Moving Average with exogeneous input)	Advantages • The model can capture the dynamics of complex processes • Joint parameterization but there is a flexibility Limitations: • Nonlinear least square approach for estimation
OE(Output- Error)	Advantages • Most preferred model because of its ability to capture the true model • No need to model the disturbance dynamics Limitations: • Nonlinear least square approach for estimation • The model may approach to the truth
BJ(Box -Jinkins)	Advantages • Among all models, this model has the maximum ability to capture the truth Limitations: • Highly complex because of the large number of parameters • Nonlinear least square approach for estimation

Conclusions:

The dynamics of the different data-driven model/time series models are explained with their utility in the pulp and paper industry. For the process industries, there are several candidate models, the specific model is chosen by taking their Auto Covariance Function (ACF) signatures. The extensions of these models such as the Autoregressive model with exogenous inputs with integrating effect (ARIMA) can be used to tackle the uncertainties like random walk process. The conventional methods that are used to train the models are regression methods. The training can be performed by using some novel methods such as Support Vector Machine (SVM) and Neural Networks (NN). There are severalstatistical methodsfor the validation of the models such as Residual test which is appliedto check the goodness of the model.

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