LAPPEENRANTA UNIVERSITY OF TECHNOLOGY

Faculty of Technology

Department of Mathematics and Physics

Simulating the performance of paper machine control

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Abstract

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Simulating the performance of paper machine control

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Supervisors: Prof. Matti Heiliö and Dr. Tuomo Kauranne

Keywords: Kalman filter, Fourier transform, data assimilation, paper machine, quality control system, simulation

The topic of this thesis is the simulation of a combination of several control and data assimilation methods, meant to be used for controlling the quality of paper in a paper machine. Paper making is a very complex process and the information obtained from the web is sparse. A paper web scanner can only measure a zig zag path on the web. An assimilation method is needed to process estimates for Machine Direction (MD) and Cross Direction (CD) profiles of the web. Quality control is based on these measurements. There is an increasing need for intelligent methods to assist in data assimilation. The target of this thesis is to study how such intelligent assimilation methods are affecting paper web quality.

This work is based on a paper web simulator, which has been developed in the TEKES funded MASI NoTes project. The simulator is a valuable tool in comparing different assimilation methods. The thesis contains the comparison of four different assimilation methods. These data assimilation methods are a first order Bayesian model estimator, an ARMA model based on a higher order Bayesian estimator, a Fourier transform based Kalman filter estimator and a simple block estimator. The last one can be considered to be close to current operational methods.

From these methods Bayesian, ARMA and Kalman all seem to have advantages over the commercial one. The Kalman and ARMA estimators seems to be best in overall performance.

Tiivistelmä

Lappeenrannan teknillinen yliopisto
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Miika Tolonen

Paperikoneen säädön toiminnallisuuden simulointi

Diplomityö

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52 sivua, 32 kuvaa, 2 taulukkoa

Supervisors: Professori Matti Heiliö ja Tutkijaopettaja Tuomo Kauranne .

Hakusanat: Kalman suodin, Fourier-muunnos, data-assimilaation, paperikone, laatusäätöjärjestelmä, simulointi

Tämän työn aiheena on monen säätöalgoritmin ja erottelumenetelmän yhdistelmän simulointi. Näitä menetelmiä on tarkoitus käyttää paperin laadun säätämiseen paperi-koneessa. Paperin valmistus on hyvin vaikea prosessi ja mittaustieto rainalta on hyvin vähäistä. Mittapalkki voi mitata rainalta vain sik sak kuviota. Prosessi tarvitsee kuitenkin mittaustiedon eroteltuna konesuuntaiseen (MD) ja poikkisuuntaiseen (CD) profiiliin. Laadun säätö perustuu näihin mittauksiin ja tarve älykkäiden erottelumenetelmien kehittämiselle kasvaa. Tämän työn tarkoituksena on selvittää kuinka älykkäät erottelumentelmät vaikuttavat paperin laatuun paperikoneessa.

Työ perustuu simulaattoriin, joka on kehitetty MASI NOTES projektissa. Simulaattori on arvokas työkalu, kun vertaillaan erilaisia erottelumenetelmiä. Tämä työ sisältää neljän eri erottelumenetelmän vertailun. Erottelumenetelmät ovat ensimmäisen asteen Bayesian menetelmä, ARMA menetelmä, Fourier muunnokseen perustuva Kalman suodin ja keskiarvo suodin. Viimeistä voidaan pitää lähimpänä kaupallista versiota, joka on nykyisin paperikoneissa käytössä.

Projektissa kehitetyillä menetelmillä näyttäisi olevan etuja verrattuna kaupalliseen versioon. Kalman- ja ARMA menetelmillä näyttäisi olevan parempi erottelutulos ja kokonaisuuden hallinta.

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The biggest acknowledgement is for my wife Anne, who helped and stood by me all this time, which I was spending doing this thesis.

Contents

List of symbols and abbreviations

Abbreviation	Description
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
CD	Cross Direction
DCS	Distributed Control System
DFT	Discrete Fourier Transform
FFT	Fast Fourier Transform
MA	Moving Average
MD	Machine Direction
MIMO	Multiple Inputs Multiple Outputs
MPC	Model Predictive Control
PID	Proportional Integral Derivative
QCS	Quality Control System
RMS	Root Mean Square

Symbol	Description
α	Exponential filtering level
a, b	Coefficients of the Fourier series
c	Complex coefficient of the Fourier series
f	Real-valued periodic function
F	Complex fourier components
x	state vector
Q	Covariance of the state vector
P	Error covariance matrix
A	The phase shift operator matrix, a model matrix.
K	The Kalman gain matrix
H	Measurement sensitivity matrix.
t, i, j, k, p	Time indices
$\hat{x}$	profile estimation
Y_t	Auto regressive moving average model
$D\delta t$	Diffusion parameter
$\hat{\sigma}^2$	variance
y	Measurement data
σ^2_{meas}	Measurement noise
u	control setting
K_i	Proportional gain
T_i	Time constant
e	difference from the set point
g	process model
J	objective penalty function
s	slack variable
$\hat{a}, \hat{b}, \hat{c}$	CD-control slip responses

Chapter 1

Introduction

Papers and Boards are typically formed in a web, which has a specific width and the web is moving forward with high velocity. The production process is based on wet web forming, where raw materials of paper or board are mixed with water. Water can be seen as conveyor for the raw material and therefore a homogeneous distribution of raw material is established in the web. The web is a thin layer of material components is known as stock. The goal for the machine is to remove water from the stock. Process is a continuous process, which is results in an end product, which is ready for the finishing processes.

The most important difference between board and paper is that board has multiple layers. The layers are unique for each board grade and basis weight is higher with board than with paper. Paper and board production methods and particularly web forming methods and machine concepts vary grade by grade.

Printing paper grades with large production volumes are newsprint, super calendered paper (SC) and coated magazine paper (LWC and MWC). Large fine paper machines most often produce copy papers and coated grades in large volumes. The most important packing board grades are packaging boards, such as folding box board, white lined chipboard, liquid packaging board, solid bleached sulfate board, carrier board and container boards. [1]

Paper and board quality variables measurements and feedback controls are part of the machine automation and a part of the mill automation framework. Control and measurement have specific requirements. The main requirement is to measure quality control variables and process measured data, quality control variables control in machine direction (MD) and cross direction (CD), producing outputs from measurement and control, control the production and report about the production. [2]

The measurement is done by a scanning sensor which takes measurements from a zigzag path on the paper or board. Processing of the measurement is then done with a assimilation method. By an assimilation method we mean an algorithm that produces an estimate of the state of any measured quality variable on the entire web. Assimilation method generalizes individual point measurement into a comprehensive estimate. The assimilation method derives profiles for different controls from these indirect measurements. The controls are working according to the profiles produced by the assimilation method. The result of the assimilation method is essential for a control system performance.

The controls are working in machine direction and cross direction. The MD-control is mainly controlling the mean variation. Performance wavelength of this control can measured in kilometres, because of the distance between the control and the measurement point. Actuators of the CD-controls are divided across the web. Actuator width is a physical limit for the performance and wavelength of this is measured in centimetres.

Implementing a new assimilation or control method for the machine needs a lot of testing time. The machines are run constantly and therefore implementation has to be done in real time. Before implementation a lot of testing has to be done with theoretical models. These models can be implemented into a simulator which contains the main features of the control and measurement system. This is an easy and cheap way of developing new control systems for the paper industry.

The purpose of this work is to compare three different assimilation methods to the current operational method. These assimilation methods were developed in the TEKES funded MASI NoTeS project. We test how these methods can replicate original variation and co-operate with the control system. For this testing purpose, it was essential to build up a user interface for the simulator. This interface makes possible easy changes in test settings which are located in several script files.

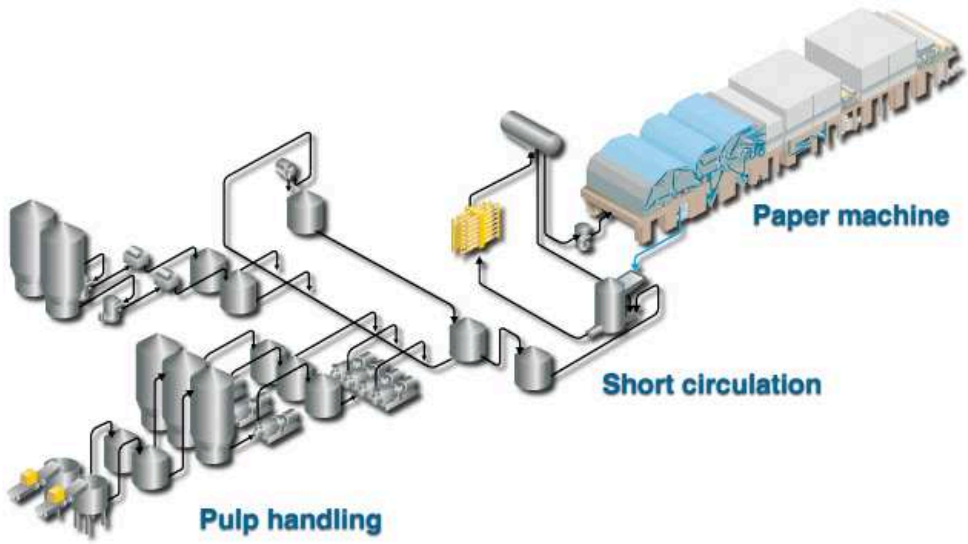


Figure 1.1: The paper or board making process machinery [1]

1.1 Paper Quality Measurement and Control

The quality of a paper product is described with quality variables, such as basis weight, moisture, caliper, ash content, colour and many other in paper and board industry. Traditionally paper or board is sold and bought according to laboratory analysis. Laboratory analysis methods can not be used in the paper or the board machine, because it is physically impossible and control loop response time would be days. Therefore online measurement and automatic control is needed. Online measurement is based on indirect measurement methods, which describe the value of a certain quality variable with the help of some other quality variable. Some variables are depend on each other, such as basis weight, moisture and caliper. Each of these linked variables can be individually controlled, but each control is affecting all the linked ones. In these cases the control is done by optimizing the affect of all controls. Each paper grade has its specific targets and limits for the quality variables. [1] [2]

During a run, paper or board quality is continuously measured by a system of scanners (Figure 1.2). The quality control variables are measured online and therefore theoretically variables can have automatic control. The automatic quality control of the paper and board machine has two directions: machine direction (MD) and cross direction (CD). The ultimate goal is maintaining a good and homogeneous quality and keeping the end customers happy. Requirements for product quality have become tighter, machine speeds have increased and higher production effectiveness and efficiency is required. Further development of the paper of board machine process and the automation is needed simultaneously. [1]

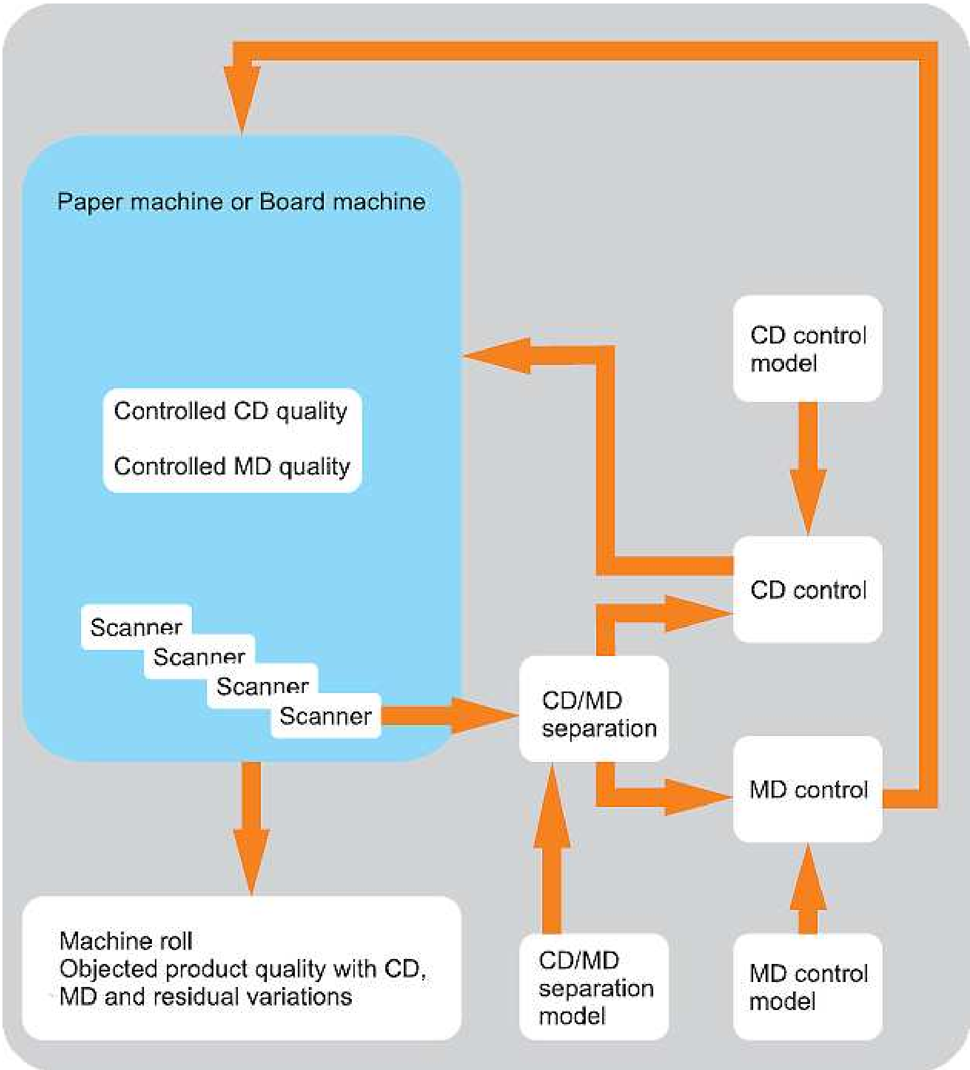
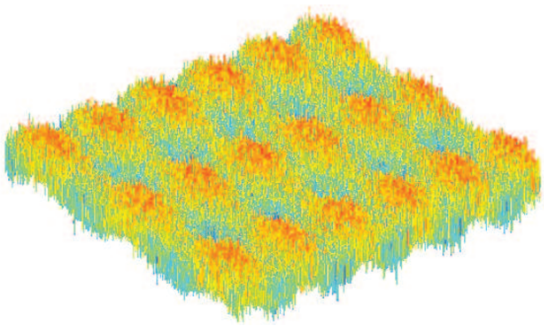


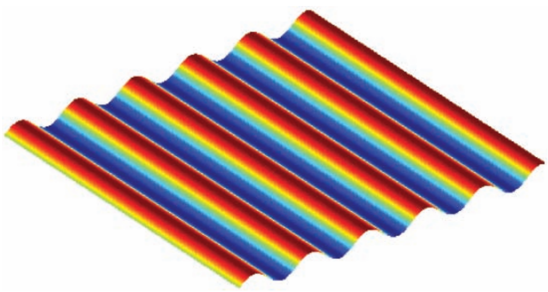
Figure 1.2: The Automation framework on the paper or board machine [14]

The automation and the control system of the modern paper or board machine is nowadays based on an integrated comprehensive system. The integrated automation system can give information on following topics: distributed basic automation, machine controls and drive controls in distributed control systems (DCS), quality measurements and controls, and higher level optimizations in quality control systems (QCS), optical fault detection of the paper web, web break monitoring and paper machine condition monitoring. [1]

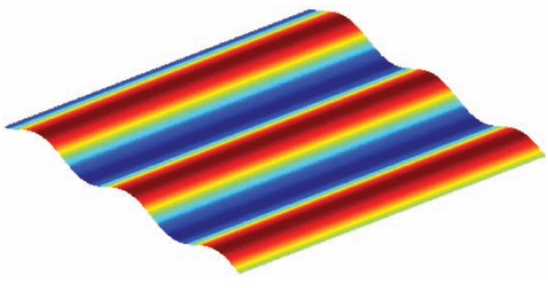
Total variation in the quality control variable can be divided into three parts (Figure 1.3). The variation in the machine direction is in the whole width of the machine web (Figure 1.3c). This variation is called temporal variation and the variation in the cross direction is called spatial variation (Figure 1.3b). The residual variation is variation, which is left when the temporal and the spatial variation are removed from total variation (Figure 1.3d). The residual variation can be seen as random noise and its cause is not known. During the run of the paper or board machine quality control variables variation in the CD or in the MD can not be measured absolutely. CD and MD profiles are always calculated from the measurement data, which is collected with a traversing scanner (figure 2.1). The controls have an impact on the MD and on the CD. For this reason, the division to the temporal and the spatial variation is natural [2]



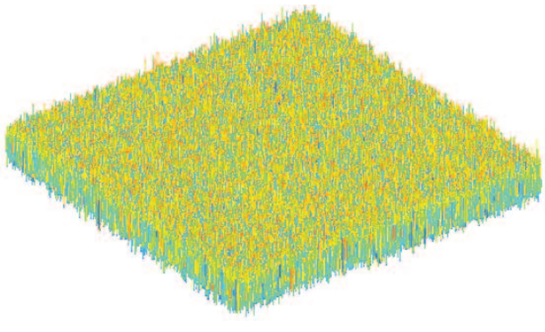
(a) Total - variation



(b) CD - variation



(c) MD - variation



(d) Residual - variation

Figure 1.3: The Separation of paper and board machine quality control variable variation

The paper quality variable value can be seen as an element in the measurement matrix. The element consist average of all measurement points added by the temporal, the spatial and the residual variation (Equation 1.1):

$$y_{ij} = y_{av} + \hat{x}_{CDj} + \hat{x}_{MDi} + \hat{x}_{ij} \tag{1.1}$$

y_{ij}	the value in the measurement matrix at the row i, column j
y_{av}	the average of the all measurement points
$\hat{x}_{CDj}$	averaged spatial variation at the point
$\hat{x}_{MDi}$	averaged temporal variation at the point
$\hat{x}_{ij}$	residual variation at the point.

1.2 Problems

The main difficulties in paper or board machine control are: severe interactions between the controlled variables and long time delays for controlling some variables. In MD control the most common interaction is between basis weight control and moisture control. The basis weight is controlled by stock flow. Increase in the stock flow will increase the amount of water entering the web. Moisture content will also increase. If steam flow increases to correct the moisture, the basis weight will decrease. Control engineering techniques must decouple such an interaction. In CD control basis weight profile control has an impact on all other variables with some degree.

Another interaction in control arises from the principle of scanning method. Each scan is measured from a diagonal path (Figure 1.4).

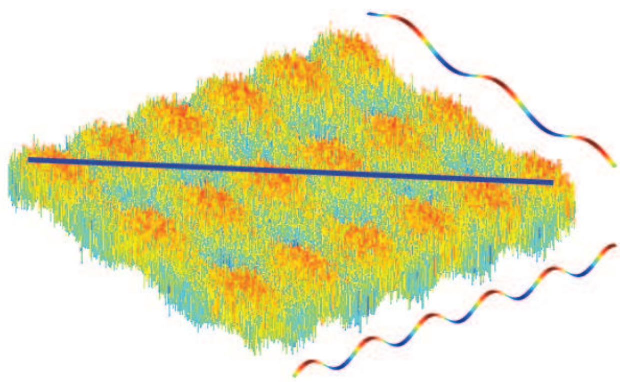


Figure 1.4: The measurement path and separation to CD and MD profiles

The measurement collected this way includes CD and MD variations. Because of this interaction determining an accurate CD profile with the information of only one scan across the moving web is impossible. To calculate an accurate CD profile, averaging profiles of many scans is necessary to separate the CD component from the total variation. The most common method is exponential trending. This combines the newest profile measurement with the old CD profile. Tuning of the exponential filter is an optimization problem. If the filtering is too light, the new profile is reflected rapidly in the CD profile. If MD variations increase, they will erroneously occur in the filtered profile. This will lead to the situation that the CD profile control will introduce variability in the final product. One way to solve this problem is to adapt the filtering factor for each data box separately. These intelligent methods are updating the profiles after each measurement. [3]

Chapter 2

Cross Direction and Machine Direction Separation Methods

Basis weight and moisture content are two fundamental properties of paper and board requiring precise control for quality. Typically they are measured by a scanning sensor which takes measurements that follow a zigzag path on the paper or board. The challenge is to estimate variations of basis weight, moisture and many others along and across the paper or board sheet from the composite measurements and to control them in these two directions.

The first generation of paper machine gauges, developed in the 1950s, was placed at a fixed cross-machine position and provided measurements reflecting only machine direction variations. Data collected in this way is called single point data and it allows control of paper machine variables along the machine direction. The second generation introduced the scanning sensor configuration in which the sensor is mounted on an "O" frame and moves back and forth in a cross machine direction, producing measurements that trace a zigzag path on the moving paper. Data collected this way is called scanned data.

The most common practice in industry is to use a weighted sum of a series of measurements from different scans at each CD position to represent the CD variation at that point and a successive scan average as the MD variation. This approach is called the basic estimator, which is a cheap way separating CD variation from MD variation since it treats all measurements as contemporaneous. This results in slow detection of disturbances and correspondingly slow control response. [4]

Sensors measuring the quality variables are attached to an online scanner (figure 2.1). The online scanner is a platform, which is moving over the paper or board web from edge to edge. The measurements are from the zigzag path and it procedures measurement data with different variations. The feedback control is only possible separately in machine direction and cross direction. Therefore a separation method is needed to divide measurement data into MD and CD components. The MD component can be measured individually by directing the scanner to a specific point on the web. While the machine is running measurement data consists of only the MD component. The CD component can also be measured individually, but it would be possible only in the case where the web is stopped. This situation is not possible in paper or board machines, so a need for intelligent methods to assist data assimilation is evident. [1]

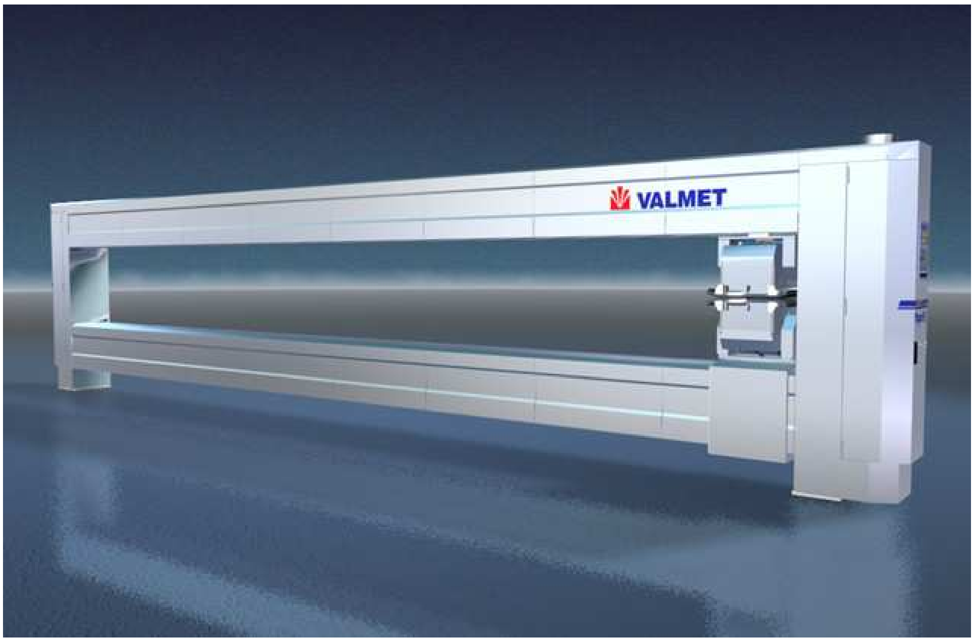


Figure 2.1: The paper or board machine online scanner [1]

2.1 Auto Regressive Moving Average

Economic, engineering, environmental and other scientific data are often taken in roughly equal spaced time intervals like: hour, day, month, quarter or year. Because of the inertia of the system such time series data are frequently serially dependent. For instance, temperature on a given day tends to be correlated with temperature on the previous day.

A popular model used to describe the behavior of a variable over time is the autoregressive model. In this model it is assumed that the current value can be expressed as a function of preceding values and a random error. If we let Y_t denote the value of the variable at time t, the pth order real valued autoregressive time series is assumed to satisfy

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + e_t, \quad t = 1, 2, \ldots \tag{2.1}$$

where the e_t are random variables. A natural estimator for α_i is the least squares estimator obtained by regressing Y_t on Y_{t-i}, including an intercept in the regression. The estimators are:

$$\hat{\alpha}_i = \frac{\sum_{t=1}^{n-i} (Y_t - \bar{Y})(Y_{t+i} - \bar{Y})}{\sum_{t=1}^{n} (Y_t - \bar{Y})^2} \tag{2.2}$$

where

$$\bar{Y} = \frac{1}{n} \sum_{t=1}^{n} Y_t$$

An autoregressive model is a linear regression of the current value of the series against one or several prior values of the series. The notation $AR(p)$ refers to the autoregressive model of p order. The first order autoregressive model is as follows:

$$Y_t = \phi Y_{t-1} + e_t \tag{2.3}$$

A moving average (MA) model treats random events which, according to order q of MA, depends on values of q preceding random values. The first oder moving average model is as follows:

$$Y_t = e_t - \theta e_{t-1} \tag{2.4}$$

Where e_t $N(0, \sigma_a^2)$ and θ is a constant.

More complex time series can be approximated by an autoregressive moving average model (ARMA). The model normally consist of two parts, an autoregressive part (AR) and a moving average part (MA). The model is then referred to $ARMA(p, q)$ where the p is the order of autoregressive part and the q is the order of the moving average part. A mixture of the first order models, i.e. $ARMA(1, 1)$ is as follows:

$$Y_t = \phi Y_{t-1} - \theta e_{t-1} + e_t \tag{2.5}$$

[7]

The ARMA estimator may be used for stochastic parameter estimation in profile estimation. The new MD and CD estimates are computed after every new measurement point from a scanner. An ARMA model is used for the MD variation estimates:

$$\hat{x}^{MD}(i,j) = y^{MD}(i,j) + \phi_1 \hat{x}^{MD}(i,j-1) + \phi_2 \hat{x}^{MD}(i,j-2) \tag{2.6}$$

The CD variation estimates for measured points of a web are computed by exponential filtering:

$$\hat{x}^{CD}(i,j) = \alpha y^{CD}(i,j) + (1-\alpha)\hat{x}^{CD}(i-1,j) \tag{2.7}$$

The CD estimates for not measured points in a web are computed by updating the previous estimates by estimation errors:

$$\hat{x}^{CD}(i,j) = \hat{x}^{CD}(i-1,j) + \beta(y^{CD}(i,j) - \hat{x}^{CD}(i-1,j)) \tag{2.8}$$

[8]

2.2 Bayesian

The Bayesian estimator is based on the Bayesian theorem, when the control variable variation is supposed to be normally distributed. The control variation in every CD-point can be described as the time dependent expectation and the variance, which describes the uncertainty of the variable estimate. A random walk assumption is implicit in this estimation. The variance of this estimated CD-point increases when the point is not measured.

The estimation is produced by calculation from the measurement signal and position information. If a point does not have a new measurement, the new estimate for this point will be the previous estimate and the variance will be increased. The increase of the variance is defined to be a diffusion parameter $D\Delta t$. This parameter is defined by the user.

$$\begin{aligned} \hat{x}(i,j) &= \hat{x}(i-1,j) \\ \hat{\sigma}^2(i,j) &= \hat{\sigma}^2(i-1,j) + D\Delta t \end{aligned} \tag{2.9}$$

When the point is measured, a new estimate is calculated with weighted average between the previous estimate and the measurement. The uncertainty of the previous estimate is taken into account. The variance is calculated from the variances of the previous estimate and the measurement.

$$
\begin{aligned}
\hat{x}(i,j) &= \frac{(\hat{\sigma}^2(i-1,j)+D\Delta t)y(i,j)+\sigma^2_{meas}\hat{x}(i-1,j)}{\sigma^2_{meas}+\hat{\sigma}^2(i-1,j)+D\Delta t} \\
\hat{\sigma}^2(i,j) &= \left(\frac{1}{\hat{\sigma}^2(i-1,j)+D\Delta t}+\frac{1}{\sigma^2_{meas}}\right)^{-1}
\end{aligned}
\tag{2.10}
$$

The separation of CD and MD estimates is done by using an average value of the estimates. The CD-estimate is calculated by removing the average from the estimate, which is produced with equations 2.9 and 2.10. The MD-estimate is the average value.

$$
\begin{aligned}
\hat{x}^{CD}(i,j) &= \hat{x}(i,j)-\frac{1}{M}\sum_{j=1}^{M}\hat{x}(i,j), \quad j=1\ldots M \\
\hat{x}^{MD}(i) &= \frac{1}{M}\sum_{j=1}^{M}\hat{x}(i,j), \quad j=1\ldots M
\end{aligned}
\tag{2.11}
$$

If adaptive noise cancellation is used, the MD-estimate is a sum of the estimate and the difference between the measured and filtered signals

$$
\hat{x}^{MD}(i) = \frac{1}{M}\sum_{j=1}^{M}\hat{x}(i,j)+\frac{1}{k(i)}\sum_{j=1}^{k(i)}(y(i,j)-\hat{x}_{filt}(i,j)), \quad j=1\ldots M \tag{2.12}
$$

The adaptive noise cancellation is used in the estimation to deduct high frequency variations in MD from the variation in CD. In the paper web MD variation can be canceled by using a local sensor along the traversing scanner. The local sensor measures only the MD variation in one CD point. This reference signal does not have to be in same quality variable, but the controllable variable and the reference variable has to have some correlation. The filtering result is not purely CD - variation, because the web is always containing residual variation and the measurement is also noisy. [9]

2.3 Kalman-Fourier

The nature of measurement information of traversing scanners is sparse and it consists of data, which is neither machine directional nor cross directional. With a frequency analysis, it is possible to detect periodical phenomena from the measurement data. A Fourier transform presents the possibility of separating a dataset into waves of different frequencies. The separation of the quality measurement data into waves of pure CD and MD variations is possible by using Discrete Fourier Transform (DFT). A Kalman filter, in general, is an optimal way to pre-process noisy measurements for a model. The model can be seen as a set of frequency components of the CD and MD variations. Therefore it is natural to combine these two excellent methods into a good data assimilation system.

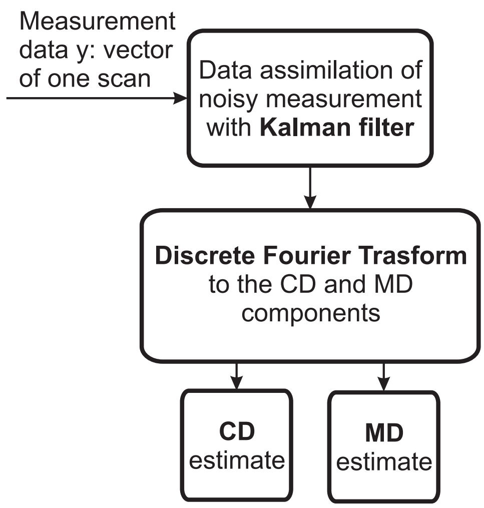


Figure 2.2: The simplified CD/MD separation model with the Kalman filter. [6]

The representation of a function in the form of a series is common in mathematics. The most common way of representation is a power series of the form

$$f(x) = \sum_{n=0}^{\infty} a_n x^n \tag{2.13}$$

We can approximate with this form for example the exponential function with the infinite series

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \ldots + \frac{n^2}{n!} + \ldots = \sum_{n=0}^{\infty} \frac{x^n}{n!} \tag{2.14}$$

There are advantages in expanding a function in such series, since the first few terms of a good approximation are easy to deal with. Term-by-term integration or differentiation may by applied or a suitable function approximation can be formed.

Power functions are only one way of representing the base functions of the series expansion. A number of other base sets can be used and the Fourier representation uses a periodic function $f(t)$ of period $T = 2\pi/\omega$ in the expansion, where the base set is the set of sine functions.

$$f(t) = A_0 + \sum_{n=1}^{\infty} A_n \sin(n\omega t + \phi_n) \tag{2.15}$$

Fourier, a French physicist, published in 1807 that an arbitrary function $f(x)$ could be represented by a trigonometric series of the form

$$f(x) = \sum_{n=0}^{\infty} (A_n \cos(nkx) + B_n \sin(nkx)) \tag{2.16}$$

Although the result met with considerable opposition from the leading mathematicians of the time (Laplace, Poisson and Lagrange).

Fourier series provides an ideal framework for analysing the steady-state response of systems to a periodic input signal. The Fourier transform extends these analysis to non-periodic functions. Fourier transforms first found most application in the solution of partial differential equations. Today Fourier transform methods are most heavily used in analysis of signals and systems.

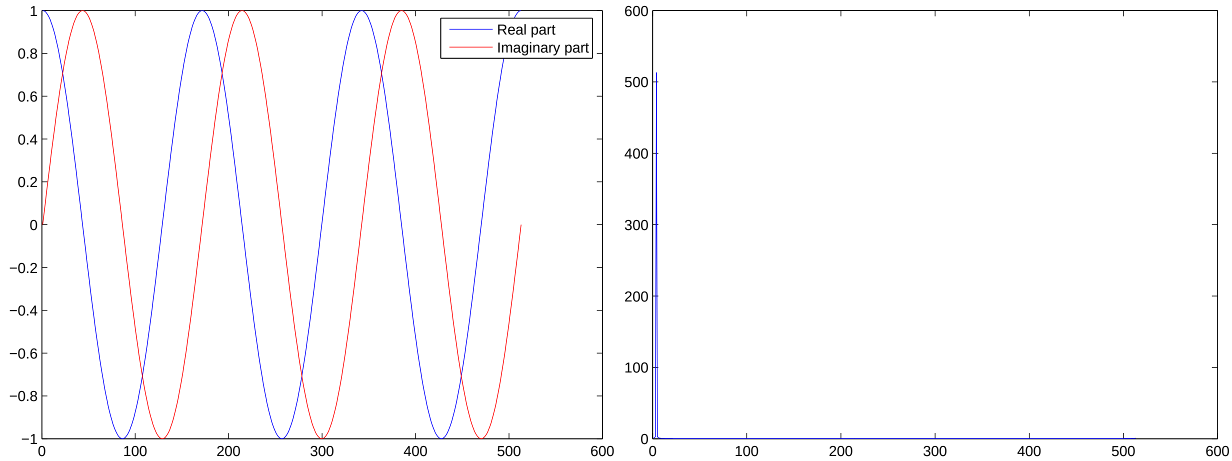
The theorem of Fourier states that a periodic function can be expressed as the sum of a number of sine and cosine functions of different amplitudes.

$$\begin{aligned} f(t) &= \frac{a_0}{2} + \sum_{n=1}^{\infty} (a_n \cos n\omega t + b_n \sin n\omega t), \quad \omega = \frac{2\pi}{T} \\ a_n &= \frac{2}{T} \int_a^{a+T} f(t) \cos n\omega t \; dt \\ b_n &= \frac{2}{T} \int_a^{a+T} f(t) \sin n\omega t \; dt \end{aligned} \tag{2.17}$$

As n approaches infinity, the Fourier series approaches the original function $f(t)$. Accuracy of the approximation is dependent on the size of n. Formula can be defined in a complex form with the Euler equation.

$$
\begin{aligned}
f(t) &= \sum_{n=-\infty}^{\infty} C_n e^{in\omega t} \\
C_n &= \frac{1}{T}\int_a^{a+T} f(t)e^{-in\omega t}\,dt
\end{aligned}
\tag{2.18}
$$

The Fourier Transform can be used in defining what frequency components a signal is containing. Figure 2.3a represents a complex signal, which has a discrete frequency of $\frac{3}{512}$. The signal contains 3 waves and the signal length is 512. Figure 2.3b represent



(a) The Complex Signal (b) The Fourier Transform

Figure 2.3: Signal $f(t) = e^{2\pi ift}$, where $f = \frac{3}{512}$

absolute value of the Fourier transform for the signal of figure 2.3a as know as absolute value of the power spectrum. From this figure it can be seen that transform has a peak at point $\frac{3}{512}$, which is the frequency of the complex signal. The transform can be used in analysis of the signal in frequency-domain.

We concentrate now on the Discrete Fourier Transform. The DFT is a transform which transfers a signal from the time domain into the frequency domain. The DFT has an inverse operator, which transfers the signal back to the time domain (The relations can be seen in equation (2.19). The paper and board making process is a continuous process, but it is measured and controlled with certain time steps. This is the reason why we can see this process as a discrete process and do analysis with DFT.

$$F(n) = \sum_{k=0}^{N-1} f(k) e^{\frac{-2\pi i n k}{N}} \tag{2.19}$$

$$f(k) = \frac{1}{N} \sum_{n=0}^{N-1} F(n) e^{\frac{2\pi i n k}{N}} \tag{2.20}$$

$F(n)$ = a vector of the complex Fourier components
$f(k)$ = a discrete signal vector
N = Length of the $f(k)$
The DFT algorithm (equation 2.19) can be also represented in matrix form:

$$\begin{aligned} F(n) &= \sum_{k=0}^{N-1} f(k) w^{nk}, \quad w = e^{\frac{-2\pi i}{N}} \\ &= \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 1 & w^1 & w^2 & \dots & w^{N-1} \\ 1 & w^2 & w^4 & \dots & w^{2(N-1)} \\ \vdots & \vdots & \vdots & \ddots & \\ 1 & w^{N-1} & w^{(N-1)2} & \dots & w^{(N-1)(N-1)} \end{bmatrix} \begin{bmatrix} f(0) \\ f(1) \\ \vdots \\ f(N) \end{bmatrix} \\ &= W^{nk} f(k) \end{aligned} \tag{2.21}$$

Each Fourier component is representing a periodical signal, which has a frequency of $\frac{k}{N}$. The fourier component is normally represented in the form of amplitude and phase of the frequency. The amplitude is $F(p) = \frac{|F(n)|}{N}$. The computation of the DFT in this manner needs N^2 multiplications and $N(N-1)$ summations and all are in the complex form. On this ground algorithm complexity is N^2. This kind of computation becomes rapidly expensive as N increases.

The DFT complexity may become a problem, when signal lengths are long. For real signals, symmetry can be exploited, but for large N, $\frac{1}{2}N^2$ is not a significant improvement over N^2. A totally different approach to the problem was needed before DFT could become a practical engineering tool. In 1965 Cooley and Tukey introduced the Fast Fourier Transform (FFT) in order to reduce computational complexity.

The FFT algorithm has three stages, matrix formulation, matrix factorization and rearranging. The algorithm is also restricted to the situation where $N = 2^m$ for some integer m. Although FFT has three stages to generate the transform, computation time saving is significant according to the DFT. The estimate of complexity on the basis of the number of complex multiplications, are often given as about $Nlog_2N$ as opposed to N^2. This difference becomes significant when a large number of N is counted [5]

The Kalman estimator is based on the Kalman filter, which can be seen as a linear-quadratic problem. The linear-quadratic problem is a problem where state of the linear dynamic system is disturbed with white noise. The Kalman filter uses measurements which are linearly related to state and corrupted with white noise. The Kalman filter is a special case of a probabilistic Bayesian estimator and it can be also used as a predictor for a likely future course. The Kalman filter estimates the state of a stochastic system by using the observations which are functions of the state. The Kalman filter used in this thesis is linear. [6]

Table 2.1: Kalman loop variables and explanations [6]

$x = (C_1, C_2, \ldots, C_n)$	Complex state vector with fourier coefficients as state variables $C_1, C_2, \ldots, C_n$
Q	Covariance of the state vector
$P = QI$	Error covariance matrix
$A = e^{-2\pi ian/T} I$	The phase shift operator matrix, a model matrix.
$K = (k_1, k_2, \ldots, k_n)^T$	The Kalman gain matrix
$R = (w_1, w_2, \ldots, w_n)$	Measurement sensitivity matrix.
H	Inverse Fourier transform matrix.
y	Basis weight measurement data point.

The Kalman estimator is using Fourier space to produce estimates. The separation model is build into the state vector. The state vector contains Fourier coefficients for the CD and MD part separately and it is processed under the Kalman loop. The Kalman loop is the base of the Kalman filter. The routine of the Kalman filter is that it first collects measurement data y from the scanner. In the following steps the Kalman filter initializes variables and starts the Kalman loop.

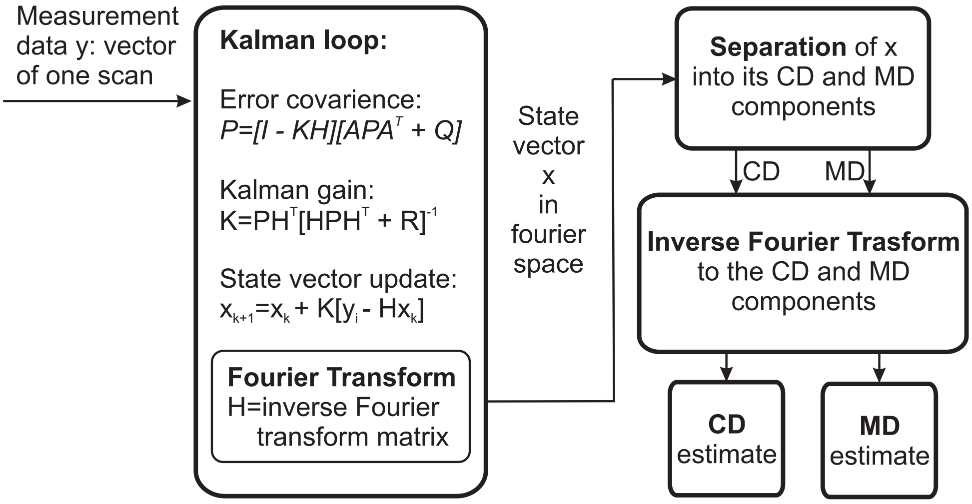


Figure 2.4: The CD/MD separation model with the Kalman filter. [6]

The Kalman loop processes every point of the input vector y. Every loop round contains updating and extrapolation of the Kalman variables. After the whole input vector y is processed in the Kalman loop. The loop returns to the final estimate of the state vector x. The state vector is in Fourier space and it has to change to the physical space. Transformation between these spaces is done by the Inverse Fourier transform. This procedure is done separately to the CD and the MD part. The Kalman filter procedure is shown in Figure 2.4 [6]

Chapter 3

Control Algorithms

The purpose of the paper or board machine control is to keep quality variables at their target levels with minimum variability. Most variables are measured online and therefore can be automatically controlled. The paper or the board machine automatic control can be divided into two separate control systems: The machine direction control and the cross direction control. The purpose of the MD control is to decrease temporal variation of the quality control variable in machine direction. MD control is controlling the quality control variable mean variation in the paper or the board machine. Normally it has been controlled by a single actuator (feeding pump). The CD control is an orthogonal control to the MD control and it affects the quality control variable variation in cross direction, known as spatial variation. These variations are locally distributed across the web. The CD control is therefore controlling every single point in the cross direction. This means that the number of the controllable points is in the hundreds and the number of the CD control actuators is in the dozens. The residual variation comprises diagonal variation, but it can not be attenuated on a paper or board machine. Therefore the probability of diagonal variation is minimized already in machine construction and planning. [2]

3.1 Cross Direction Control

The cross direction control is done with actuators each of which have a unique affecting area on the web. The purpose for the control is to minimize variation in quality control variables in cross profile. The basis weight control is normally done in a paper and board

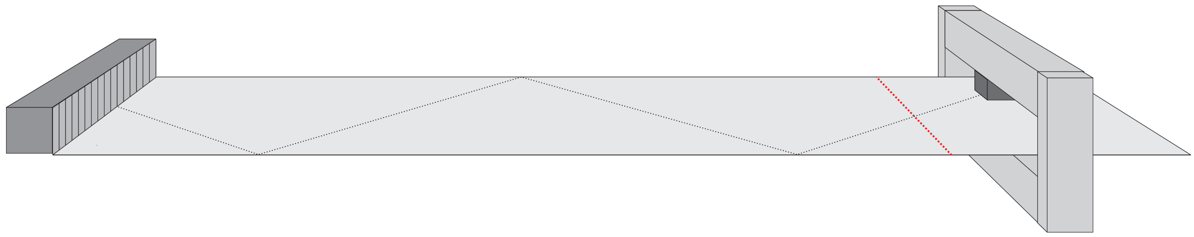


Figure 3.1: The basis weight CD control consists of hundreds of measurements points and dozens of actuators in the head box.

machines with a slice opening or with a dilution head box. The slice opening head box is a traditional way of performing cross direction control of basis weight. The control is done by changing the position of the slice lip of the head box. The slice lip is in some cases the most suitable method, but it has certain characteristics that are requiring attention. One of these is the interaction between neighboring slice lip positions. The slice lip have an affect area on basis weight, which is many times wider than the slide lip is (Figure 3.2).

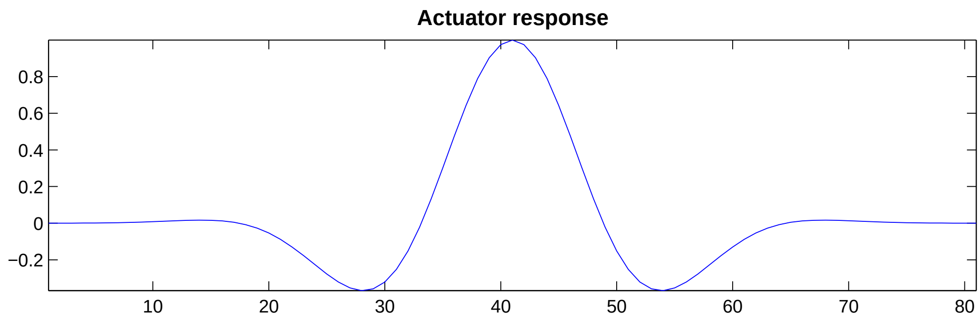


Figure 3.2: The slice lip response to the basis weight

The impact is determined with a step response test, where this actuator setting is changed with a certain step. The result is measured and saved as the response of the actuator. At the same time process characteristics dead time and time constant are measured. The dead time is the delay from control action until it starts respond in measurements and time constant describes how fast the quality control variable responses to the change of control. [2] [3]

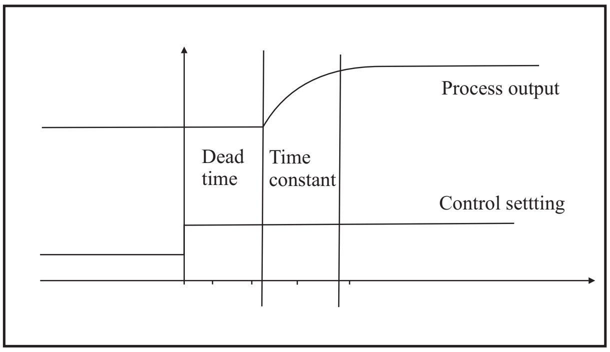


Figure 3.3: Definition of dead time and time constant

This interaction between control lips must be eliminated. If the responses to all actuators are similar and symmetrical around the actuator positions, the following simple model is suitable

$$\Delta y = B\Delta u \tag{3.1}$$

Where Δu are changes in slice position at each actuator and Δy are changes in the weight profile at corresponding positions. Where B is a matrix, which contains the interaction between actuators.

$$B = \begin{bmatrix} \hat{a} & \hat{b} & \hat{c} & 0 & 0 & 0 & \dots & & & 0 \\ \hat{b} & \hat{a} & \hat{b} & \hat{c} & 0 & 0 & \dots & & & 0 \\ \hat{c} & \hat{b} & \hat{a} & \hat{b} & \hat{c} & 0 & \dots & & & 0 \\ 0 & \hat{c} & \hat{b} & \hat{a} & \hat{b} & \hat{c} & \dots & & & 0 \\ \vdots & & & & & & \ddots & & & \\ 0 & & & & & & & \hat{c} & \hat{b} & \hat{a} \end{bmatrix} \tag{3.2}$$

In (3.2) $\hat{a}$, $\hat{b}$ and $\hat{c}$ are responses of one slice lip in five neighboring actuator positions. Calculation of the optimal control uses the following the equation:

$$\Delta u = \alpha B^{-1} \Delta y^{*} \tag{3.3}$$

where Δy^{*} is the desired output. [3]

3.2 Machine Direction Control

The general principle for the MD controls has been the same since the very beginning of quality control systems for paper machines. The controller controls mean variation of the quality control variables. The controllable variables in MD are normally dry weight, moisture, color and filler. In the current MD control systems these are controlled predictively with a multiple input multiple output (MIMO) controller. Challenges for the MD controller are the long dead times and the time constants. The long dead time is a result from the physical background. MD variations are controlled in the wed end of the paper machine and measured in the dry end of the paper machine. The mass traversing time between the controller and the measurement device is the dead time. The time constant represents process slowness, it tells how fast the controllable variable reaches 63% of the setpoint. Setpoint is desired output of the process.

3.2.1 Proportional and Integral Control

PI-control is the most common form of feedback control. The PI controller output is the sum of two terms: a term which is proportional to the error, a term which is the integral or sum of the error over time. P refers to proportional control and I refers to integral action. [10]

PI or the proportional plus integral control adds the integral of the error to the proportional term. The PI control consists two tunable parameters, which are the K_i proportional gain and the T_i reset time constant. The tuning of the control consists of the determination of the right values for the parameters K_i and T_i. For this tunings several methods have been developed, like a step response method, an oscillation method and a lambda method. Equation (3.4) is form for the continuous PI control and the equation (3.5) is form for the discrete PI control. Both are consisting $u(t)$ and $e(t)$, which are control input and difference from the set point.

$$u(t) = K_i \left(e(t) + \frac{1}{T_i} \int_0^t e(s)ds \right) \approx K_i \left(e(t) + \frac{T}{T_i} \sum_{i=0}^{t} e(i)ds \right) \tag{3.4}$$

$$\begin{aligned}
u(i) &= K_i \left(e(i) + \frac{T}{T_i} \sum_{k=0}^{i} e(k) \right) \\
u(i-1) &= K_i \left(e(i-1) + \frac{T}{T_i} \sum_{k=0}^{i-1} e(k) \right) \\
u(i) &= u(i-1) + K_i \left(e(i) - e(i-1) + \frac{T}{T_i} e(i)) \right)
\end{aligned} \tag{3.5}$$

Normally processes contains significant dead times. Therefore the control can not be controlling the state at the current time, because response to the state of the system is a response to the history. This requires the controller actions to be extreme small to avoid instability. This leads to a low loop gain and poor control. [10]

3.2.2 Model Predictive Control

Model predictive control (MPC) refers to a class of control algorithms, where process model estimator is utilized to predict future response of the control. The system itself has a long history. The first references to this method has been done in the 1960s, but industrial use started spreading widely in the 1990's. The MPC is especially planned to compensate for long dead times and time constants in closed control loops. [11] [12]

The MPC was developed as a multi variable controller. A multi variable process has several inputs and outputs. The interactions between variables are often strong. This means that change in any input influence several output variables. The simplest way to handle multivariable processes is to ignore the interactions and design simple, separate control loops. This approach works sufficiently for most cases. If severe interactions exist, an oscillation or even unstable system can result. Multivariable control is necessary in cases where separate control loops influence each other. This results in decreased control performance with the previously mentioned strategy when interacting control loops respond to set point changes or load disturbances. To assure stability, separate control loops must be excessively tuned. This decreases their performance. One possibility to decrease the effect of interactions is to add a compensator into the original diagonal control structure (Figure 3.4). The design of this compensator starts from the situation where the selection of input and output pairs is as good as possible. The compensator and the system should form a system that is as diagonal as possible. Then the control using separate controllers is possible. [3]

An important part of the MPC is a process model. The model is used to define, what is the connection between the control action and the output variable (Figure 3.5). It can be derived from theoretical aspects or from empirical data. Theoretical models can be used widely over the whole field, but empirical models can be used only on the range where data is collected. Paper and board process models are developed from empirical tests and the models are defined to be in Laplacian form (Equation 3.6). Paper and board

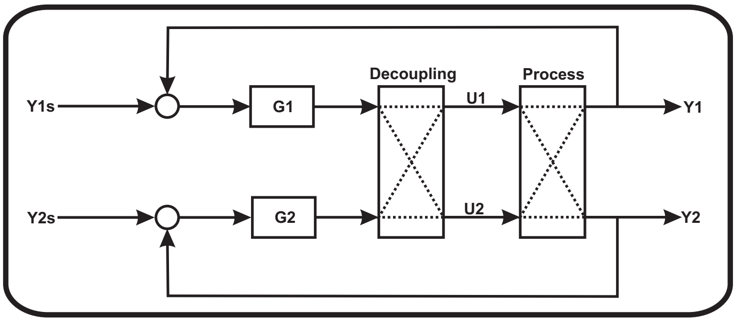


Figure 3.4: Decoupling controller for 2×2 process.

processes have small variations in quality variables and therefore theoretical models are not needed.

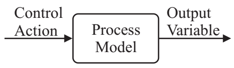


Figure 3.5: The Process model is a connection between a control action and an output variable.

$$y(i) = g(i)u(i) = \frac{K_{pro}}{t_{const}i + 1} e^{-t_{dead}i} \quad u(i) \tag{3.6}$$

The main concept of the MPC controller is that, it predicts the process state ahead over a certain number of discrete time steps (Figure 3.6). At the current time k the behavior of the process is predicted over the horizon p. The prediction horizon p for the controllable variable is calculated by using the model from the process. The control action is then chosen in a way that the prediction meets the target. At the time k the controller uses only the first calculated control action. At time $k+1$ the controller repeats the calculation of horizon, which is moved ahead with one time interval. [11]

The basic form of the MPC is presented with state models, where the next state of the process is defined with the equations (3.7)

$$\begin{aligned} x(k) &= Ax(k-1) + Bu(k-1) \\ y(k) &= Cx(k) \end{aligned} \tag{3.7}$$

where $x(k)$ is the state, the vectors $y(k)$ and $u(k)$ are the process output and control input and A, B and C are transfer matrices. By this method the prediction horizon can be calculated over the horizon time p. The second step for the controller is to determine

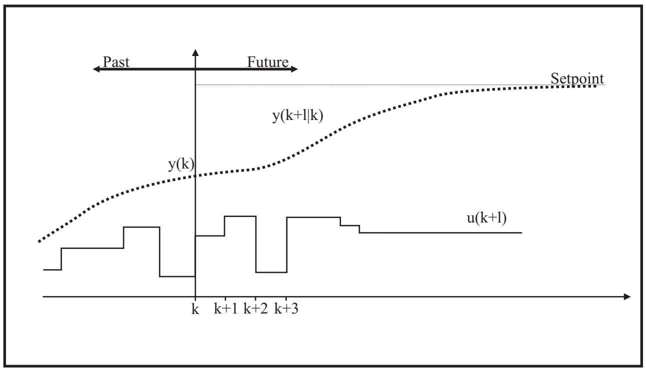


Figure 3.6: The moving average of MPC [11]

how prediction differs from the target value and how much correction should be done. In the third step, the controller is calculating a new control input for the process.

The case discussed above is a simple MPC algorithm, where one controllable variable is without any constrains. Current commercial MPCs are MIMO controllers, where, for example, four inputs are affecting four outputs (Equation 3.8). The change in one input variable has an impact on all output variables.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & g_{13} & g_{14} \\ g_{21} & g_{22} & g_{23} & g_{24} \\ g_{31} & g_{32} & g_{33} & g_{34} \\ g_{41} & g_{42} & g_{43} & g_{44} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} \tag{3.8}$$

y_1	Dry Weight	u_1	Stock flow
y_2	Moisture	u_2	Steam pressure
y_3	Ash content	u_3	Stock flow
y_4	Machine speed	u_4	Speed set point

Because one input is affecting all others and the processes are having physical and chemical constraints, the controllers are constrained physically and the process does allow small changes in control inputs. This leads to a situation where each control action should be optimized. Depending on the process and the control complexity the optimization algorithm will be linear programming, quadratic programming or genetic programming.

Most MPCs are using following objective functions (Equation 3.9) [13]

$$
\begin{aligned}
J(u^M) \quad &= \quad \sum_{j=1}^{P} \left(\left| y_{n+j}^{pr} - y_{n+j}^{r} \right|^T Q_j \left| y_{n+j}^{pr} - y_{n+j}^{r} \right| + s_j^T T_j s_j \right) \\
&+ \quad \sum_{j=0}^{M-1} \left(\left| u_{n+j} -_s \right|^T R_j \left| u_{n+j} -_s \right| + \left| \Delta u_{n+j} \right|^T S_j \left| \Delta u_{n+j} \right| \right)
\end{aligned}
\tag{3.9}
$$

J	objective penalty function
u^M	optimum process inputs
y_{n+j}^r	desired outputs
s_j	slack variable
u_s	steady-state inputs.

Chapter 4

Paper Quality Control Simulator

Paper making is a very complex process and information from the web is very sparse. The scanner can only measure a zig zag path on the web and it produces measurements from MD and CD simultaneously. The control is only possible separately in CD and MD. Therefore scanner measurement data has to be separated into CD and MD components. The key of getting good control is to have good estimates of the CD and MD profiles. Tighter limits in the paper or board quality have increased the need for intelligent methods to assist in the data assimilation. Implementing a new assimilation method to the online system needs a testing environment. Environment is important, because it makes it possible to make comparisons between existing assimilation method and methods which are under development. This should be done before a new system is implemented into a paper or board machine.

Requirements for the simulator are that it can simulate variations in the paper or board web. The quality control variable measurement and separation into CD and MD component estimates is the starting point for the control. The control is done separately with the CD and MD estimates. Measurement and control are continuous over time. The control has an impact on the whole web. The simulator basic structure should also be easily modified so that it is possible to implement new control methods or new separation methods into it easily. There should also be a possibility to switch off the control. New estimation methods can be more easily implemented without the control. [9]

Initially our testing environment is built with Matlab. The environment is made user friendly through a user interface (Figure 4.1). The paper machine itself can be presented by a system model, which in this can be considered to be a disturbance model. Variations in CD and MD are based on densely scanned real paper basis weight measurements or the variations can be introduced by the user. The control in CD is considered to be a slice opening and in MD a feeding pump pumping rate. MD control algorithm can vary between a PI- and an MPC - controller. The control in MD includes dead time and time constants, CD controls are without dead time and time constants.

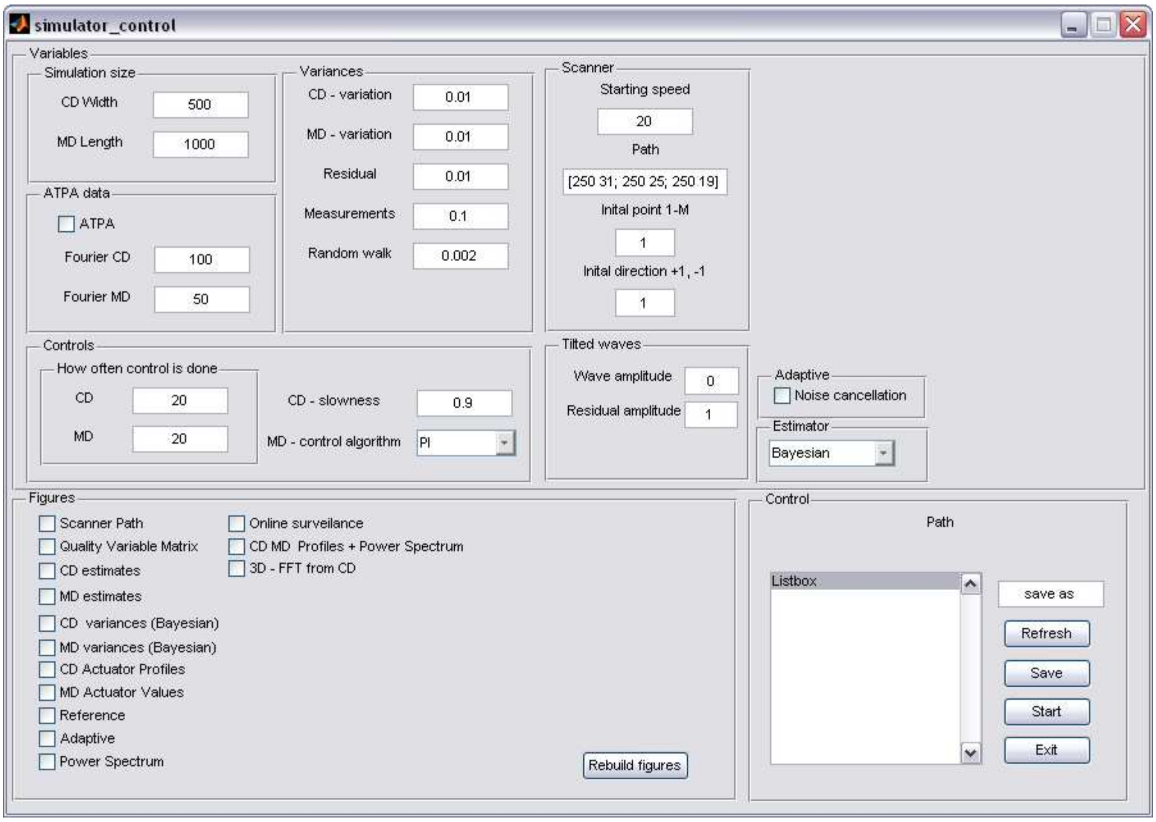


Figure 4.1: The Simulator User Interface

Matlab is published by Mathworks Inc. and it is a high level programming language and interactive numerical computing environment. Matlab allows easy matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs in other languages. Although it specialises in numerical computing, optional toolboxes allows it to be a part of a full computing environment. [15]

In our simulator, the paper or board quality control variable variation is defined as a matrix, where each column represent a position in CD and each row represent a position in MD. Each point in CD can be seen as one centimeter in real life and each MD row as a second. [9]

The simulation is done in the loop, where one round in the loop is one row in the quality control variable matrix. Before the loop the user has to define the variation of quality control variable, scanner path, assimilation method and the control method. Then the row is processed with different steps, where the assimilation and the control is are carried out (Figure 4.2). Each step of the simulator is done with a separate function. Separating the

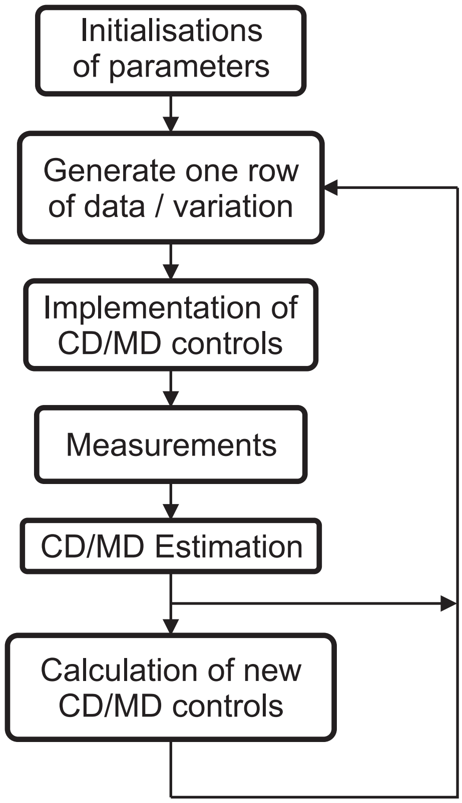


Figure 4.2: The Simulator Steps

simulator into separate functions helps modifications and implementation of new features

The simulator comprises five different assimilation methods. These methods are the Bayesian method, the ARMA method, the Kalman-Fourier method, an exponential method and the basic method. The first three are explained in details in chapter 2. The two remaining methods are consired to be current operational methods. The exponential method is an exponential filter. The exponential filter method uses the newest measurement for the estimation with a weight of $\alpha \in [0, 1]$ and the previous estimate with the weight of $1 - \alpha$. In this way noise in the data can be canceled from the measurement. The basic estimator uses the four last measured scans to obtain an estimate of CD and MD variations. The CD estimate is a average from four last scan points which are arbitrary on the same place. The MD estimate is a moving average over the last scan. The value is updated after each measurement and averaged over the length of the last scan.

Chapter 5

Simulation Results

The purpose of these tests was to determine how well developed estimators can replicate the original variation on a real paper web with constant speed. The CD variation was constant over the simulation time 2000 rows and the MD variation is set to change during the simulation time. Variations are put in the simulator residual so, that each method should not have knowledge of the variation before the measurement.

Both variations are originally industrial samples, which are then smoothed with the Fast Fourier transform. Industrial sample is obtained with the help of a special analyser. This procedure needs a special environment and institutes to make this kind of analysis. These institutes have specialists in making high resolution measuring of the paper web. In detailed this is detailed in the Piotr Ptak's master thesis [16]. FFT removes unnecessary noise from the sample and fixes the resolution of the sample for the simulator. The simulator uses cm as the unit in CD and MD is described in s. The industrial sample has both units in cm so a resolution fixing is needed to implement this sample to the simulator.

The purpose of the displayed residual variation is to show how much is out of the range of the estimate. When the residual is nearly white noise, it can be said that estimation has succeeded. Good control performance is the result of good estimation. Controls have limitations which can not be affected by the estimation. But as optimal performance of controls is depended on the performance of the estimation.

5.1 Simulations without Control

In the first part of the simulations control was switched off. In this way we can see how the controls are seeing the original variation. Without good estimation you can not have good control.

5.1.1 Basic

The Basic method has good performance in CD (figure 5.1). This is mainly a consequence of the fact, that CD variation is constant over the simulation. The CD estimate is a moving average over the last four scans, therefore a constant profile is well established. Estimation performance with fluctuating CD profile would miss the higher frequencies of the variation. The MD estimate is missing higher frequencies, this is caused by the nature of the estimator. The MD estimate is a moving average over the last 500 points.

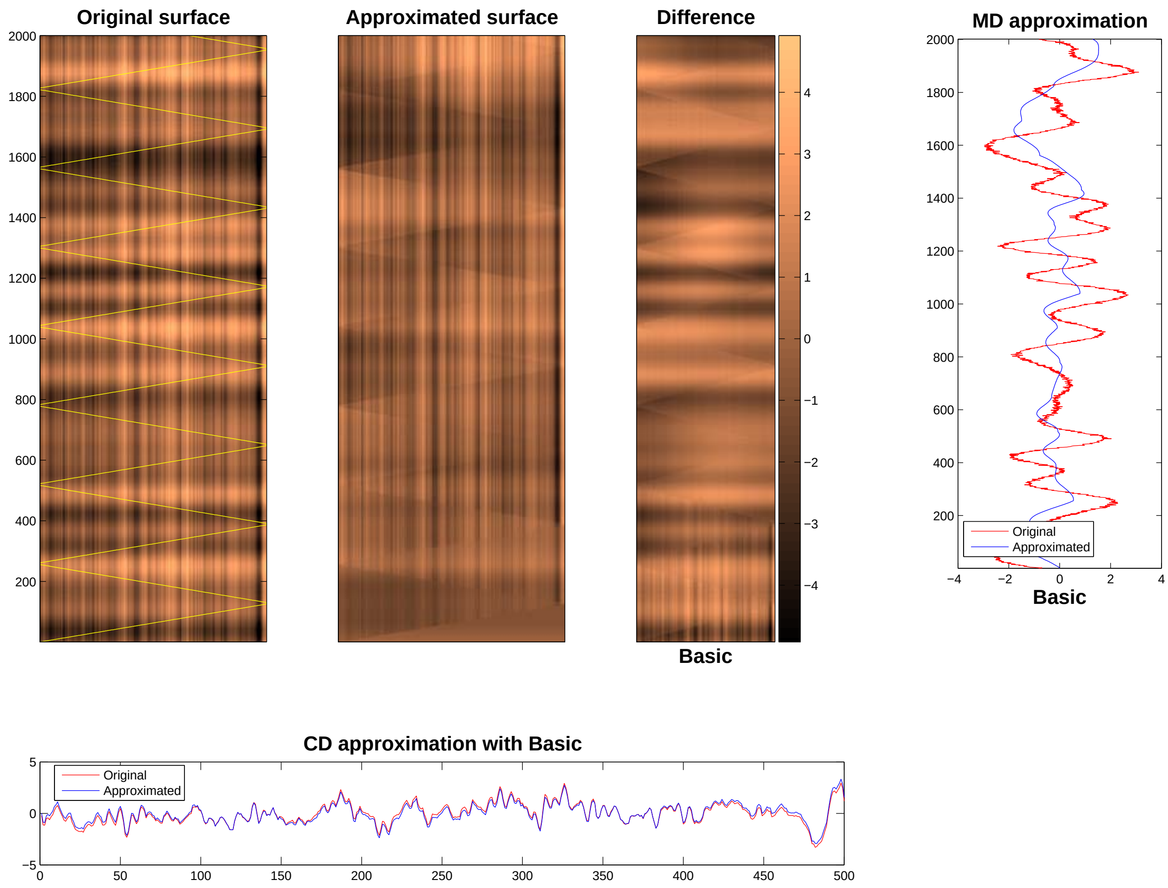


Figure 5.1: Basic

The Root-Mean-Square of the residual is $1.13\,\frac{g}{m^2}$ and the standard deviation for the MD residual is $1.18\,\frac{g}{m^2}$ with the scanner speed of 4 measurement points from the same row. If the scanner speed increases the industrial method would catch higher frequencies, but the method has limitations due to moving average. The calculation time can be held as 1 to the basic method. The newly developed systems are compared to this basic method, because it is currently used in online systems.

The analysis of the wave spectrum of the input data and estimation also proves a loss at the higher frequencies in the MD (figure 5.2). The spectrum shows that the estimator can follow variations up to 400 cm with high accuracy in the MD. The estimator can follow the MD variation with half accuracy up to 200 cm. The CD variation is well established because of the constant CD profile. The estimator would face difficulties if the CD profile would be changing. The reason for this is the fact that CD-estimate is average over the last four scans. Therefore variations within four scans are missed.

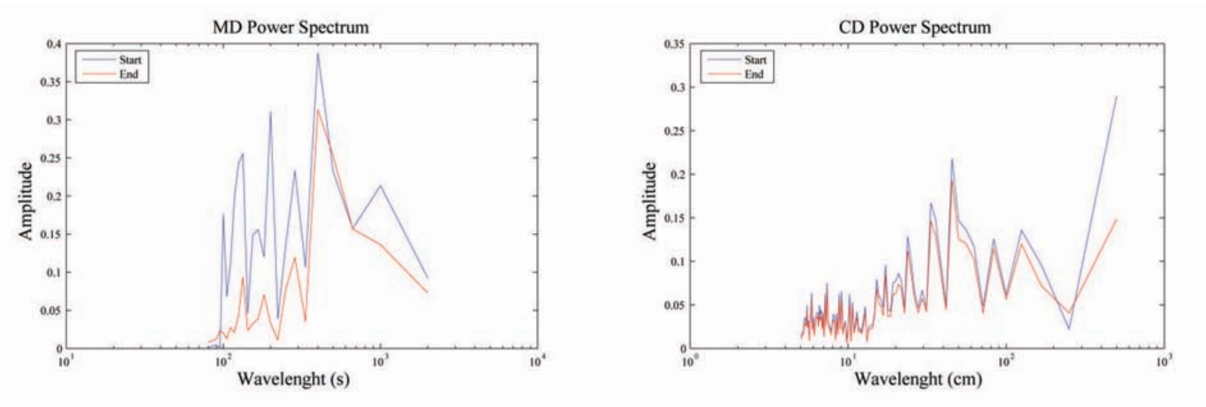


Figure 5.2: Basic estimation FFT analysis

5.1.2 Bayesian

The Bayesian estimator produces estimates well, when the quality control variable variation change is slow (figure 5.3). It has problems when the change of the quality control variable variation is high. The estimator is increasing the variance of the estimate point when it is not measured. If the change in MD of quality control variable is within one scan, then the CD estimate is mixed with MD estimate. This causes a wave, length of 500 into CD estimate.

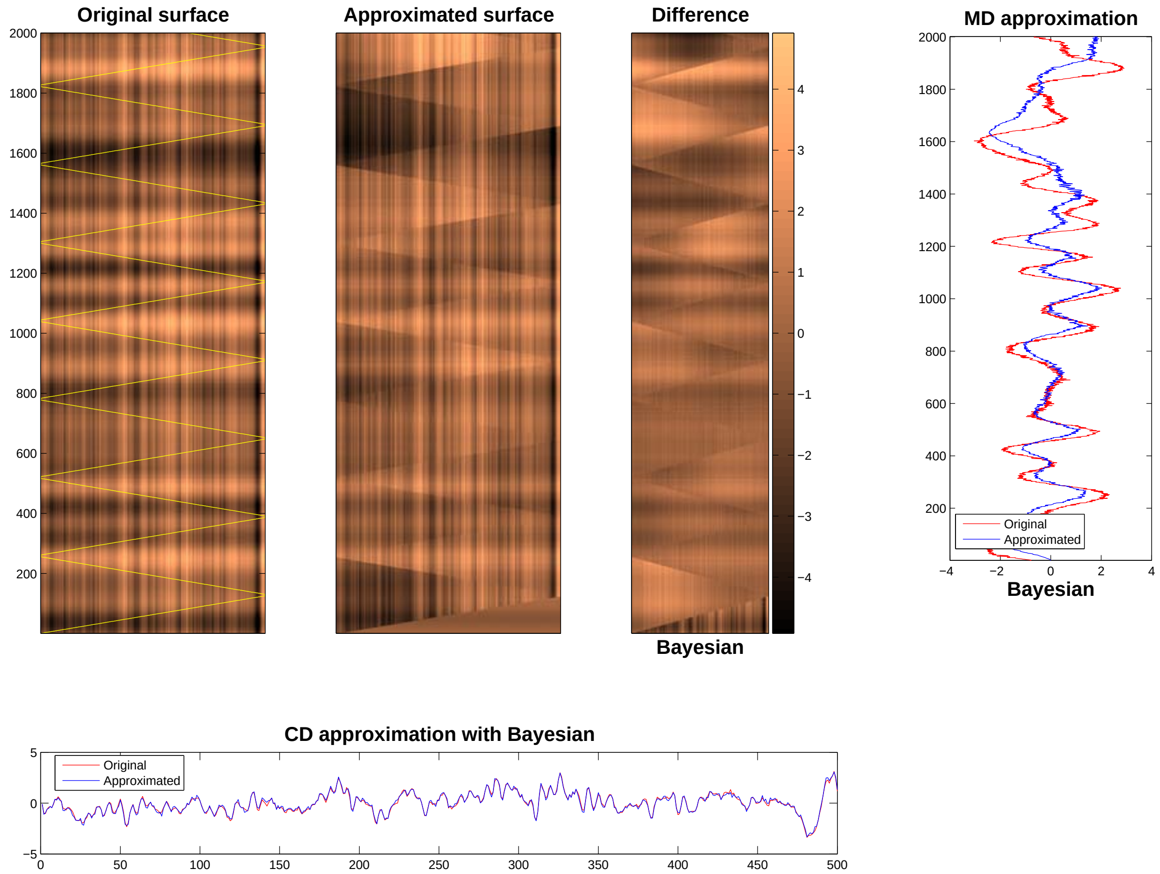


Figure 5.3: Bayesian

RMS for the residual is 0.85 and the std for the MD residual is 0.89 with the scanner speed of 4. The comparable calculation time is 3.7 times the industrial method

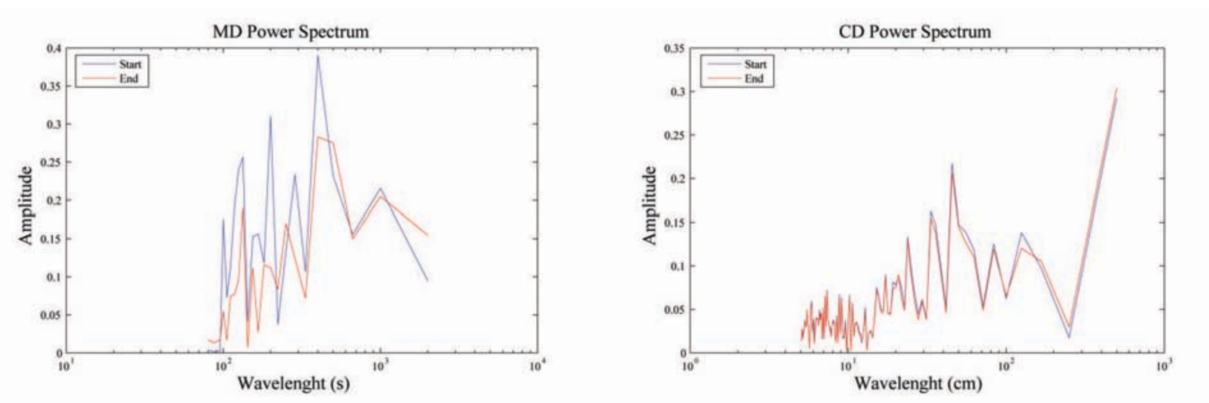


Figure 5.4: Bayesian estimation FFT analysis

The wave spectrum analysis shows that the Bayesian estimator is handling the variation in the MD steadily(figure 5.4). The accuracy level is high at the whole wave spectrum area. The CD analysis is showing that the estimator is finding the CD variation with good accuracy. Although the CD estimation accuracy is having problems when MD variation change is within one traversing scan.

5.1.3 ARMA

The ARMA approach into estimation seems to be excellent in combining fast calculation and good estimation (figure 5.6). The ARMA estimator is really case sensitive. The reason is that the model parameters have to be defined separately for each case. But when the model parameters are correct the estimator can be driven even with low scanner speeds.

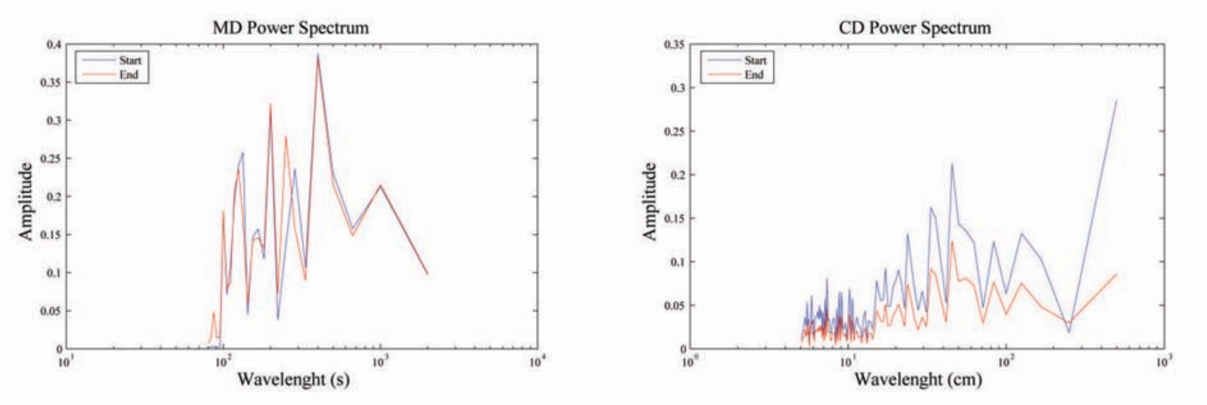


Figure 5.5: ARMA estimation FFT analysis

Root-Mean-Square for the residual is 0.59 and the standard deviation for the MD residual is 0.48 with the scanner speed of 4. The comparable calculation time is 1.1 times the industrial method. This time can be retained as fast as the basic method, because exact knowledge of optimity of our basic method is not known.

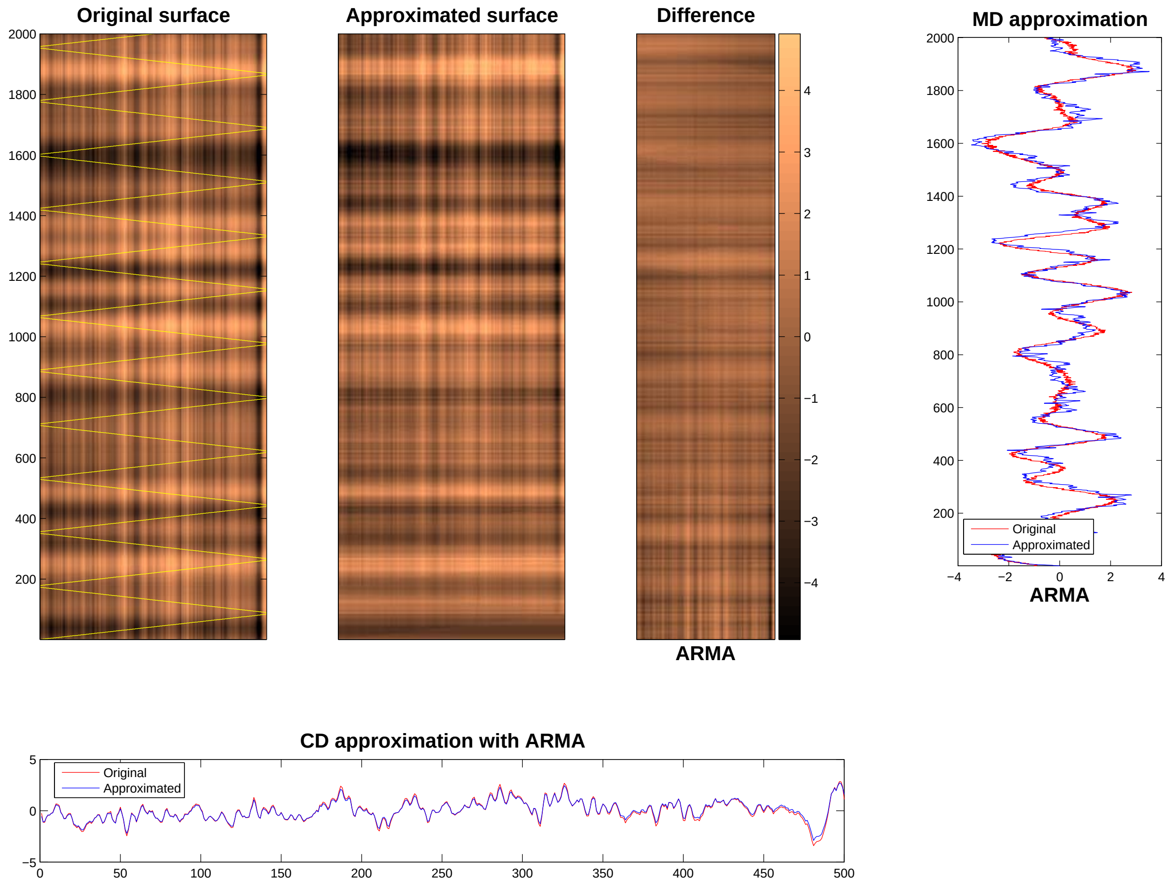


Figure 5.6: ARMA

The ARMA estimator seems to over fit the MD variation according to the wave spectrum analysis (figure 5.5). The amplitude levels are higher than the original levels with the whole spectrum space. The CD estimate is slightly different from the original. This is caused by the small amplitude in the longest wave component. The main cause for this might be in wrongly defined model parameters.

5.1.4 Kalman-Fourier

The Kalman-Fourier estimator is smoothing the CD estimate to reduce calculation time and because of the physical limits of the CD control (figure 5.7). The highest controllable wavelength in the CD control is twice the actuator width. The MD estimate can be estimated almost twice the accuracy than MD control can have any impact upon. In the start the Kalman-Fourier estimator is updating the covariance matrices and for that reason it needs a couple of runs to make the estimates.

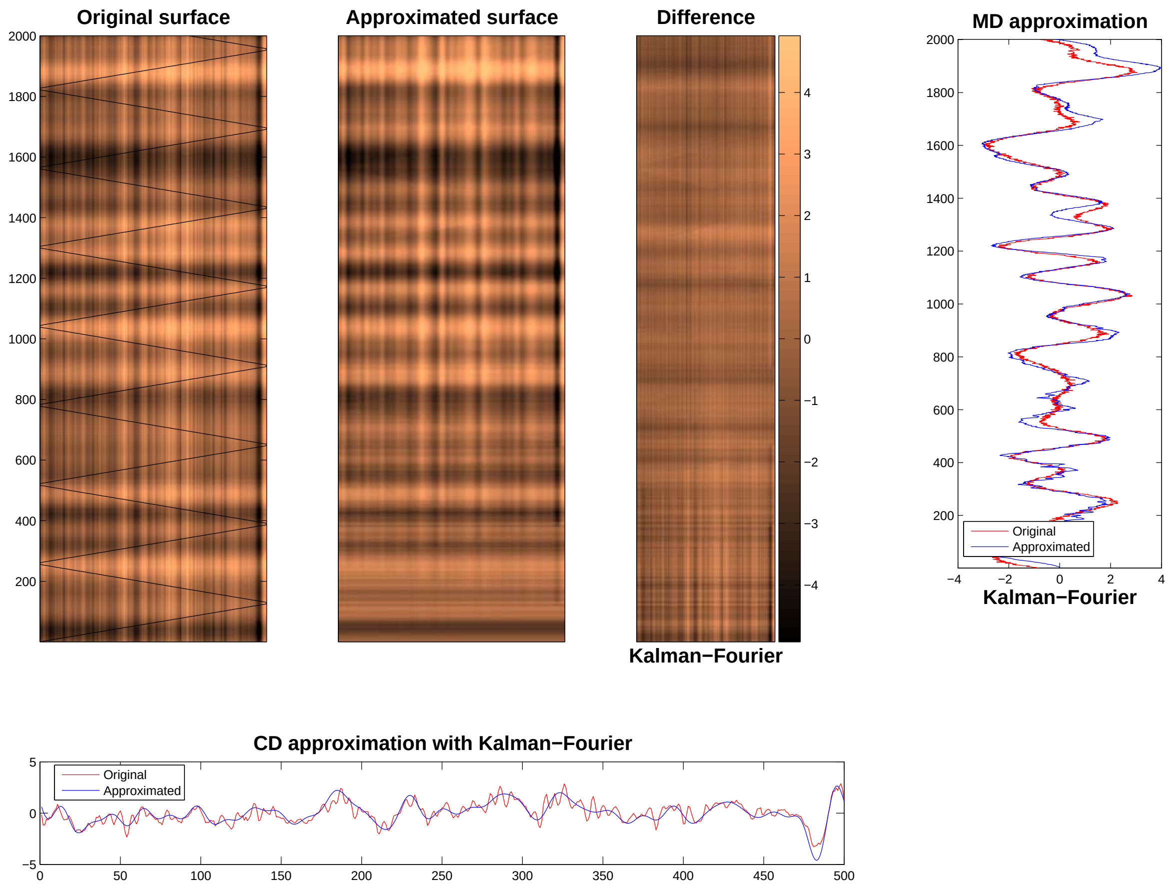


Figure 5.7: Kalman

RMS for the residual is 0.63 and the std for the MD residual is 0.50 with the scanner speed of 4. The comparable calculation time is 3.6 times the industrial method.

The wave spectrum analysis shows the fact from the Kalman-Fourier estimator that the CD estimate is missing high frequencies (figure 5.8). The MD estimate is following accurately also the high MD frequencies.

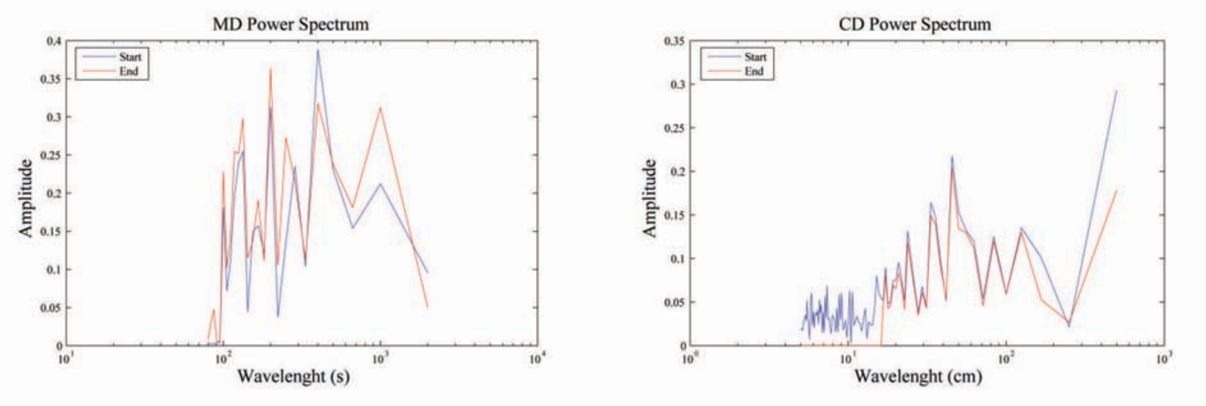


Figure 5.8: Kalman-Fourier estimation FFT analysis

Comparison Table				
Method	RMS	MD residual	Calculation time	Comparison to Basic
Basic	1.12	1.18	7.4	1
Bayesian	0.85	0.89	27.7	3.74
ARMA	0.59	0.48	7.8	1.08
Kalman	0.63	0.50	26.6	3.59

Table 5.1: Statistic summary of the simulations without control

5.2 Simulations with Control

The second part of the test was to determine how well the estimators can co-operate with the control system. The variations are basically the same as in the test without the control system. This time the control system is reacting according to the estimation made by the estimator. Still the main fact is that good estimation is required to produce good control on quality variables. The defects of estimators can be seen better than without the control, because the control is reacting to estimation. The control is therefore increasing the variability on the web if the estimator reaction time is slower than the variation on the quality control variable.

5.3 Basic

The basic method is having problems when the controls are on. This is caused by poor estimation in MD. MD-estimation is missing the highest peaks of the variation. Therefore defects in the MD-estimation are transfered to the CD-estimation and it causes long diagonal waves into approximated surfaces (figure 5.10). The estimator is making the CD-estimate according to the last four scans and within these scans the lack of MD-estimation is not constant and it shows as a diagonal wave. MD-control can only affect the longest MD-waves and it increases the variability on the middle section (figure 5.9). This middle section is seen by the estimator but it is not on the range of the control system. The control system is therefore increasing variability

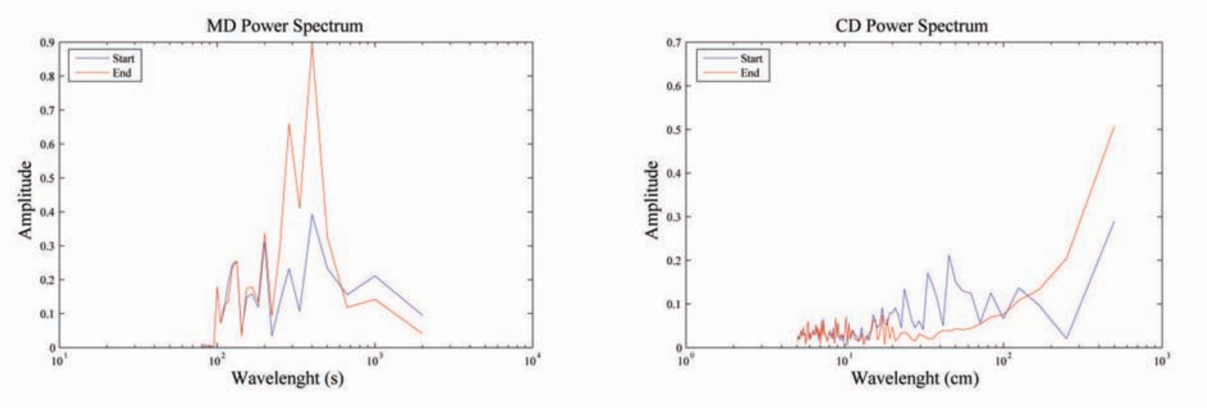


Figure 5.9: Basic estimation FFT analysis

The control strategy should be as steady as possible for the basic estimator. Rapid changes in quality control variable are missed. Highest changes on the quality control variable should be dealt with before the variable enters to the paper machine.

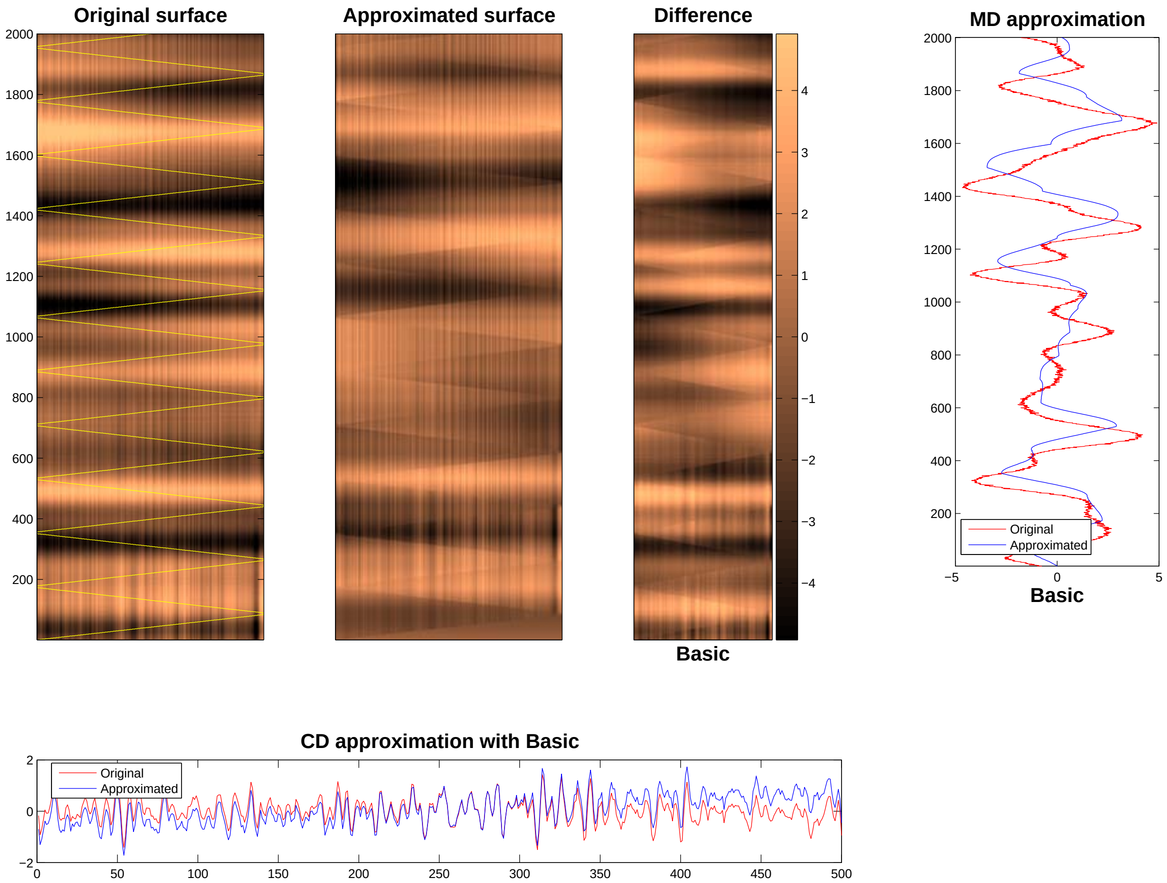


Figure 5.10: Basic

5.3.1 Bayesian

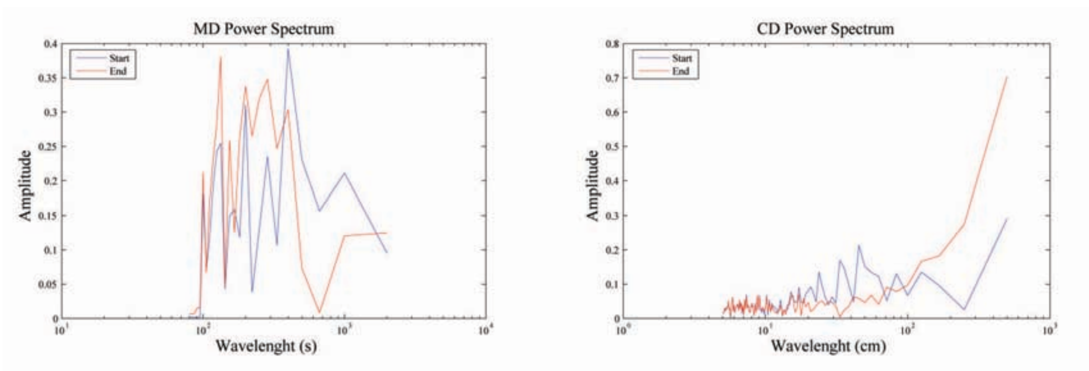


Figure 5.11: Bayesian estimation FFT analysis

The Bayesian estimator is having same problems as the Basic estimator. Rapid changes in MD are missed and the part which is missing from the MD-estimation is transfered into CD-estimation. Because there is not any smoothing between the scans, defects are visible very well at the end of the simulation (figure 5.12). When the change of the quality control variable is in the range of the estimator in the MD. The estimators estimation result in both directions is good and the control can react to waves which are on the controllable range.

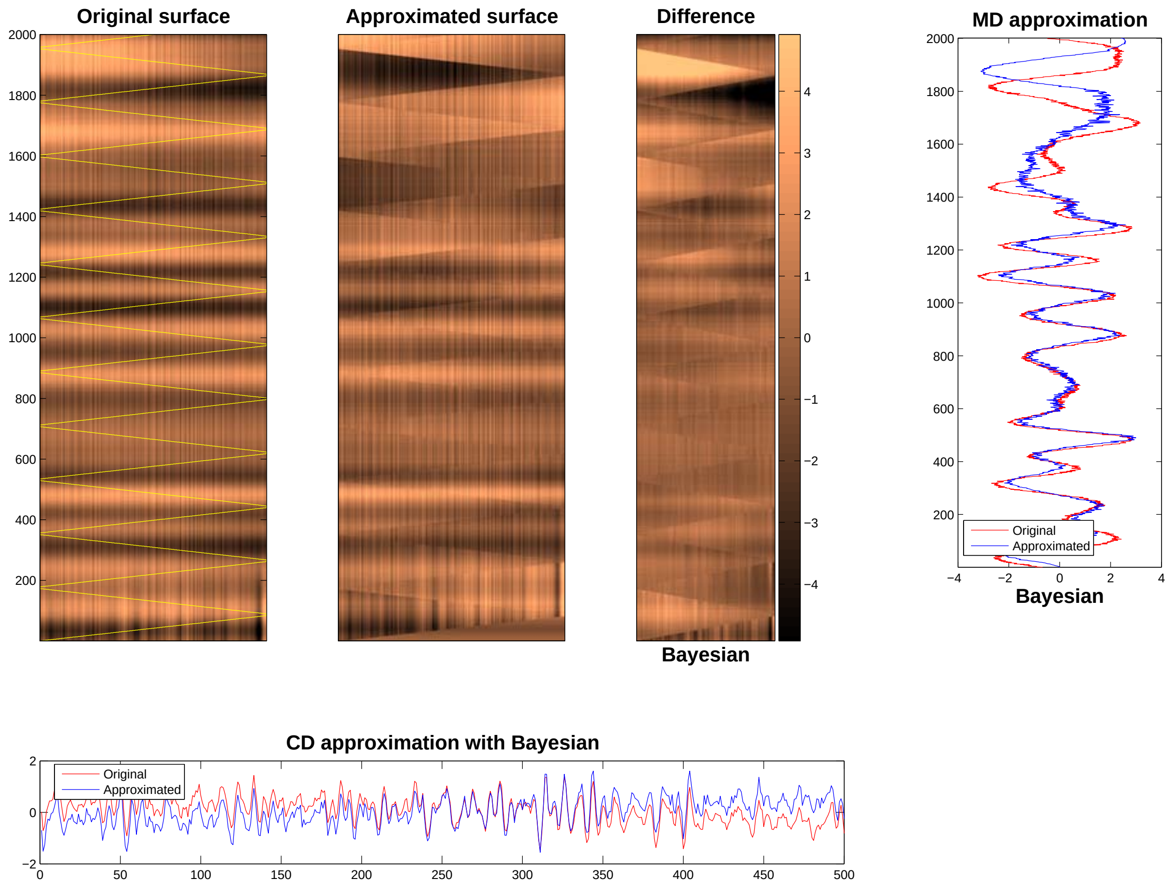


Figure 5.12: Bayesian

5.3.2 ARMA

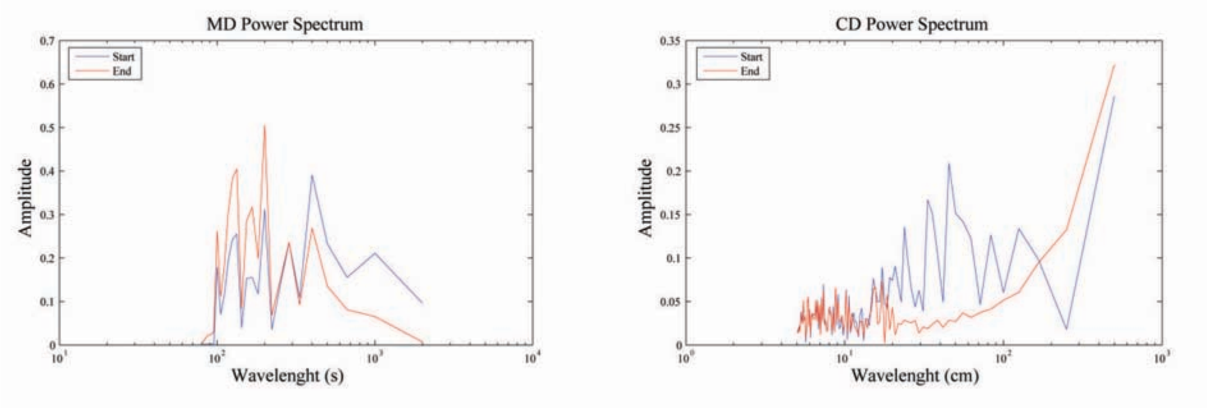


Figure 5.13: ARMA estimation FFT analysis

The ARMA estimator is performing well in both directions. Tuning of the parameters was successful in this case. Efficiency of the estimator caused higher variability on the quality control variable in MD (figure 5.13). If the control system can not remove variability in a wave range it is increasing it on that range. The ARMA method is reacting much faster to changes than the previous two systems. The good estimates in this case produced also good result in control system performance.

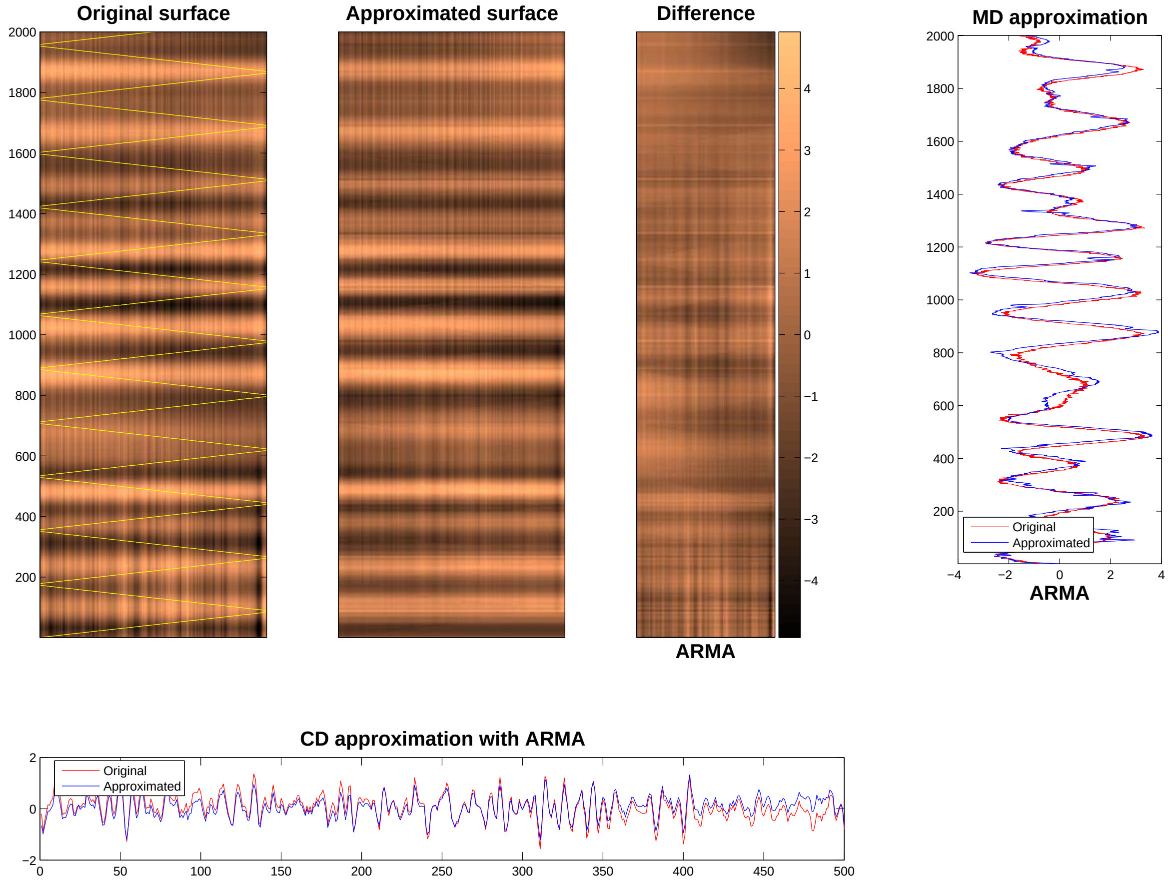


Figure 5.14: ARMA

5.3.3 Kalman-Fourier

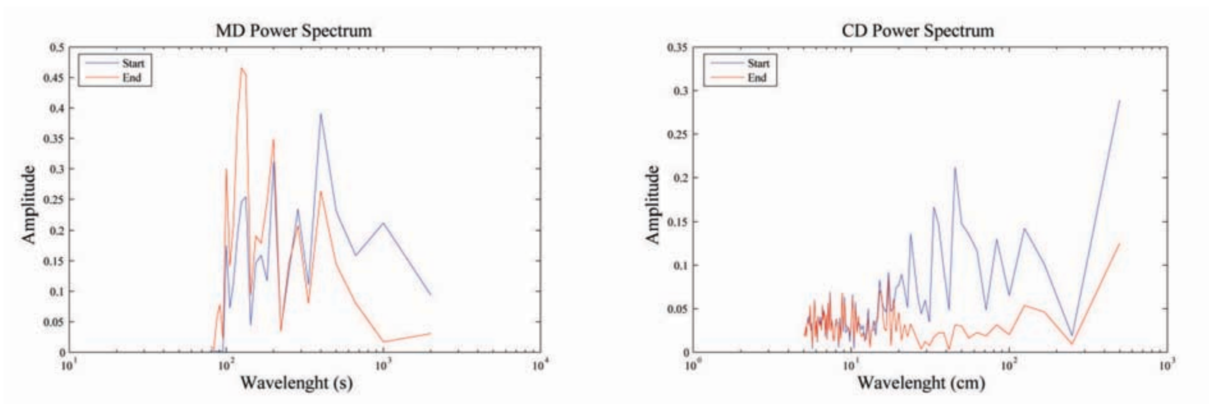


Figure 5.15: Kalman-Fourier estimation FFT analysis

The Kalman-Fourier is reacting firstly slowly on variation in the CD-direction. This is caused by the fact that the system has to initialize its covariance matrices. Initialization can not be rapid because then control actions on the CD are changing web formation rapidly. Estimator will get unstable if the update is too fast. In the MD-direction the estimator is even thinking that change has higher amplitude than it really is. The ARMA estimator is performing slightly better than The Kalman-Fourier.

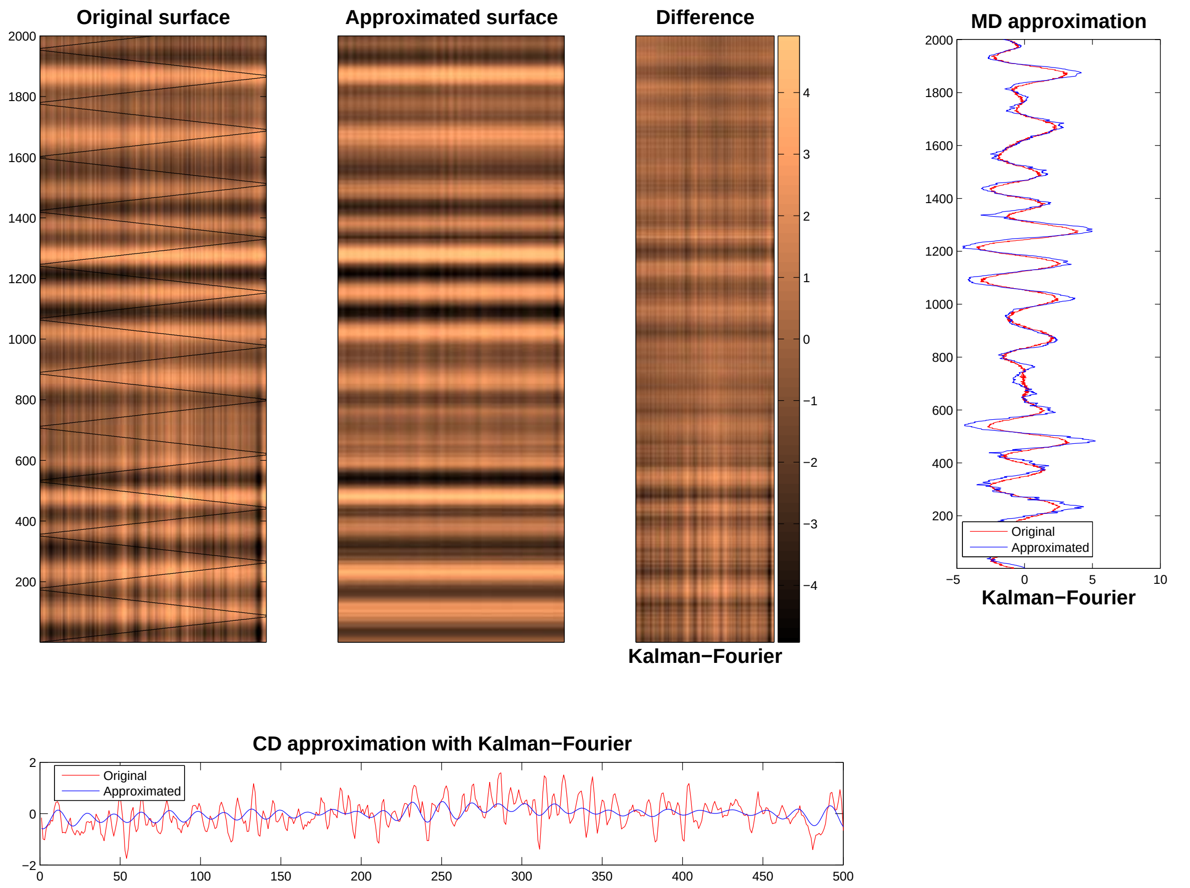


Figure 5.16: Kalman

Chapter 6

Conclusions

The Purpose of this work was to determine how intelligent assimilation methods are affecting paper web quality. Control performance is consequence of estimation performance. The main focus in this thesis was on the fact that without good estimation you can not have good control performance. The control system has a huge impact on the final product, but it can not work without the help of an assimilation method. Therefore co-operation between the assimilation method and the control system is essential.

Assimilation methods which were developed under the TEKES funded MASI-NOTES project were better than the industrial method. The Basic method is current assimilation methods in paper mills. The new methods have advances in collecting higher frequency variance from the web. Especially the Kalman-Fourier and the ARMA method were superiors in assimilation. These methods performed well without and with the control system. Downside of the Kalman-Fourier estimator is that it consumes much more calculation time than the others. Even it produces more accurate estimations from the web than the others. The scanning frame could be driven with lower speed or the machine can be run faster. The ARMA method was almost as fast as the basic method in calculation time. It produced accurate estimation with proper settings. The ARMA method is having the downside of heavy case sensitive. For this reason it should be tuned separately for every different variable and type of paper or board. The Bayesian method performed almost as well as the two previous estimation methods. Calculation time for this method is in same scale as in the Kalman-Fourier estimator. Assimilation result is having troubles when the change in quality control variable is rapid.

The next step would be combining the Kalman-Fourier and the ARMA-method. The ARMA is fast concerning the calculation time and the Kalman-Fourier is an intelligent method which can tune parameters online. Therefore a combination of fast calculation and automatic learning would be interesting.

The assimilation systems which were tested in this work would increase the accuracy of the estimation in a paper or board web. The methods are having great potential of being later on a part of the quality control system of a paper or board machine.

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