Helsinki University of Technology Control Engineering Laboratory

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HYBRID MODELING OF PAPER MACHINE GRADE CHANGES

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Hybrid Modeling of Paper Machine Grade Changes

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Opponent(s)	Professor Pentti Lautala, Dr. Smail Menani
Supervisor (Instructor)	Professor Heikki Koivo, AS-74

Abstract

A grade change is a product quality change on a paper machine. A grade change is typically a basis weight change but on some machines the production concept is changed from the raw materials to the finishing of the product. Only small grade changes are executed with automatic grade change applications or the change is started with automatics and then continued with manual actions.

A new hybrid model is proposed as a basis for the development of a grade change automation on a paper machine. The hybrid modeling method combines simple physical models with empirical models. In practice the goal was to develop models that could predict the outcome of a grade change accurately enough by comparing the modeling results to the actual measurements collected from a paper machine. The standard deviation of the prediction error of the proposed hybrid model was found to be about 40% better than the performance PLS model.

The thesis contains for the first time an overall approach to the paper machine grade change covering the process from raw materials to the on-machine coaters. Also a presentation of coat weight and coat moisture grade change is given that has not been reported earlier.

Keywords grade change, hybrid modeling, papermaking

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PREFACE

The research work for this thesis was carried out at the Control Engineering Laboratory, Helsinki University of Technology and Chemical Engineering Department, University of California, Santa Barbara.

I would like to express my gratitude to my supervisor, professor Heikki Koivo for his help, support and guidance and the staff of Control Engineering Laboratory in Helsinki University of Technology for creating an enjoyable surrounding for research. Special thanks go to professor Dale Seborg and his staff at the University of California Santa Barbara for introducing me to multivariable statistical modeling and for positive atmosphere in their research laboratory. During last four years my colleagues at PIC Engineering have been very understanding when I showed up in the mornings tired after writing the thesis during long nights. I thank my reviewers of this thesis, professors Pentti Lautala and Kauko Leiviskä for their constructive comments how to improve the thesis. Most of all, I am obliged to my wife Tarja for her understanding and continuous support.

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Helsinki, May 17, 2004

Paavo Viitamäki

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LIST OF ABBREVIATIONS

ARX	Auto Regressive with eXogenous input
CDF	Cumulative Distribution Function
CVA	Canonical Variate Analysis
DCS	Distributed Control System
GC	Grade Change
ICOMP	Information COMPlexity criterion
IR	Infra Red
LWC	Light Weight Coated (paper)
MIMO	Multiple Input – Multiple Output
MPC	Model Predictive Controller
MLR	Multiple Linear Regression
OLS	Ordinary Least Squares
PLS	Partial Least Squares
SEC	Specific Energy Consumption
SIC	Subspace Information Criterion
SISO	Single Input – Single Output
STD	STandard Deviation
TMP	Thermo-Mechanical Pulp

1. INTRODUCTION

Customer needs and global competition have made specialized and tailor-made products an essential part of the economic success in the paper industry. As a result more paper grades are manufactured nowadays than earlier. In some paper machines this has increased the number of grade changes. On the other hand there has been many mergers and acquisitions (M&A's) lately and large global corporations have been formed. One advantage of the M&A's is that the products of similar paper machines can be allocated effectively between several machines. The result is that the number of grade changes per machine can be decreased. However, this has not happened in practice. Thus an efficient grade change is still an important competitive factor and it is of course always a competitive advantage to be able to make large grade changes without excessive amount of off-quality product (broke).

The research leading to this thesis was started in 1991 when Technical Research Centre of Finland (VTT) launched a joint program with other research institutes. In the study several Finnish paper mills were surveyed on the topic of flexible papermaking (Ranta et al. 1992, Välisuo et al. 1997). The aspects of production control, the actions of operators and procedures of grade change automation in the context of flexible papermaking were studied.

It was found out that production, purchase and market control should be integrated more closely to process automation in order to increase flexibility. It was also discovered that web breaks are a very significant source of disturbances (Kallela and Tuominen 1992). The most important finding related to this thesis was that grade change automation is not used extensively (Viitamäki 1993a, 1993b).

The study reported in this thesis is a continuation to the research on grade changes mentioned above. The research on paper machine grade changes was to discover why the grade change automation is not used even though it was installed in nearly every paper machine. The survey was repeated to the same mills in 2001 with almost the same results. The grade change automation was not used in large grade changes.

1.1. Grade change on a paper machine

There are many ways to improve grade changes. As mentioned earlier, one way is to divide production between several similar machines and thus to decrease the number as well as the difficulty of the grade changes. Other methods to improve the operation of paper machine are the training of operators or improvement of grade change algorithms. The best result is achieved by using all these actions in combination by carefully analyzing which actions will give the highest profit. Due to the low usage of the existing grade change automatics, it was decided that to improve the operation of automation is one of the key points of a successful grade change.

The problem with the existing models seems to be that they predict the change of target value inaccurately or even to the wrong direction. The challenge of the modeling is to predict future values of paper quality variable for example moisture. The papermaking process is known to drift and the data that is available is strongly correlated and noisy. The problem is also that measurements do not exist for all the variables required for the modeling, for example temperatures of web in the drying section.

To improve the modeling the approach was to develop hybrid models that would combine a priori knowledge and empirical data in an efficient way. The starting point for the hybrid modeling was the Ph.D. thesis of Kemna (1993). He used canonical variate analysis (CVA) models and simple first-principles model as the building blocks of hybrid models. CVA is a dynamic subspace modeling method that for example removes correlation from the modeling variables.

Most of the grade change methods presented in the literature are based on empirical modeling. The fact that the measurements from a paper machine are correlated has not been taken properly into account in the previous research concerning grade changes. That is why in this thesis the partial least squares (PLS) models are used in the empirical part of the hybrid model. PLS is known to perform well even in the case of correlated modeling variables.

A major portion of the physical part of the hybrid model consists of the model of drying of web because it is the dominating section due to its non-linear behavior and long time constants. Mori et al. (2000) used a simple physical model for the modeling of grade changes but they did not use a hybrid modeling approach. Usually first-principles models are too complicated for the on-line or off-line use with grade change automation. That is why simplification of the models is needed and in this work for example the Ph.D. thesis of Heikkila (1992) forms the starting point of modeling moisture in web and coating.

There will be new grades and changes to the paper machine machinery during its life cycle. That is why the modeling of grade change must also perform properly with only finite number of modeling samples. This requirement has not been taken into account in the previous literature. The only reference where that is mentioned is Viljamaa et al. (2001). By tuning models with a large number of parameters compared to the number of samples with optimizing is a challenging task. In order to successfully do modeling with finite samples the theory of learning has to be applied (Cherkassky and Muller 1998). A conclusion of the theory can be interpreted so that the penalty of optimizing must at same time contain the degree of freedom and the interdependence of samples to overcome this problem. One that fulfills these requirements is information complexity criterion (ICOMP) that was presented by Bozdogan (2000).

There do not exist many literature references that would contain performance statistics of grade change methods. Only Murphy and Chen (2000), Viljamaa et al. (2001) and Mori et al. (2000) give indication that an improvement from 15 % to 35 % of the standard deviation of the grade change duration could be achieved.

The scope of the thesis is to model paper machine grade changes. Models are constructed for moisture, basis weight, coat moisture and coat weight. In addition to hybrid models also PLS model is used and these are compared with the performance of the existing grade change system.

1.2. Objectives

The main objective of this research was to develop a model structure and a methodology that would make faster and more reliable paper machine grade changes possible. The approach of the modeling is to expand the existing methods and to apply them in a new way and to a different field.

In practice the goal is to develop models that could predict the outcomes of a grade change accurately enough by comparing the modeling results to the actual measurements collected from a paper machine. This would make it possible to execute large grade changes with small amount of lost production and thus increase the flexibility of papermaking.

The contributions of the thesis

1. An extensive presentation of grade change practice that has not been reported earlier. The thesis contains for the first time an overall approach to the paper machine grade change covering the process from raw materials to the on-machine coaters. The results of grade changes in coating are completely new.

2. A new hybrid model method is developed to solve modeling problems of paper machine grade changes.

3. A significant contribution of the thesis is an extensive reporting of the results of prediction performances of modeling methods validated by real process data.

The prediction accuracy of the proposed hybrid model was found to be very promising. It can be even better if slice opening is taken into the model. It was shown that the hybrid model had the standard deviation of prediction errors over 40% lower than PLS model for the moisture of base board. The performance of hybrid model with coat weight and coat moisture was better that PLS only on coaters that had many operation modes. This is partly due to the lack of proper physical models.

1.3. Thesis content

The content of the thesis is as follows. Chapter 2 reviews paper machine grade changes and techniques discussed in the literature. Chapter 3 presents methodology that has been applied to further develop the hybrid modeling. It also gives a short survey of multivariable statistical subspace modeling methods that are used in the empirical part of the hybrid modeling approach. Presentation of hybrid models of drying of base paper, basis weight, drying of coating and coat is also included. Chapter 4 presents the experimental methods and techniques. Chapter 5 contains the results of the thesis and chapter 6 gives a discussion about the results. Finally, chapter 7 closes the thesis with the conclusion.

2. PAPER MACHINE GRADE CHANGE

A grade change is a product quality change on a paper machine. In some paper mills the grade change is a change of a customer code even though there was no real quality change in the produced paper. Most of the grade changes are basis weight changes but sometimes the production concept is changed from the raw materials to the finishing of the product.

In a wide context a grade change has an important part in the production control environment. It acts as an intermediate task between short term scheduling and process automation and executes the requests set by the production control task. Thus a grade change plays a significant role also when the efficiency of a production line is considered.

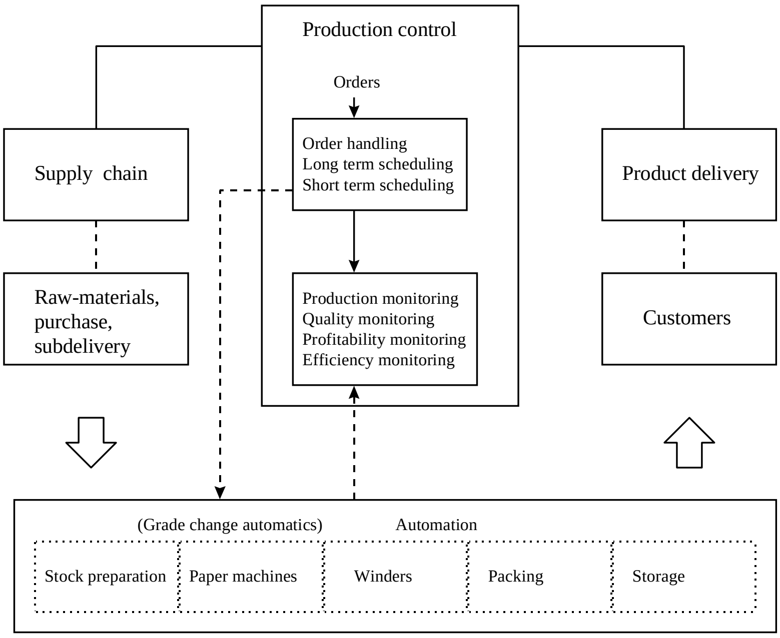

Figure 1.1 The interaction between functions of production control and the process.

The time spent on grade changes depends much on the paper type to be produced (Table 2.1). For example 3 % of the production time of LWC (Light Weight Coated) paper is being used on grade changes. On the other hand grade changes take only 0.01 % in newsprint production. The lost sales income when producing 200 000 tons of LWC can be calculated to be worth about 20 million FIM (4 million USD) per year (Table 2.1). It was estimated that at least 50 % of the losses could be saved, if appropriate automatic grade changes could be used (Viitamäki 1993b, Viitamäki 2001).

Table 2.1 Estimation of lost sales income for yearly production of 200 000 ton based on numbers from Ranta et al. (1992).

Product	Price FIM/ton	Grade changes annually	Time spent for grade changes (min)	Total time (%)	Lost sales (FIM)
News, standard	2200	30	450	0.001	4 400
News, special	2500	400	12000	2.5	12 500 000
Uncoated print (SC) standard	2800	40	800	0.02	112 000
Coated print (LWC) special	3300	500	15000	3	19 800 000
Fine, uncoated standard	3500	250	7500	1.5	10 500 000
Fine, coated special	4500	700	28000	5	45 000 000

In the following chapters first the structure of a paper machine is presented from a grade change point of view. Then grade change methods applied in practice at paper mills, new solutions proposed by researchers and grade change automatics of the major vendor are surveyed. The chapter closes with a conclusion.

2.1. Paper Machine

A modern paper machine consists of series of unit processes such as a stock preparation system, wire section, wet pressing, dryer section and often on-machine coating units (Figure 2.2). Paper mill uses different raw materials such as chemical pulps from pulp mills and mechanical pulp from chip refiners. Part of the pulp comes dried so that it has to be pulped first in the stock preparation before adding into the process. Pulps are also refined to disintegrate the flocks or to achieve the required product quality.

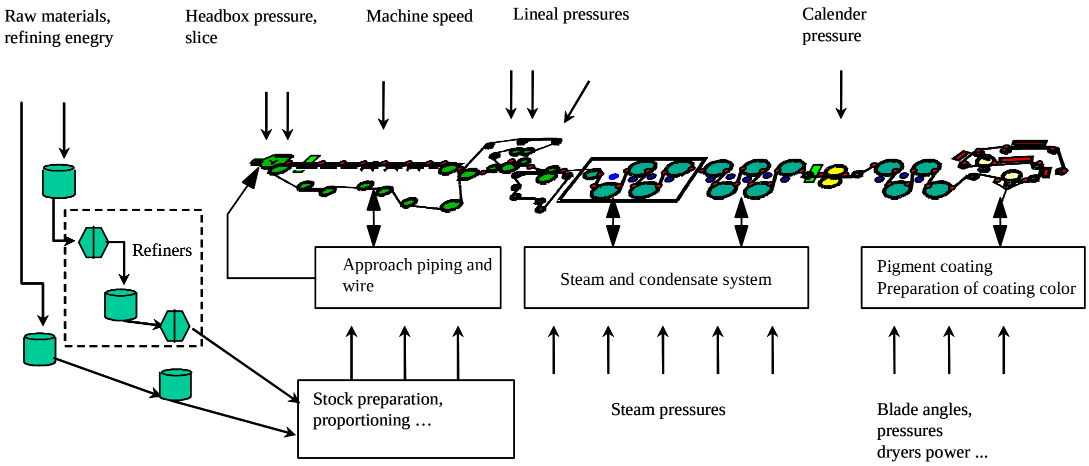

Figure 2.2 Schematic presentation of a paper machine.

In the off-quality production, the broke is fed into the stock preparation system. The excess broke is stored in a separate bin. The broke forms usually a significant percentage of the stock composition. This backward flow of broke is part of long circulation (Figure 2.3). After mixing, cleaning and diluting the pulp stock is fed into the white water system of a paper machine. A white water system consists of a head box, a wire and a circulation system of white water. White water (a filtrate from the wire) is used to dilute the stock to the desired consistency (0.3-1%) for the paper web forming process. The white water system is also called short circulation. Head box spreads the flow of stock onto the wire and paper web is formed when water is filtered away through wire. After that water is removed first by wet pressing and then by contact drying with steam heated cylinders. Along with these there are several support systems such as broke system, chemical preparation plant, coating color preparation plant, etc.

Paper machines are designed either for bulk or multiple grade production. For example the volume of the intermediate storage chests is smaller in a paper machine than that used to produce multiple grades than in a bulk production machine. The volume of the chests increases the time constant of wet end system so that the response in a grade change is slow. Also the lag in the short and long circulation of process water has adverse effect to mass flow response during a grade change. Grade change can be made shorter by decreasing the volume of the chests and minimizing backward flows in the process. The newest paper machines exploit this feature (Meinander and Olsson 1998, Pekkarinen et al. 1999).

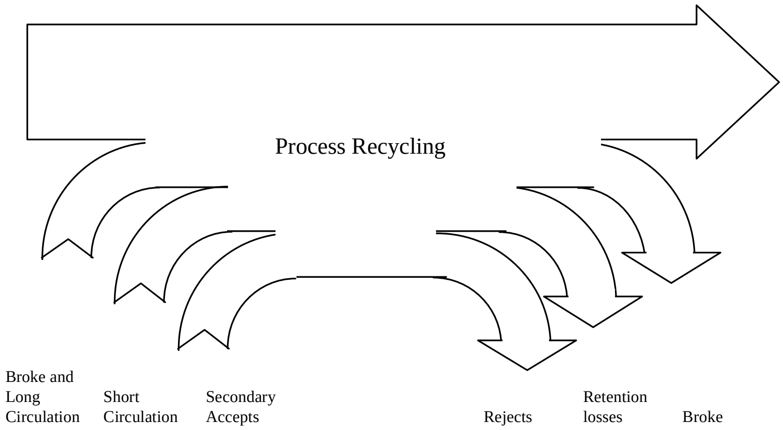

Figure 2.3 Schematic presentation of process recycling

Modern paper machines have often also on-machine coaters that apply the pigment coating color on the surface of the paper (Figure 2.4). The paper may be coated on both sides and the coating can be even double or triple layered. Blade coating is the most common method to apply coating color onto web. The coating is dried with infrared (IR) and air dryers. Both of these are non-contact methods in order not to impair the applied coating surface. Contact coating is used at the end of the drying also to keep the tension of the web in control. A more comprehensive description of the coating process is given in chapter 3 section 3.7 Hybrid model for a coating weight.

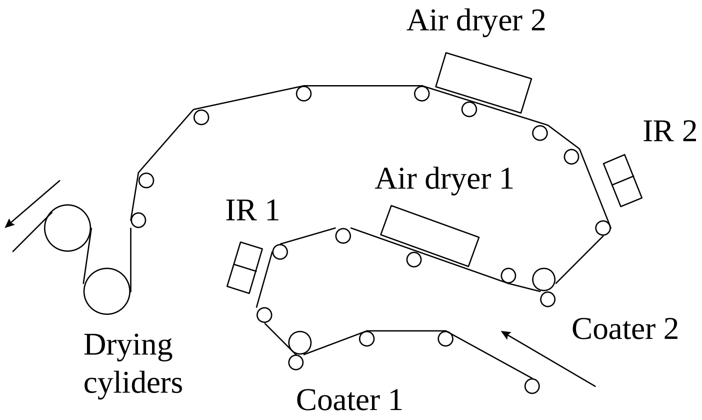

Figure 2.4 Schematic picture of two-sided coating with infrared (IR) and air dryers.

2.2. Grade Change Methods

Grade changes can be done manually and automatically. However, there are several tasks that are not executed automatically due to their nature or insufficient instrumentation in the paper machine. For example, the washings of coaters or the adjustment of wet line on the wire are typical manual tasks. The tasks of an automatic grade change are calculation of target values and dynamic coordination of manipulated variables. For example the speed, the stock flow and steam pressures are adjusted in a basis weight change. It is crucial to a successful manual or automatic grade change that the new target values are accurately calculated. The target values for steam pressures are the most important due to long time constants and dead times in the drying process of paper web.

Basis weight is the most common quality measure to be adjusted in a grade change. The basis weights that are in a production schedule are run in a cycle (Figure 2.5). The cycle is usually optimized so that the basis weight changes are as small as possible. The ideal condition is that the allowed ranges of the sequential grades overlap. However, if large grade changes could be made with low amount of off-quality production, the production could be more flexible.

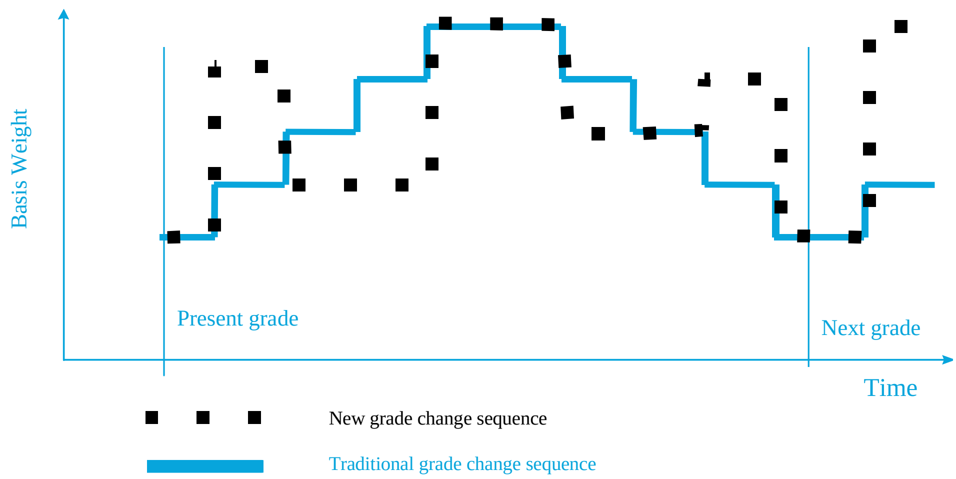

Figure 2.5 Graphical presentation of traditional basis weight change sequence and a new flexible one.

In a comprehensive grade change, several manipulated variables of the paper machine are changed. These are for example: proportioning of raw materials, refiner loads, stock flows, head box settings, machine speed, lineal pressures in wet pressing, steam pressures and coating. The elements in this table are selected to point out that a grade change can have an effect on the whole paper production line from pulp refiners to the coaters and in addition on the finishing department. A detailed description of papermaking process can be found for example in Smook (1989) and about grade change automation in Leiviskä and Nyberg (2000).

A grade change can be divided into three phases: preparation, execution and termination (Figure 2.6, Viitamäki P. et al.1995). Preparation is an interactive phase where automation system calculates the initial values or the operators pick up the previously used values of grade change parameters and feed them into the system. During the execution phase the target values calculated in the preparation phase are made active and the grade change is started. The termination phase starts, when quality variables are inside acceptance limits but there may still be oscillation present. These phases can be found in manual and automatic grade change procedures.

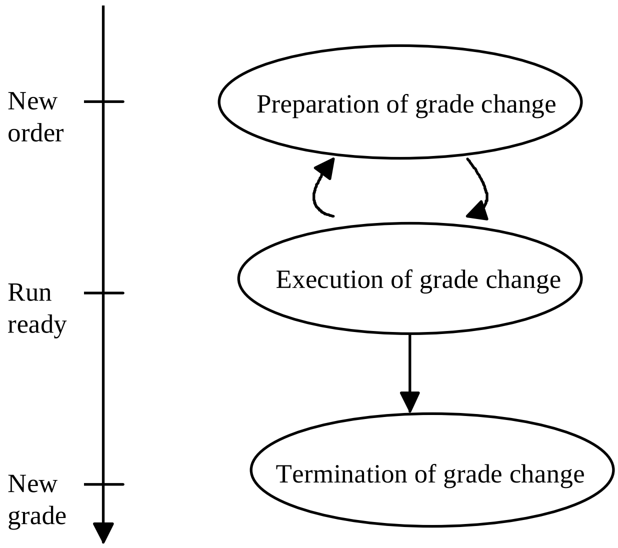

Figure 2.6 Phases of grade change.

A grade change is very often performed manually or after an interruption during automatic action continued manually. That is why a manual grade change is considered in a separate chapter. After that automatic grade change methods are discussed in detail.

2.2.1. Manual grade change

According to the interviews of papermakers there seem to be two ways to perform the tasks of a manual grade change. The most common is a more cautious method than the other one. The tasks in the two procedures are almost the same but the timing and the manner of execution is different. In the 'cautious' method the tasks are executed in a sequential order with small changes and they are executed in an iterative fashion. In the 'courageous' method all the changes are executed at the same time and in one step.

The grade change effects sometimes the operation of the whole paper production line. The adjustment of proportioning, refining, on-machine coating, etc. can make a grade change quite extensive. Due to long dead times the timing of the proportioning of raw materials, chemicals and additives and the changes in the refining pulps should be executed with care. In the following there is a simplified description of a 'cautious' basis weight change that is based on the practice at several paper mills.

Preparation phase

The preparation phase starts when there is about an hour to go to the grade change. Of course the availability of raw materials has to be established earlier. The machine tender takes care of most of the tasks. First, the values of proportioning recipes are checked and maybe some minor adjustments are done. Then the target values for machine speed, mass flow and steam pressures are calculated.

In practice the adjustment of steam pressures is performed according to the knowledge of the workers at the dry end (Figure 2.7). The final target speed is calculated by assuming that the production rate can be kept constant. Sometimes the flow of stock, the machine speed or production rate is a limiting factor and the calculation must be changed accordingly. Some machine tenders also use the values of the previous run with similar changes. There is also an upper and lower limiting factor due to the flow in the headbox which has to be taken into account. This means that besides the actions mentioned previously, perhaps, also the slice and as a result the headbox consistency has to be adjusted. However, the change in the slice setting is very difficult to predict and thus it has to be adjusted during the execution phase. Finally, the time instant for the start of the grade change is calculated from the production rate and from the size of the order.

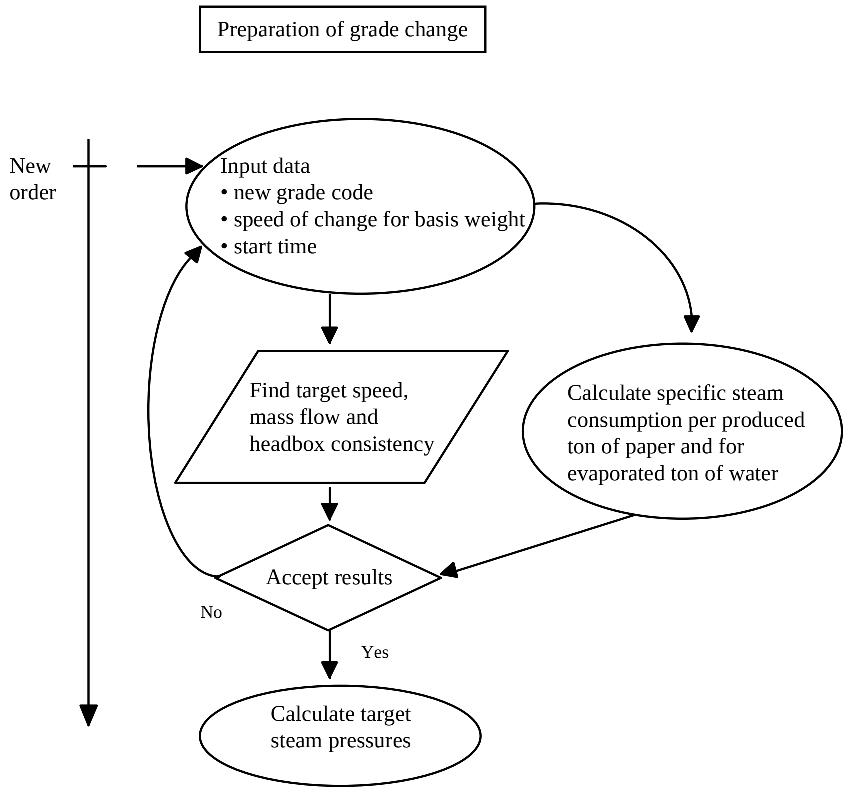

Figure 2.7 Preparation phase of a basis weight grade change.

Execution phase

The execution phase is a team effort that is coordinated by the machine tender. The machine tender executes the basis weight change while the other team members are checking out that the paper machine is functioning properly. Sometimes the web is cut before the pope so that the quality measurements are still on-line (Figure 2.8). In some paper mills the production during the grade change is run on top of the tambour or the split between tambours. The production can be run also onto a new reel or directly to the broke system.

First, the adjustment of machine speed change is started when the run is full. Sometimes small changes are done in advance to move the manipulated variables to the direction of the coming grade change but still staying inside the acceptance limits of the grade. When the run is full, the speed is either decreased or increased step by step. At the same time the slice has to be adjusted so that the headbox consistency, the dry line on the wire and headbox flow are inside the specified values. At the dry end, the cylinder tender adjusts the steam pressures according to his/her experience by observing the moisture readings. The adjustment of steam pressures is difficult, because the changes of mass flow and machine speed arrive to the dryer section at different times. As a result the moisture may swing first to the opposite direction than anticipated. In control literature this is called minimum phase behavior. When the manipulated values have reached the target set points the execution phase has ended.

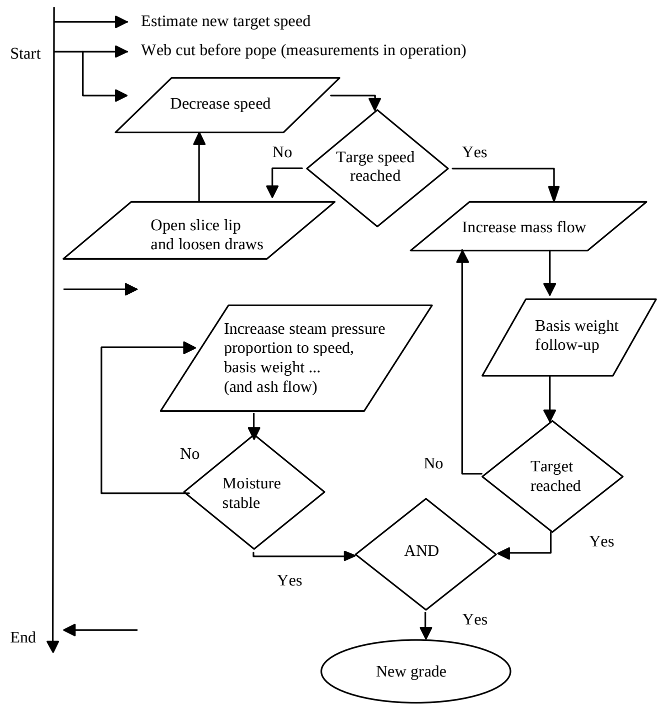

Figure 2.8 Execution of a basis weight grade change.

Because the basis weight change is the most common grade change, its step size is usually minimized. Consider a paper machine that produces grades in the range of 35-55 g/m2. Then basis weight changes under 3 g/m2 can be run without broke but over 5 g/m2 cause the production of broke for about 10 min. Basis weight changes more than 10 g/m2 are considered very difficult and they are seldom done.

Also an increase in the brightness of a web is very difficult to achieve, when there is a change in the raw materials. The timing of the changes in the proportioning of raw materials is difficult. For example when the brightness is changed, the information of the grade change must be at suppliers of chemical pulp, thermo-mechanical pulp

(TMP) and stone groundwood pulp several hours before the start.

During a grade change the process may run into production bottlenecks or into a regime where the process is more difficult to control than usually. Typical bottlenecks are dewatering units and headbox. For example, drying section may become a bottleneck when a high basis weight is run or surface sizing is started. The situation may be deteriorated by the fact that it is preferable to run the web too dry than too wet. This is because a wet web breaks more easily than a drier web. Also, the cross-direction variations of moisture are smaller in quantity when the web is dry. It was also mentioned that a manual grade change is more difficult at the highest speed and it was stated as a rule that the extreme grades are the most difficult to run.

Headbox itself may be a limiting factor due to its design but also the capacity of a feed pump may be too low for the required production rate. Headbox settings during a grade change may be very important. For example a change in the felting property of pulp fibers during the consolidating of web on the wire may cause problems with dewatering all the way to the drying section. This is caused by a change in the position where the jet from the headbox hits the forming board. Especially during large grade changes the lateral position of slice has to be adjusted forward or backward so that the jet will always hit the same position on the forming board.

Termination phase

In the beginning of the termination phase, the machine tender waits for the process to stabilize and does final adjustments to the manipulated variables. When the quality variables have been stabilized to the required levels, the grade change has ended (Figure 2.9). Then the information about the used target values as well as successfulness of the change can be stored in the records. These can be used for further analysis or for reuse, when the same grade change is run next time. Typically, the machine tender keeps track of the grade changes in his/her folder.

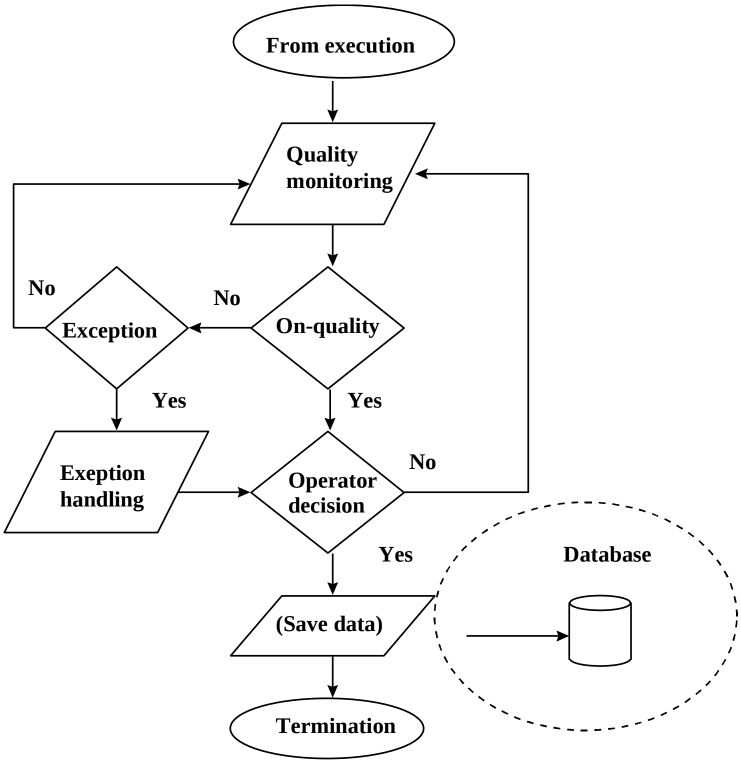

Figure 2.9 Termination of a grade change.

2.2.2. Automatic grade change

The automation system of a paper machine consists of basic loops, quality controls, supervisory controls and a production control system. Typical quality measurements are basis weight, moisture, ash content, coat weight, opacity, color and caliper. These are measured in machine and cross direction with scanning gauging supervisory control system (Figure 2.10). Along with an automation system there exist also separate fault and diagnostic systems for both the process and the quality of paper. For example, the preventive maintenance system uses on-machine vibration monitoring to detect the wear of bearings and the quality monitoring uses an optical analyzer to detect holes and spots in the web. The grade change automation is a part of supervisory controls that adjusts the set-points of lower level controllers. It has tight connections also to the production control system.

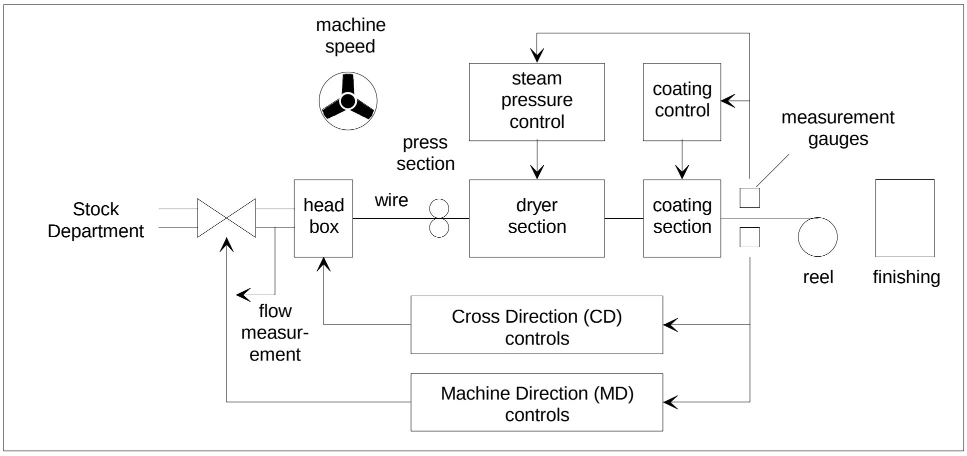

Figure 2.10 Paper machine control, a schematic graph (Välisuo et al. 1996).

An automatic grade change can be presented in the same framework as the manual one. Preparation, execution and termination can also be found in the automatic change. Also the tasks are relatively similar so that the only difference is that some of the actions are performed by automation system. The degree of automation is the definition how the basic tasks of grade change are divided into manual and automated tasks. These tasks interact sometimes with each other and with the information system. The actual implementation and the automation degree depend on the paper machine itself and on the capability of the grade change application. In the following an automatic grade change is portrayed as it is executed in paper mills.

Preparation phase

The preparation phase is mostly performed manually. The initial values for the next grade are either typed into the automation system or acquired directly from the database of information system. A user can change the speed of change if needed. The automation system then calculates the parameters to the grade change procedure according to the tuning and settings that have been done during the commissioning of the automation system. In the commissioning phase the models in the automation system are tuned according the grade that is run most frequently. Normally there are no grade specific models. The models are sometimes adapted to different basis weights and dead times and calculated according to machine speed.

Execution phase

During the execution phase, typically, only basis weight and coat weight changes are performed in the automatic mode. Some systems also provide color change automation. The major interactions with the control variables (basis weight and moisture) are decoupled at steady state. In some grade change automatics the paper machine tender can adjust the speed of change, but all the other tuning is done only by the vendor personnel. Automation vendors used to have so-called baby sitter at the mills that took care of all the maintenance and tuning of the paper quality system. Usually the tuning of grade change automatics required an expert analyst that was not in the baby-sitting crew. Thus, the problems with the grade change automatics took long time to be fixed.

The end of the current grade is usually calculated by the automation system. The decision of the time instant, when the new grade is started, is on the operator. An automatic grade change is usually started with a push of a button or a sequence program is started. The paper machine tender has to look after that the manual operations are coordinated properly with the automatic actions. When the grade change automation has finished the transition, it usually stops or waits for an operator interaction. If the target values have not been reached at this point the operator usually runs the rest of the grade change manually.

Termination phase

There does not exist any automatic action by the automation systems during the termination phase. The machine tender turns the stabilizing controllers to the auto-mode when the quality measures have reached the target zone. He then signals to the system that the production of the next grade has begun. The paper mills do not usually store detailed information about the success of grade changes in their database although there has not been any technical reason why not to implement it.

Almost all the applications of automatic grade change are active in the execution phase. At least three approaches have been presented in the literature (Ihalainen and Ritala 1996, McQuillin and Huizinga 1994, Smail et al. 1998, Viitamäki 1993b, Välisuo 1996). The simplest is the ramping the manipulated variables to the target values. One of the commercial products uses model predictive control approach. There are also reports of using optimizing controllers for the grade change. An outline of these automatic grade change methods is given in the following chapters.

2.2.3. Automatic grade change with ramping controls

The most common method to execute a grade change is ramping in an open-loop fashion (Figure 2.11). It is a straightforward extension to the ramping functions already existing in the automation systems. Ramping is a natural way to automate grade changes because it simulates the actions performed in the manual grade change. An open loop-control method is appropriate to a grade change, because there are no exact target values for basis weight and moisture. It is satisfactory, if the quality values will reach the acceptance range at the end of grade change.

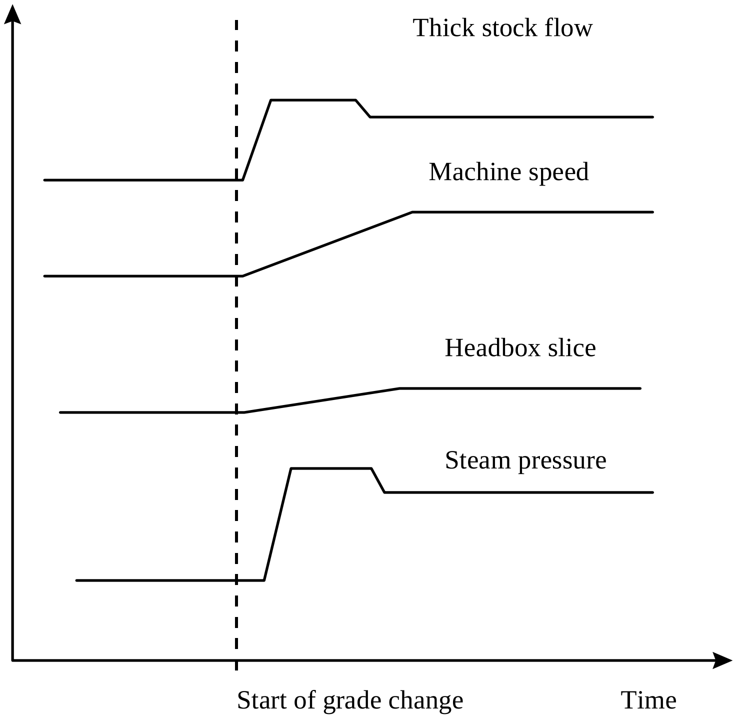

Figure 2.11 Grade change by ramping the manipulated variables.

Several timings of machine speed, thick stock flow and slice opening ramps have been tested by Johnston and Kirk (1970) and Smail et al. (1998). The result of Johnston and Kirk (1970) was a scheme for a sub-optimum basis weight change numerical optimization of linear models. Smail et al. (1998) developed an identification algorithm for the ramping responses. As a result dynamic multiple-input multiple-output (MIMO) models could be identified for control purposes. This will make automatic dynamic controllers for grade changes feasible.

Similar optimization could be carried out also with a benchmark model for a paper machine (Hagberg and Isaksson 1995). Miyanishi et al. (1988) also did a simulator study of a grade change. They pointed out that the first-pass retention plays a significant role in a grade change. If the first-pass retention is low, the time constants of different furnish components will be long and vary according to their retention percentages.

The adjustment of steam pressures is used to control the moisture of the web. However, when stock components, thick stock flow or machine speed are adjusted, the moisture will change also. The interactions with these manipulated variables combined with long time constants and dead times make the calculation of the target values difficult. For example, accurate estimation of steam pressures is the key point to a successful basis weight change also. Besides the previously mentioned function, also the timing of all the manipulated variables is critical. Due to the spatial position of actuators and that the speed can be manipulated only by using linear ramps, an over- or undershoot in the moisture occurs during a grade change. The methods mentioned in the literature handle the above situations very well but they do not take into account the mix of different raw materials or the processing of pulp as for example refining.

The drying rate of web depends among other things on the incoming moisture content to the drying section, production rate, thickness and structure of web and hygroscopic properties of web components. Thus the calculation of target values to the steam pressures is a very difficult task. These effects have not been estimated in any research to my knowledge.

Dynamic grade change systems are usually based on transfer function or impulse function models. The transfer model of the process upon which the controller is based on is usually a first- or second-order linear dynamic model with dead time (Koivo and Peltonen 1993). The most suitable control structure for this kind of model is thus Smith Predictor algorithm or its variant. However, the actual control is performed with ramps.

Due to simplified models and controllers the model mismatch is a serious problem with the previous approach. A regime based approach could solve this problem. For example, Sun and Kosanovich (1997) proposed a transition control method based on variable structure control theory. The method uses a process model library (candidate model library) and Smith predictor controllers are calculated according to these models (Figure 2.12). Transition supervisor switches the controller into the feedback loop that produces the smallest prediction error.

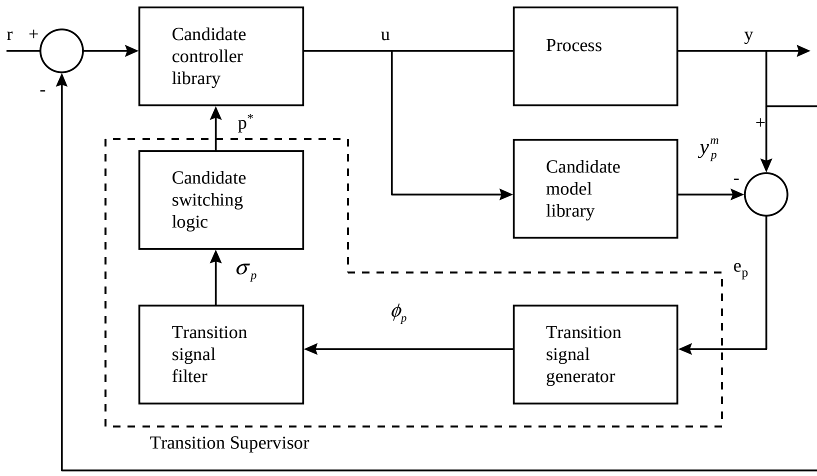

Figure 2.12 Transition control structure according to Sun and Kosanovich (1997).

An intermediate method between dynamic and optimizing controller applications is a method where the optimization is executed in the preparation phase. The resulting optimal control actions are then applied in the execution phase in a dynamic control fashion. The optimization is done usually with a simulator. Ihalainen and Ritala (1996) applied their method to optimize basis weight, ash content and moisture in a grade change on a paper machine. Miyanishi et al. (1988) have also presented similar ideas in the optimizing of filler response during a grade change.

In all the models and controllers presented above the common problem is the model mismatch. If you cannot predict the target value of the controllers accurately enough there will be a long time period before the new control actions can take place. Due to long dead times of papermaking process this means longer grade change duration. One approach to improve the performance of grade change controllers is to decrease the time when the new control actions take place. This could be called automatic grade change by optimizing controls.

2.2.4. Automatic grade change with optimized controls

Perhaps the most straightforward method to apply optimizing controls to a grade change, is model predictive control (MPC). It uses a mathematical model of the process to predict the response of control actions (Figure 2.13). MPC plans optimal future control inputs, feed-forward compensation and dead-time compensation. Model predictive control is a promising method to be used in the grade change automation. Its advantage compared to the Smith Predictor algorithms is to use several controlled and feed-forward variables at the same time.

MPC context has given rise to several control configurations. In the preparation phase the models to be used are for example retrieved from a model bank or the models are identified from the process (McQuillin and Huizinga 1994). The control actions can also be optimized by the dynamic programming methods with nonlinear physical models in the preparation phase. In the actual execution phase the controls are calculated by using MPC with linearized models (Ohshima et al. 1994). Välisuo et al. (1996) proposed the use of simplified physical models for the implementation of a nonlinear MPC method. In the following paragraphs the approaches made by McQuillin and Huizinga (1994) and Välisuo et al. (1996) are discussed in more detail.

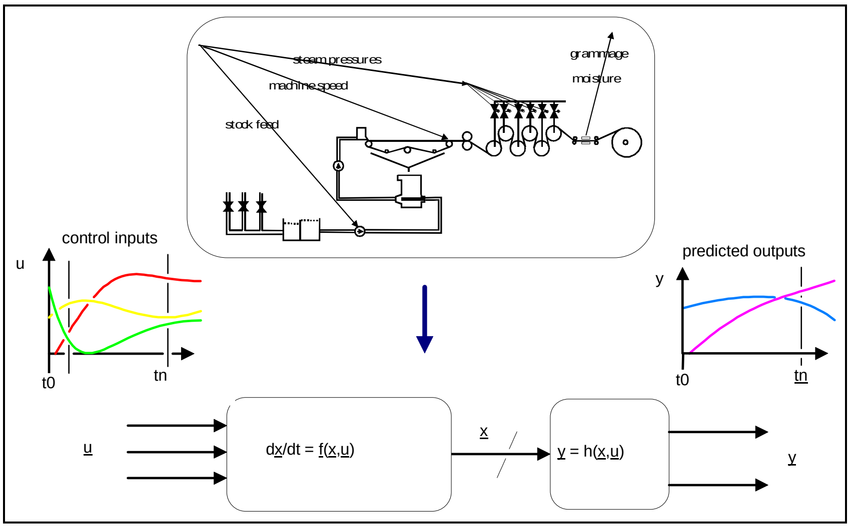

Figure 2.13 Schematic diagram of a state space model of a paperboard machine. State variables x represent physical parameters some of which usually cannot be measured, like cylinder temperatures (Välisuo et al. 1996).

Honeywell's grade change automation uses impulse function models in their MPC scheme. The models are tuned in a single-input/single-output (SISO) fashion by so-called bump tests (McQuillin and Huizinga 1994).

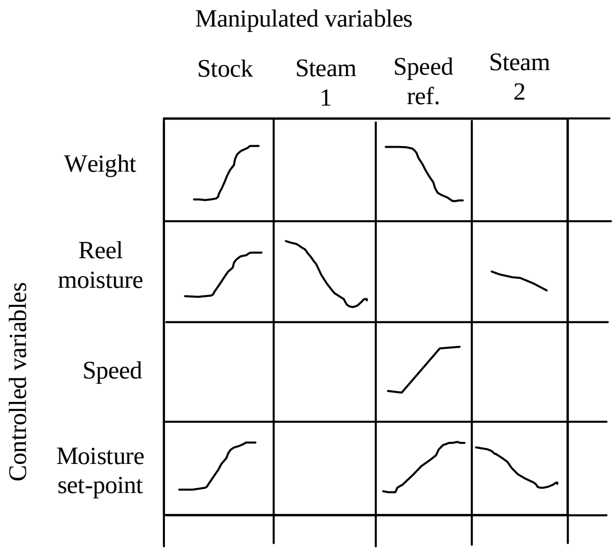

Figure 2.14 Tuning Visualization of Model Predictive Control Method by Honeywell.

There is no need of state estimation, when linear impulse function models are used. However, if a state space representation is chosen, it is not always possible to measure all the states. An example of this is temperatures of dryer cylinders in the dryer section of a paper machine. Thus certain initial states (x(0)) must be estimated in the preparation phase of grade change (equation (2.1)). A more general optimal control problem can be presented by the equations (2.1) - (2.3) (Välisuo et al. 1996).

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t),\ \mathbf{y}(t) = \mathbf{h}(\mathbf{x}(t), \mathbf{u}(t), t),\ \mathbf{x}(0) = \mathbf{x}_0 \tag{2.1}$$

$$L(\mathbf{x}(t), \mathbf{u}(t)) \leq 0 \tag{2.2}$$

$$J = \int_0^T g(\mathbf{x}(\tau), \mathbf{u}(\tau), \tau)d\tau + g_T(\mathbf{x}(T), \mathbf{u}(T)) \text{ ; minimize w.r. } \mathbf{u}(\tau) \tag{2.3}$$

where **x**(*t*) is the state variable vector, **u**(*t*) is the control input vector and **y**(*t*) is the output vector. Final time T is constant and represents the duration of a grade change. Functions **f** and **h** represent the nonlinear dependencies between the state variables and inputs. Function g in the cost function *J,* is a quadratic penalty that is derived from the deviation of the predicted outputs from the reference values (for example moisture and basis weight) and a penalty of the variations of the manipulated variables. Function g can also contain penalties that limit selected state variables into a certain range or the penalty can depend on the phase of grade change or prediction horizon (from 0 to T). Vector function L represents the constraints.

This optimization problem is solved by changing it into a two-point boundary value problem. If the equations are linear it can be solved analytically, otherwise a numerical solution is needed (for example shooting method). The result gives a sequence of control inputs $u(t_0 + i \cdot \Delta T), i = 0..n$, where t_0 is the current time and ΔT is the control time interval. If functions g and g_T in the cost function are chosen properly, the result of the control action is the best possible response in the sense of the performance criterion. It will also assume that none of the constraints in L will be severely violated. The method is very complicated but is quite effective if dynamic optimal solutions are required. Ihalainen and Ritala (1996) found that the convergence of the optimization algorithm was best when quadratic penalty functions were used.

In the MPC approach the first in the sequence $u(t_0)$ is used to control the process and the optimization is repeated after time ΔT. In this way the disturbances and possible model mismatches can be compensated. Similar optimized coordination scheme for a basis weight change is also found in Äkesson and Årzén (2002) and Kuusisto et al. (2002).

Murphy and Chen (2000) used a combination first-order plus delay models including total head coordination model for the headbox. McQuillin and Huizinga (1994) reported the use of a model predictive control. Kuusisto et al. (2002) used second order transfer function models (ARX) in the MPC control.

Another approach to improve the grade change method is to estimate the target values of manipulated variable more accurately. Yoshitatsu et al. (2000) used a simple physical model drying of web and basis weight. One of the latest studies uses a fuzzy system for the estimation of target values of grade changes (Viljamaa et al. 2001).

Banerjee and Arkun (1997) proposed a regime based method that combines linear models identified in individual regimes of steady-state based on the data collected during plant transitions. The model mismatches are compensated by a state estimator that is evaluated before each control action.

A couple of the authors presented some performance figures of the algorithms. It seems that the basic assumption has been that the model mismatch can be compensated by MPC optimization. It is also probably difficult to asses the performance improvement with MPC without extensive data or plant testing. This is partly due to the feature that the MPC creates various future control movements in each grade change situation. Also nonlinear control movements are not always feasible on a paper machine due to limitations of control actuators.

Much development work has been done in the field of optimizing controllers such as MPC and they are already in industrial use. However, if the gain of the model and thus the target values of the manipulated variables could be estimated more accurately, all the grade change approaches would benefit from it. For example in the MPC, the control actions could be performed earlier than before.

When there is only a short dead time in the controlled process the significance of the correct target values is even clearer. This kind of process is a coater that is often on-machine with the paper machine so that it has a direct influence on the total duration of a grade change. In the following chapter a short survey is given on the subject.

2.3. Grade change on a coater

Grade change has not been considered in the literature for coater. The grade change on a coater was performed manually in the paper machines that were studied but it can be done also automatically. The degree of automation is usually lower in the coater section than in the paper machine that makes automatic grade changes difficult to do. The operation of a coater is also greatly influenced if it is combined with the paper machine (on-machine coater) or if it is an independent unit (of-machine coater).

Due to many manual tasks in the operation of a coater an application of grade change automation is difficult. For example, a runtime for a blade is 8-12 hours so that it must be changed once a shift or during breaks. Also when there is a color change or some requirements due to foodstuff legislation, the coating color circulation has to be washed. The washes take roughly 10-15 min and during that time, as in the blade changes, the production is run to the reel. The result is that the advantage of automation is not as obvious as during basis weight change.

An automatic change in the coating weight is done by ramping the position and the angle of the coater blade. The direction of the change of the blade angle must not change during the grade change or at least it must be minimized because it causes unnecessary wear of blade (Luomi 1991). The settings in drying section of the coaters must be adjusted so that the dewatering profile is kept the same or changed to the new target (Mäkinen et al. 1998). This is because the gloss and surface roughness variations are formed during coating consolidation.

Because the dead times and time constants are significantly shorter in the coating process than in the base paper, feedback from the measurements is readily available when the web has been threaded to the pope. The problems in coating and drying are more related to the calculation of the target values of the manipulated variables and especially of the start-up situation (Nuyan et al. 1997).

2.4. Conclusions

A brief discussion of the subject about the units and variables of a paper machine and its structure is reviewed. The practice of making grade changes in the Finnish paper mills and survey the research is presented.

The practice of grade change is a summary of interviews of personnel of six paper mills and is reported in detail. A grade change is split into preparation, execution and termination phase. The automatics are typically intended for the execution phase. On the other hand, there is no good tool for the preparation phase. The preparation of a grade change is based on previously performed similar changes and the performance is greatly dependent on the expertise of the personnel of a paper machine.

Only small grade changes are executed with automatic grade change applications or the change is started with automatics and then continued with manual actions. Automatic changes are done with ramping, dynamic or optimizing controls.

It was noted that improvement in the duration of a grade change could be achieved by calculating the target values of the manipulated variable more accurately than in the existing approaches. A method, hybrid modeling is proposed in this thesis.

3. MODELING OF A PAPER MACHINE FOR A GRADE CHANGE

The availability and the low price of number crunching power has made it possible to apply calculation intensive process control solutions in industry. Thus it is possible to use for example larger physical models and more calculation intensive empirical models on-line than before. It is known that long time constants and non-linearity in the drying section are the most dominant obstacles to speed up grade changes. The model of a paper machine presented in this thesis is intended to be used as a static model to predict moisture, basis weight, coat moisture and coat weight. Physical and empirical modeling is applied.

In the following chapter, the simple physical models that can be applied to various paper or board machines are presented. The parameters of the chosen models are found relatively easily from the literature and in addition there exists measurements from different paper machines that can be used in tuning of the models.

Another possibility is to use empirical models. There exists a wide range of model structures available for empirical modeling from simple regression to neuro-fuzzy models. PLS models are used for empirical modeling due to their insensitivity to the multicollinearity in the modeling samples.

Intuitively it would be possible that a combination of different types of models could improve modeling results. In this work this kind of model is called a hybrid model. It is believed that by using the existing information (for example first-principle models, structure of paper machine) combined with empirical models a better result will be achieved than using them separately.

The hybrid models can be used in the modeling of paper machine grade change as shown in the Figure 3.1. Each physical model (paper machine drying section, coat weight and coat moisture) is complemented with an empirical model. The empirical models will use all the available data that is not included in the physical models.

The main contribution of this chapter is a new method for modeling paper machine grade changes with a hybrid model. Contributions of this chapter include also the survey physical and empirical modeling methods in the context of grade change modeling.

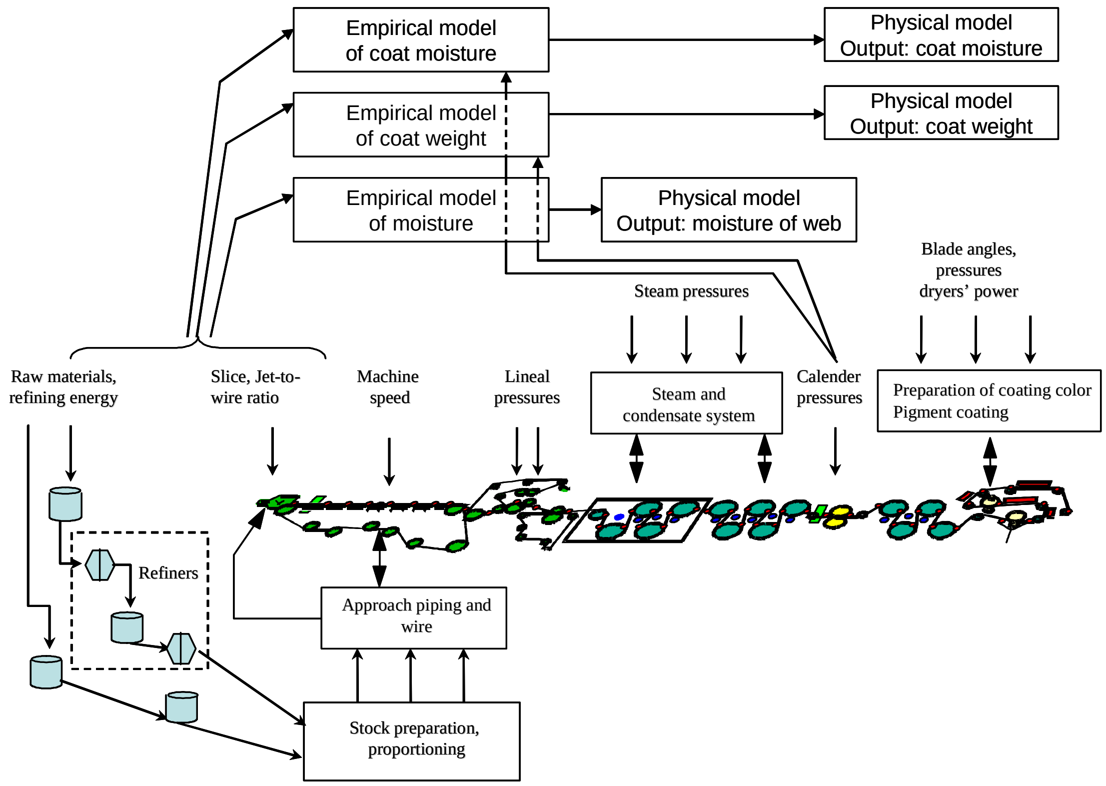

Figure 3.1 Overview of the hybrid model structure

In this chapter the objective is to present hybrid models that would predict static moisture, basis weight, coat weight and coat moisture changes reasonably well. It should catch the variability of the process that would be difficult to model solely with empirical models. The method for tuning of hybrid model was developed that uses special penalty for the interdependencies of the model. The use of hybrid model is presented in chapter 4 'Experimental methods and techniques'.

First physical modeling of a paper machine is surveyed. Modeling of drying is presented to show some recent modeling philosophies applied to this challenging problem. Then in the subsequent sections, simplified modeling for drying of web, basis weight, coat weight and drying of coating are given. A coat weight model for a beveled and for a low angle blade coater are reviewed. In the drying of coating, both infrared and air drying are considered. Empirical modeling is also briefly surveyed and Partial Least Squares (PLS) method is presented after physical modeling. Then hybrid modeling is reviewed. Finally, a conclusion ends the chapter.

Models are only surveyed in this chapter. Detailed mathematical developments are not given because it would require very extensive treatment. Exact physical modeling equations and references to the literature are presented for drying in Appendix B, for drying of coating in Appendix C and for coat weight in Appendix D.

3.1. Physical models for a grade change on a paper machine

The drying section of a paper machine presents a challenge to the modeling of a grade change. In order to control it properly it is required at least that static gains, time constants and dead times are known. In this work the scope is limited to static gains so that the knowledge of dynamic parameters is only required in the sampling of data for the modeling.

Typically physical models are used in the modeling of moisture of web, coat weight and coat moisture (Figure 3.2). For example, Yoshitatsu et el. (2000) used simple physical models to develop a grade change automation to a paper machine for moisture and basis weight.

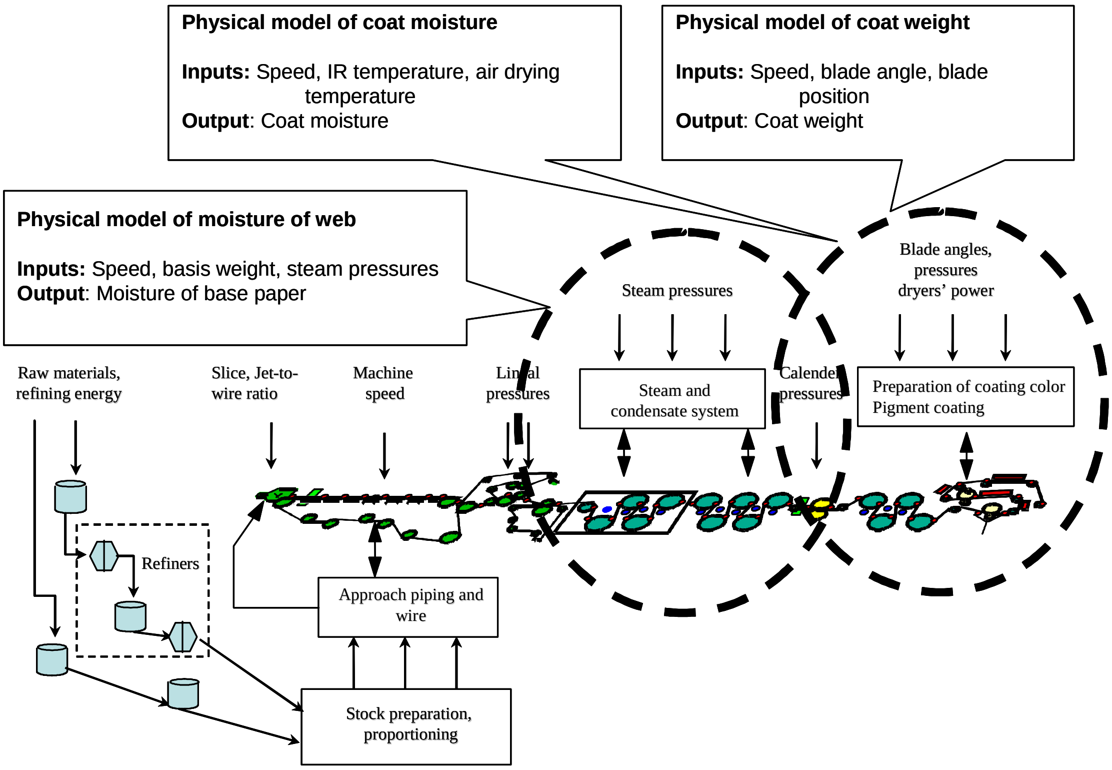

Figure 3.2 Examples of physical models for the grade change on a paper machine

Moisture of web is modeled with simple heat conduction and evaporation equations. There exists a wide collection of models available for the task. Also physical modeling the drying of coating has been applied in Heikkilä (1992) and Fisera et al. (1998). Basis weight is modeled with a simple mass balance due to the fact that there do not exist as many problems as for example with the modeling of moisture of web. However, there do not exist many references in the literature about application of physical modeling to coat weight on a paper machine.

The advantage of a physical model is that it is easy to implement the nonlinear properties, known physical laws and to extrapolate and interpolate between the data samples in a grade change model. This means that the tuning of a physical model does not require many samples of data that is relevant especially in the modeling of drying. Also it is important that the structure of the process and on and off type operations can be expressed in the model. For example, there are several sections in the IR dryers that can be on or off and there can be also two to three coating units of which any combination can be used. The modeling of structure, such as number of drying cylinders and lengths of free draws in the drying section, will help to make more general models.

The disadvantage of physical models is that in order to make them realizable they have to be simple and as a result they are susceptible to modeling errors. There are dedicated models for the diffusion of moisture inside the web but there does not exist an on-line measurement with which to verify the model (Lehtinen 1992, Paltakari 2000). A simple physical model can be applied in a narrow area of the process. For example, a physical moisture model does not take into account the changes in the raw materials or in the refining of pulp.

Due to these disadvantages an empirical model is also considered in modeling grade changes.

3.2. Empirical Modeling

Empirical modeling has been used in most of grade change modeling references found in the literature (Kuusisto et al. 2002, Smail et al. 1998, and Chen 1995). There exist several empirical modeling methods available for a grade change. If linear model is chosen the application and analysis of the system will be a straightforward procedure. The tuning of linear models with large amount of data and MIMO (multiple input - multiple output) structure is also a standard procedure. For example an empirical model of moisture of web can have data from raw materials, refining, stock preparation, head box (slice, jet-to-wire) and of course speed and stock flows (Figure 3.3). It is also an advantage that linear empirical models can easily be applied to dynamic modeling as in the references mentioned above.

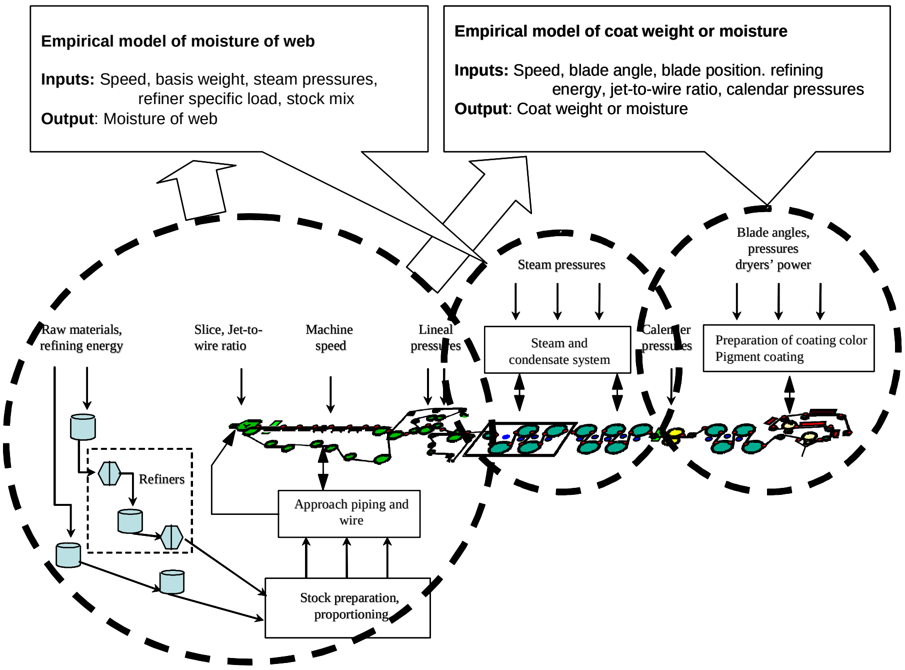

Figure 3.3 Overview of empirical modeling of a grade change

The development of an empirical model for a grade change requires to have data from controlled testing but this is not usually possible due to high expenses of lost production. The data has to be collected during normal grade changes instead. It is also very typical that many variables are required in the modeling in order to get an appropriate fit to the data. The list of variables is in Appendix A.

As mentioned in the introduction, multicollinearity is one of the problems arising when several variables are used in the ordinary least squares modeling. That is why statistical multivariate methods are used for empirical modeling. The multicollinearity means here that there are two or more highly, but not perfectly, correlated variables in the modeling data set. For example, it is generally known that correlation coefficients that are greater than 0.7 are significant (Grapentine 1997). Also if there is an uneven distribution of eigenvalues, the data can be suspected to be multicollinear. There is not a unique coefficient that could be used to determine if the samples are multicollinear.

Linear modeling methods are often based on ordinary least squares (OLS). It should be noted that if the modeling data set (X) has two or more perfectly correlated variables, the inverse $(X^T X)^{-1}$ used in OLS does not even exist. Several problems will arise from the multicollinearity. For example the components of $(X^T X)^{-1}$ have large values due to high correlation of variables. Also the variance of the estimates of regression parameters (*ß)* increases because it is linearly dependent of $(X^T X)^{-1}$ according to equation $V(\hat{\beta}) = \sigma^2 (X^T X)^{-1}$. As a result if the variance of the regression parameter is high, the predictions with the regression equation will also be inaccurate.

The model may give a good fit with the modeling data set but may give an unexpected result when used for prediction. OLS uses all the information in the data and in theory produces unbiased estimates of the parameters. The paradox with OLS is that when you aim towards accuracy, you lose the robustness (Hyötyniemi 1998). The multicollinearity can be circumvented by using statistical multivariable subspace methods that use only part of the data and project it into independent variables (latent variables) before OLS calculation.

PLS model was introduced by Wold in late sixties and is reported extensively in Geladi and Kowalski (1986). Therefore only a brief summary is given here. In a PLS process, data matrix $X \in R^{n\times k}$ and output matrix $Y \in R^{n\times m}$ are decomposed into principal components (Figure 3.4). The so-called outer calculations are defined by the following equations:

$$X = t_1 p_1^T + t_2 p_2^T + ... + t_a p_a^T + E_a \qquad (3.1)$$

$$Y = u_1 q_1^T + u_2 q_2^T + ... + u_a q_a^T + F_a \qquad (3.2)$$

where m are sampled measurements, n is the number of process variables, $p_i \in R^a$ and $q_i \in R^a$ are loadings vectors, $t_i \in R^a$ and $u_i \in R^a$ are score vectors, $E \in R^{m\times k}$ and $F \in R^{m\times n}$ is residual matrix.

The components for both blocks are rotated simultaneously, so that the covariance is maximized. Thus PLS finds out the variations in the process variables that are most influential in the calculation of output values (Höskuldsson 1988, Geladi and Kowalski 1986, MacGregor and Kourti 1995). After the outer calculation, the score vectors are related by a linear inner model:

$$u_i = b_i t_i + r_i \qquad (3.3)$$

where b_i is a coefficient that is determined by minimizing the residual r_i.

There does not exist a stability problem in solving b_i by MLR because the scores are independent. After the first dimension of scores and loading vectors have been calculated, the residuals F_2 and E_2 are denoted as new Y and new X respectively (Figure 3.4). Then the second dimension is calculated using these values and the same is repeated when higher dimensions are calculated.

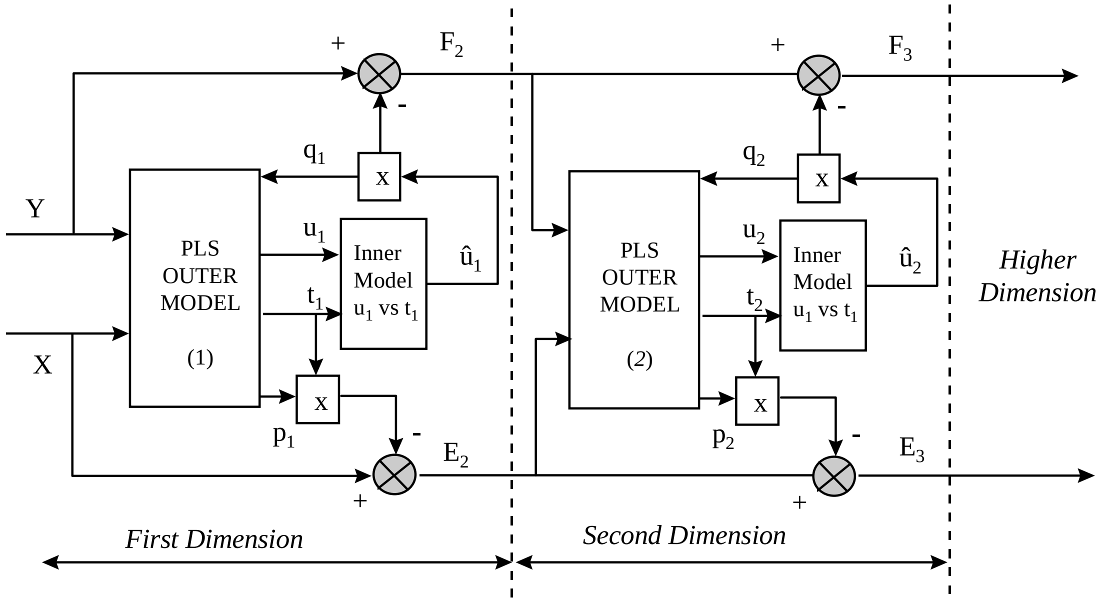

Figure 3.4 Standard linear PLS algorithm (Lakshiminarayanan & al 1997).

Multivariate statistical methods have been used previously in the modeling of pulp and paper processes for example in refiner pulp quality predictions (Tessier et al. 1998) and the fault detection of paper web (Sorsa et al. 1992). Lakshiminarayanan & al (1997) developed a dynamic PLS model structure and used it to model a chemical process.

By projecting the samples onto a lower dimensional subspace with orthogonal new variables, the correlation in the input variables can be removed. This still leaves much work for the user as for example the determination of the variables to be used in the modeling of grade changes and the estimation of the number of principal components in the PLS model. The methods are presented in detail in Chapter 4 'Experimental methods and techniques'. The next chapter will give a short survey on an approach called hybrid modeling that is used in this thesis.

3.3. Hybrid Modeling for a Paper Machine Grade Change

Hybrid modeling is a combination of empirical and physical modeling. It is one way to exploit a priori and experimental information in a modeling context. The term has been defined for example by Psichogios and Ungar (1992) as a method that combines first-principle knowledge with neural networks. Similar combination of neural network/mechanistic models was also reported by Wilson and Zorzetto (1997). Lindskog and Ljung (1994) called the combination of a black box model and a physically parameterized model as semi-physical model. Sørlie (1996) also called his similar structure a grey-box model. Kramer et al. (1992) used the term hybrid model and later Thompson and Kramer (1994) proposed serial and parallel approaches in order to combine prior knowledge with neural networks. They called it also a semiparametric design approach because it combined an empirical (neural network) model with a fixed form parametric model. Kemna (1993) called his approach also hybrid modeling. He also considered the use of linear and nonlinear models in different combinations in the identification context.

The structure of a hybrid model can be either in serial or parallel connected form or the empirical model can be used to estimate the parameters of the physical model (Figure 3.5). The serial and parallel structure were presented for example by Kemna (1993). Psichogios and Ungar (1992) presented a hybrid model where a neural network estimates the process parameters, which were used as input to the first-principle model. Hybrid modeling approach can also be used in a regime based modeling method (Johansen 1994). A regime can be chosen according to a priori known quality measurements in order to divide the data into suitable regions.

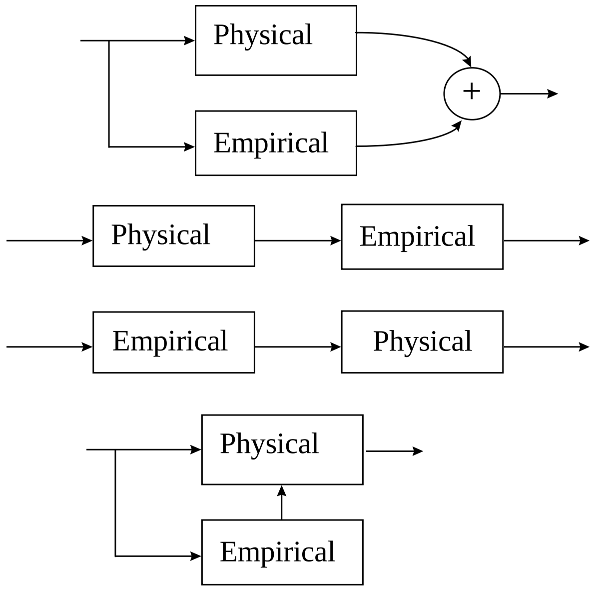

Figure 3.5. Hybrid modeling approaches to combine prior knowledge with empirical models.

The new hybrid model that is proposed in the thesis consists of a combination an empirical model and a physical model that has adjustable parameters (Figure 3.6). These parameters are calculated as a dot product of selection coefficients from the genetic optimization and measurement values from the process (input 2) and forms thus a similar structure to a feed-forward control. This improves the flexibility of the modeling and the selection coefficients can be used in the optimization scheme.

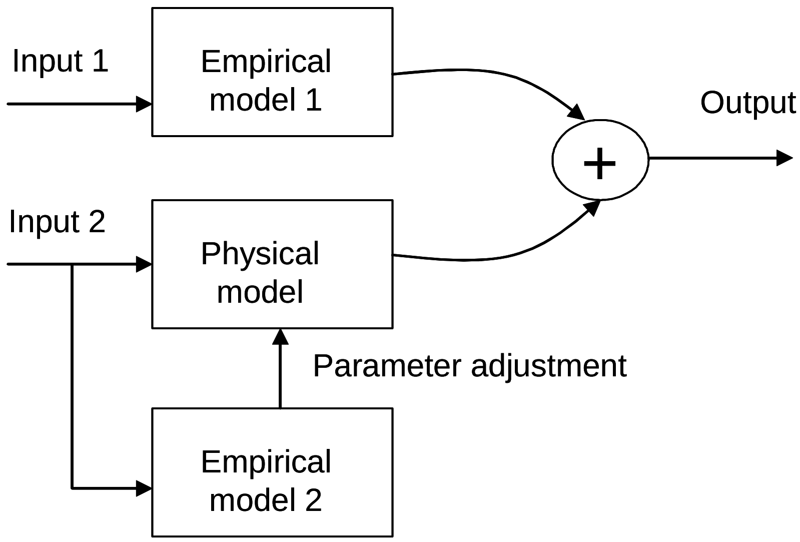

Figure 3.6 Structure of the proposed hybrid model

The empirical model consists of a PLS model and a physical model that is a combination of simple models. The set of models can be chosen according to the structure of the target paper machine. It is the task of the optimization to choose and adjust the parameters of the physical models. This kind of hybrid modeling structure has not been presented previously according to my knowledge. It brings in a new way to implement a priori information in the hybrid modeling scheme.

The models are very simple, but they satisfy the requirement that there exists only a minimum amount of unknown parameters and most of the information is available as measurements from the dryer section. In the following chapters hybrid models for the drying of paper, basis weight, drying of coating and coat weight are presented The detailed equations are supplied in Appendix B, C and D.

3.4. Hybrid models for drying of paper

The hybrid model of drying of paper consists of a physical model of drying section and an empirical model (Figure 3.7). The empirical model corrects the modeling error of the of the physical model. The physical model uses the information of the drying section and the empirical model uses the data from the raw materials of the stock flows. The target values of head box settings (slice, jet-to-wire) and lineal pressures of the press section are not usually known before grade change. However, it is possible to include them in the static model for the evaluation of possible grade change options.

A separate empirical model can be used to adjust the parameters of the physical model as described in Figure 3.6. This is done similarly to a feed forward control and it uses the same data as the other empirical model. The list of variables that are used in the empirical modeling is given in Appendix A.

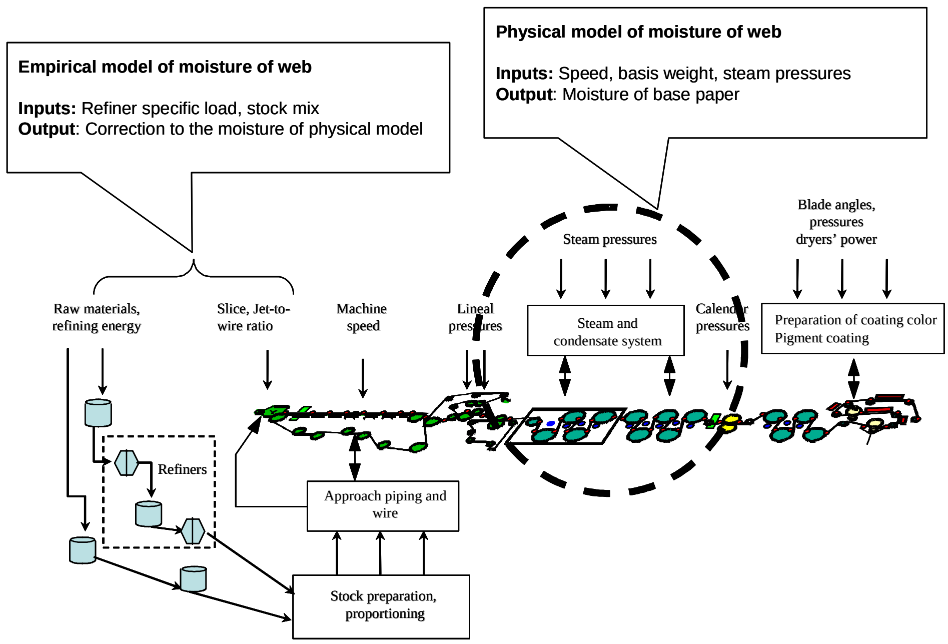

Figure 3.7 Hybrid modeling of moisture of web.

The overall physical model for the drying section of a paper machine consists of cylinder drying units (Figure 3.8). These units are combined in the same way as in the target machine. For example, diameters of cylinders, the lengths of free draws and cylinder bars can be configured to the appropriate place in the drying section. This makes it possible to tailor the drying section according to the paper machine in question. In principle, it would also be possible to visualize the drying conditions in the drying section assumed that the used physical models were good enough.

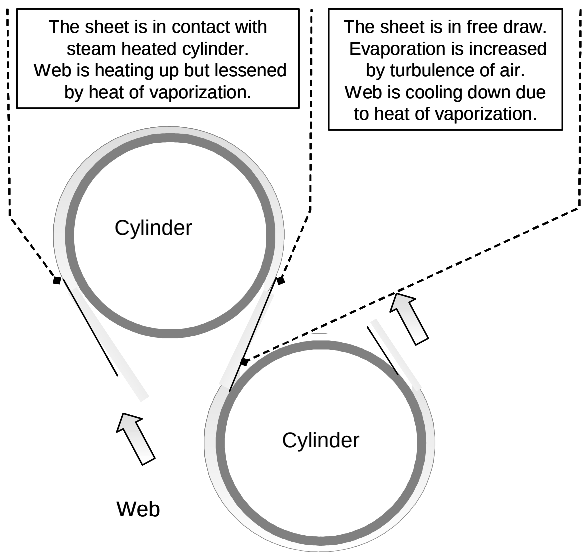

Figure 3.8 Overview of a physical modeling of a drying cylinder.

Modeling is done in two areas. The area where the web is in contact with the cylinder and where the web is in the free draw (Figure 3.8). Most of the equations that describe the heat transfer and evaporation phenomena are given in Heikkilä (1992), and Roihuvuo (1986) and heat transfer coefficient in a free draw is in Karlsson (1984). A large list of equations for the modeling of board machine is also given in Lappalainen (2004). The most important equations are supplied in Appendix B.

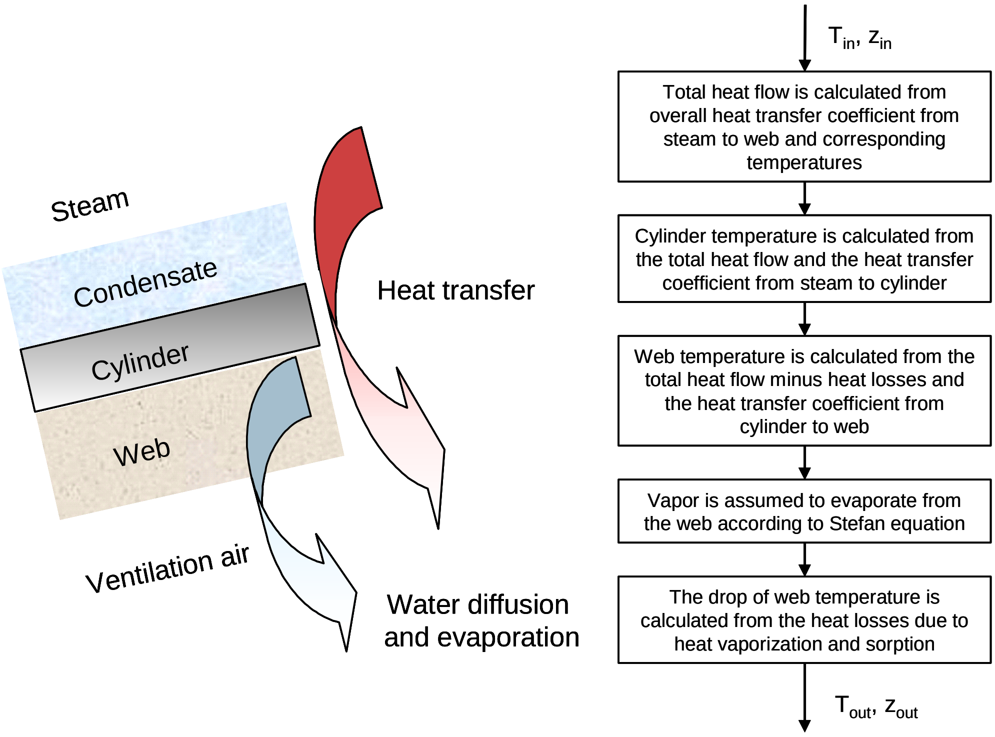

Figure 3.9 Overview of calculation of temperature and moisture ratio in the physical modeling of moisture on a drying cylinder.

An overview of the calculation of temperatures and moisture ratios in the drying cylinder is presented in Figure 3.9. Calculation of the cylinder temperature is done without using iteration. It is assumed that this does not produce a major error compared to the other simplifications done in the model.

It is also assumed that the material properties of the web are constant in the thickness direction and the evaporation from the surface does not depend on a drying wire and is evenly distributed. Because the temperatures and moisture ratios are unknown in the ventilation pockets of the drying section, the temperature of the evaporation zone in the pocket is assumed to be the same as in the web. Also the moisture ratio is assumed to be a constant due to appropriate ventilation (isothermal dryer).

The dryer section needs the initial temperature and moisture ratio of the web as an input data (Figure 3.9). The temperature can be assumed to be the same as the surrounding temperature. Because the incoming moisture ratio is not measured, it has to estimated.

3.5. Hybrid model for basis weight

The steady state value of the basis weight can be considered to depend mostly on the machine speed and thick stock flow (Figure 3.10). However, several variables are included in the empirical model.

The flow from the head box is spread machine wide and the amount of dry material per square meter in the machine direction will be determined by the wire speed. The thick stock flow determines the production rate of the paper machine even though it effects also the basis weight. To be exact there exist leaks and recirculation of material so that not all of the dry material will end up to the reel. However, the leaks from the overflow of the head box and wire pit and the reject from the cleaning system can be considered minor compared to the total feed to the system.

The trimmings that are cut from the edge of the web during the process have to be taken into account in the accurate mass balance calculations. The recirculated material that is redirected to white water due to low retention will mostly effect the dynamic response of the system. Basis weight depends also on shrinkage and elongation of the web due to drying and winding stress.

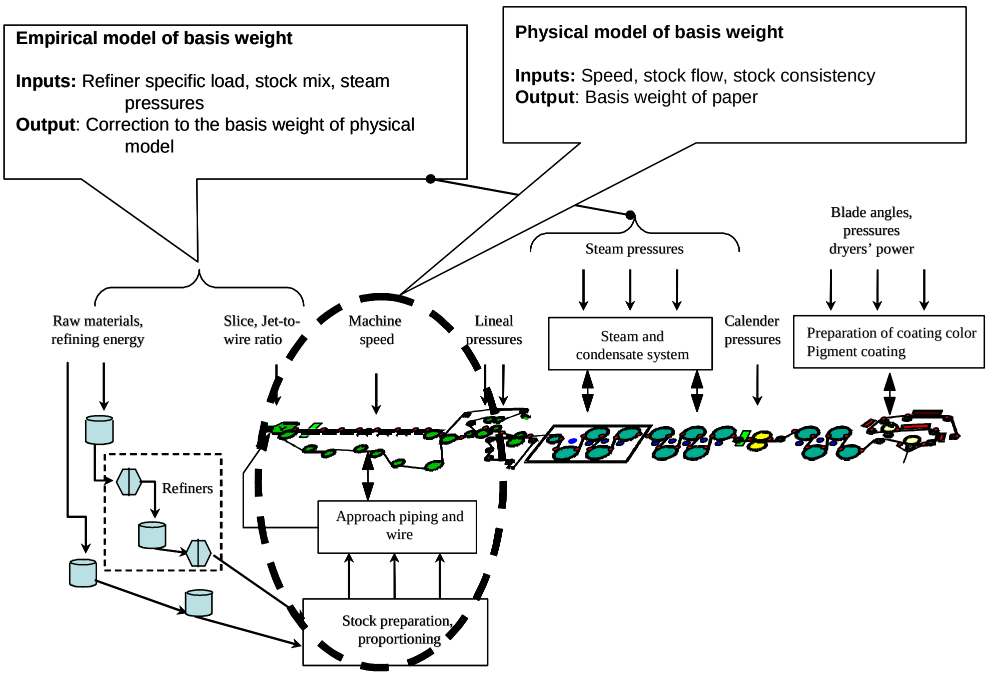

Figure 3.10 Overview of hybrid modeling of basis weight.

In this work a very simple physical basis weight model was used to predict the new basis weight after the grade change. The same model can be used also to predict target values for machine speed and thick stock flow. First, a basis weight coefficient K_{BW} that includes the losses and reformations of web was calculated at the beginning of a grade change:

$$K_{BW} = BW_{act} * v / q_{stock} \tag{3.4}$$

where BW_{act} is the basis weight before grade change, v is the speed of the paper machine and q_{stock} is the total flow of stock to the headbox(es).

Then the prediction of the new basis weight at the end of a grade change was calculated:

$$BW_{pred} = K_{HYB} K_{BW} q_{stock\,Pred} / v_{pred} \tag{3.5}$$

where BW_{pred} is the predicted basis weight at the end of grade change, KBW is the basis weight coefficient, K_{HYB} is the tuning parameter of the hybrid model, v_{pred} and $q_{stockPred}$ are the corresponding speed of the paper machine and the total flow of stock to the headbox(es).

The empirical model is used to correct the gain of the physical model. The empirical model includes for example variables from the proportioning, refining, head box (slice, jet-to-wire ratio) and steam pressures. The steam pressures are expected to take into account the shrinkage effects into the model. The complete list of variables is in Appendix B.

3.6. Hybrid model for drying of coating

The hybrid model for the drying of coating has physical and empirical parts. The input to the physical model includes machine speed, IR temperatures and air dryer temperatures (Figure 3.11). The completing empirical model has for example refining energy, and jet-to-wire ratio of the head box as inputs. The complete list of variables is in Appendix A.

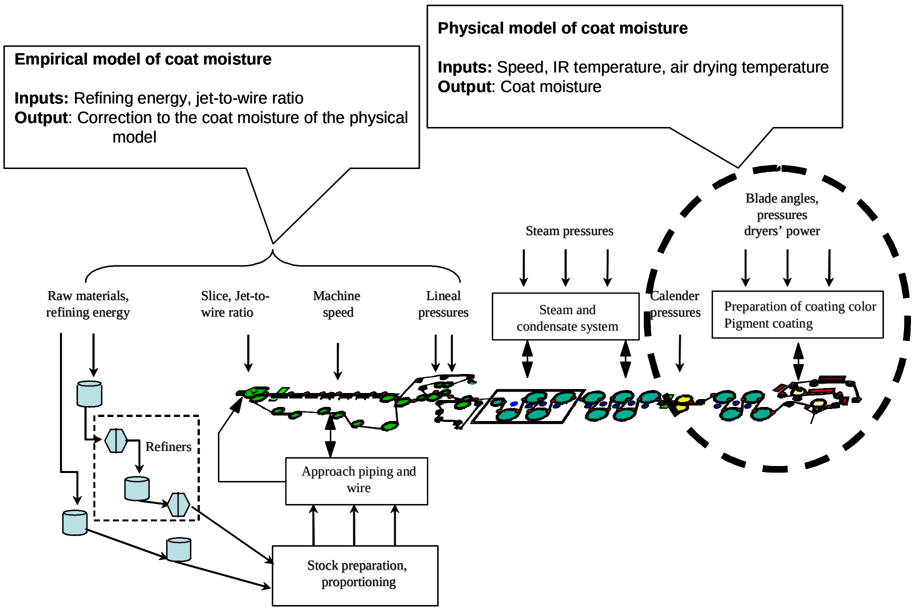

Figure 3.11 Overview of hybrid modeling of coat moisture.

The drying of coating is modeled in four parts each separated by a free draw that are modeled as in the case of paper web. First the moisture of the web is increased due to application of coating color on the surface of web (Figure 3.12). Then IR drying (gas burners or electric radiators) is modeled with an appropriate equation completed with the on-off information of the IR elements. After that the drying with heated impingement air (gas burners) is modeled including on-off information of burners. Finally cylinder drying is modeled the same way as in the case of paper web except that the parameters are different (Heikkilä 1992). The equations of the physical model of coat moisture are in Appendix C.

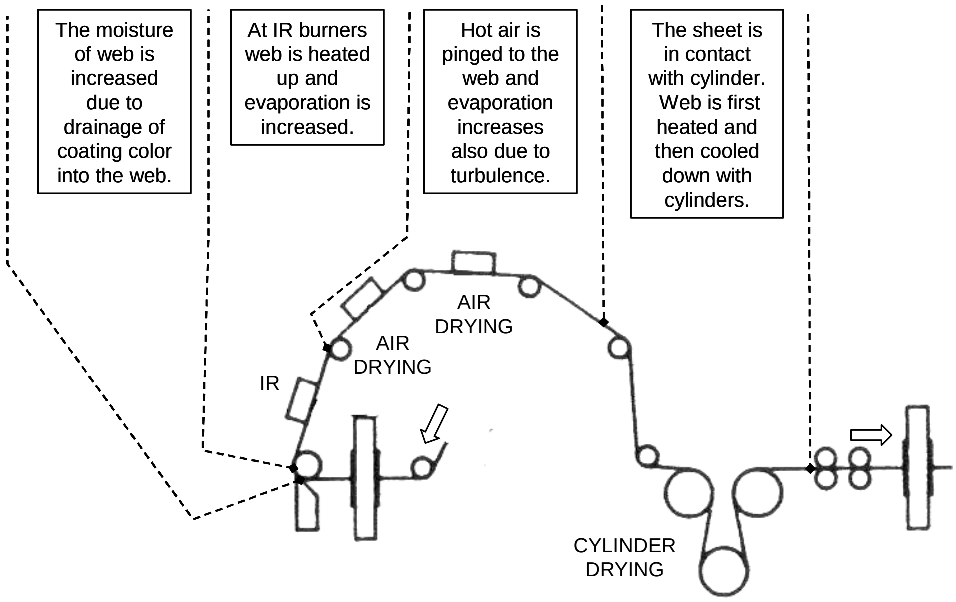

Figure 3.12 Physical modeling of drying of coating.

3.7. Hybrid model for a coating weight

The hybrid model of coat weight consists of a physical model of a blade coater and an empirical model (Figure 3.13). The physical model uses machine speed, blade angle and blade pressure (position) as inputs. The empirical model uses for example refining energy and jet-to-wire ratio of head box as inputs. The complete list of variables is in Appendix A.

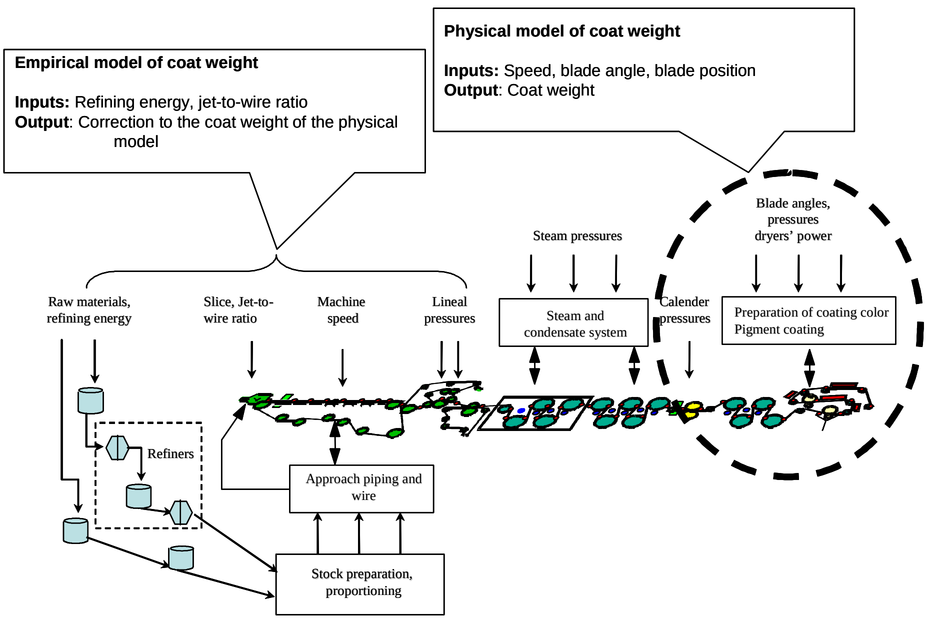

Figure 3.13 Overview of hybrid modeling of coat weight.

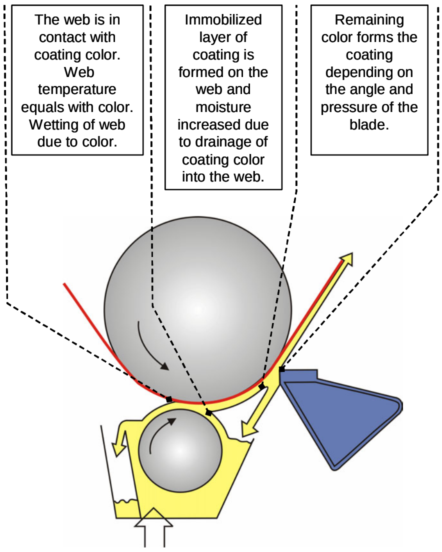

Figure 3.14 Physical modeling of coat weight of web

A coating unit is modeled in three parts (Figure 3.14). First the coating color is applied on the surface of the web. Then the coating color is drained into the web and as a result a static coating layer is formed on top of the web. Finally the excess of coating color is removed by the blade. The dependence of the blade pressure to the amount of coat weight is not known exactly. Qualitatively it is reported by Eklund and Kahila (1978) that the amount is inversely proportional with a beveled blade and directly proportional with a low angle blade (Figure 3.15).

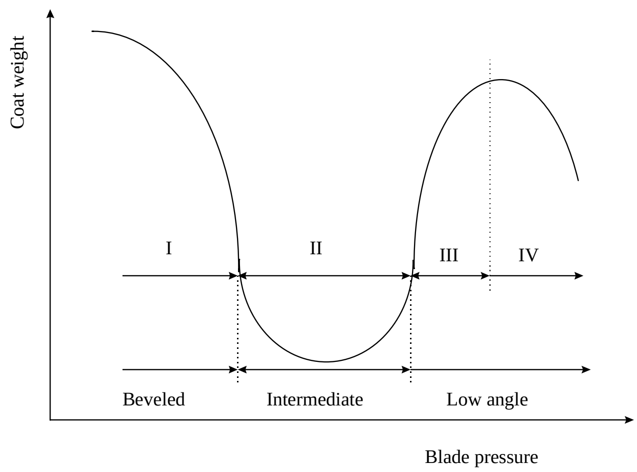

Figure 3.15 Relationship between coat weight and blade pressure (Eklund and Kahila 1978).

The empirical nonlinear model that relates the blade angle and pressure to the coat weight, dates back year 1978 and no other models exist in the literature. This means that in the hybrid modeling the empirical part will be more important than in the other cases. The contribution of the physical model will come from information of the on-off modes of the coaters and method of application (beveled or low angle blade). The most important models are presented in Appendix D.

3.8. Conclusions

The hybrid modeling method is defined as a combination of simple physical and empirical modeling. The objective is to get the best from both methods. If the modeling data is collected during normal process operation, the data will contain correlated variables or in other words the data is multicollinear.

Statistical multivariable subspace methods such as PLS can be used to avoid the adverse effects of correlated variables. A short introduction is given about PLS in order to present the basic properties of statistical multivariable subspace methods and to list the most important references.

A hybrid modeling structure that combines simple physical models with PLS in parallel and another empirical model that is used to adjust parameters of the physical model is proposed to complicated modeling problems of grade change on a paper machine.

An introduction to the modeling of moisture of base paper, coating and weight of base paper and coating is presented. The emphasis is on simple models that could be used for practical modeling of a paper machine. All the models can be tuned to fit to a response from a paper machine if there exists detailed temperature information of the drying and coating section. Usually a detailed study has been done in order to improve the efficiency of a drying section and the needed temperatures can be compiled from the results. The same cannot be necessary said about the coating section.

A survey of structure of paper and of different drying theories gives background to the simplified model of drying of web. A good model for drying of web is a key element to a successful grade change because it is assumed to be the most significant factor of performance improvement.

Modeling of coat moisture and coat weight is presented also in detail because a successful base paper change can occur especially in an on-machine coater. It is also noted there does not exist many studies about a grade change on a coater in literature.

Modeling of coat moisture and coat weight is presented also in detail because a successful base paper change can occur especially in an on-machine coater. It is also noted there does not exist many studies about a grade change on a coater in literature.

4. EXPERIMENTAL METHODS AND TECHNIQUES

A good approach to start a modeling research is to clarify to oneself the operation of the process and the practice the operators run the process. The modeling starts already in the data collection because it is essential for the validation of models. The collected data from the process forms the raw material for the empirical modeling and for the estimation of parameters of physical models. Typically there is abundant amount of collected data so that there is a need to select the most influential variable for the modeling.

In the modeling, the predictive properties of the models are emphasized due to the objectives of a grade change. The models should be readily applicable to different processes and the tuning should be possible with a finite amount of samples. Due to adaptive tuning with a large number of variables the model is explicitly defined without losing some of its ability to generalize.

The most important contribution of this chapter is the presentation of a procedure for adaptive tuning of hybrid models with a very large number of parameters. Also a significant contribution is the procedure of the application of this hybrid model to the target board machine with four on-machine coaters.

The chapter starts with a short description of the target board machine. Then the collection and selection of grade changes, variables and samples are surveyed. Then the procedure for the selection of the structure of PLS model is presented. After that the hybrid modeling method is summarized. The chapter concludes with a summary of calculation results.

4.1. Modeling methods of a grade change on a paper machine

The hybrid modeling methods are applied to a board machine. It includes 8 refiners, 3 headboxes, a drying section with 60 cylinders and 4 on-machine blade coaters (Figure 4.1). The refiner lines are for the softwood. Hardwood lines are for the top and bottom layer and for the middle layer of board. Broke and an extra pulp line have also refiners of them own. The three headboxes correspond to the top, middle and bottom layer of the board. The drying section is modeled to the first measuring frame that is just before the sizing unit.

The coaters can apply double coating to both sides or even triple coating to one side. The first two coaters use beveled blades and the next two low angle blades. Drying of each coating is done with infrared (IR), air drying and cylinder drying.

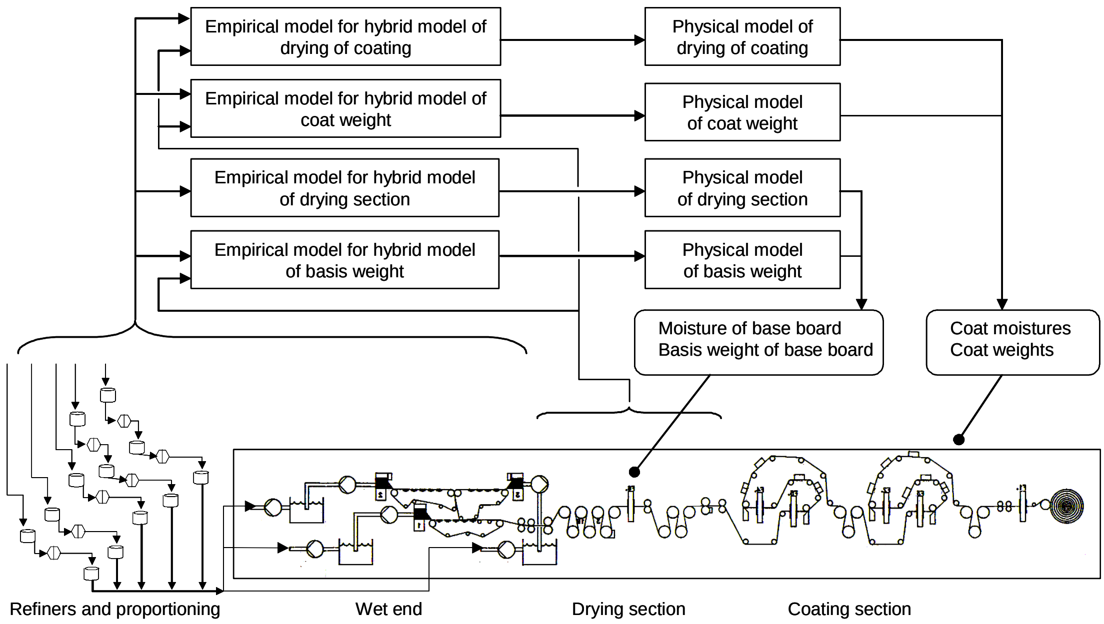

Figure 4.1 Modeling sections of a grade change on the target board machine

The modeling is done with two data sets. The first set contains dedicated detailed data that include temperature and moisture data from the drying section and coaters for two grades and is used to tune the physical models. Then another larger set, in this case 30 grade changes, is used for modeling. The sampling and selection of variables are presented in the following sections.

The modeling procedure is applied to the target board machine. The modeling structure is defined in the following sections. The survey on modeling was given in Chapter 3 ‘Modeling of a paper machine for a grade change’ and the list of variables are in Appendix A. Details of physical models for moisture of base paper are given in Appendix B, for drying of coating in Appendix C and for coat weight in Appendix D.

4.2. Collection and selection of grade change data

Data collection of the grade change modeling was done automatically from the distributed control system (DCS) and the quality control system of a board machine. The data collection software transferred data every 5 second from the DCS to a personal computer. Altogether 217 grade changes were saved successfully for further analysis during the time period of one year. Only 173 grade changes were accepted to the hybrid modeling due to faults in the data. Table 4.2 shows a list of measured variables from the coating section.

Table 4.2 Examples of collected variables from the coaters to the reel.

Name
Total gas flow to IR-burners
Infrared dryer on/off (for each block)
Airfoil air temperature (for each unit)
Airfoil running on/off (for each unit)
Moisture (before coating 1)
Basis weight (before coater 1)
Caliper (before coater 1)
Moisture (before each coater)
Coat weight (before each coater)
Blade pressure (on each coater)
Blade angle (on each coater)
Basis weight (at pope)
Moisture (at pope)
Caliper (at pope)
Pope speed
Grade change on/off

The moisture of base board for example is effected by all steam pressures, machine speed, mix of stock components, chemicals and refining of stock components (Figure 4.2). The sampling instants are chosen just before and after the first actions of a grade change. The first actions are denoted in this thesis to be performed by the original automation that is a combination of the actions taken by the personnel and automation. Samples were also taken far from the grade change after the process response had stayed 10 to 20 min within certain range. These were used as reference values if setpoints were not available. Modeling of moisture grade change was also tested with this data. The efficiency of a grade change is estimated for example by comparing standard deviations of errors at the first actions and prediction of models. Also the standard deviations of modeling error of PLS and hybrid models were compared.

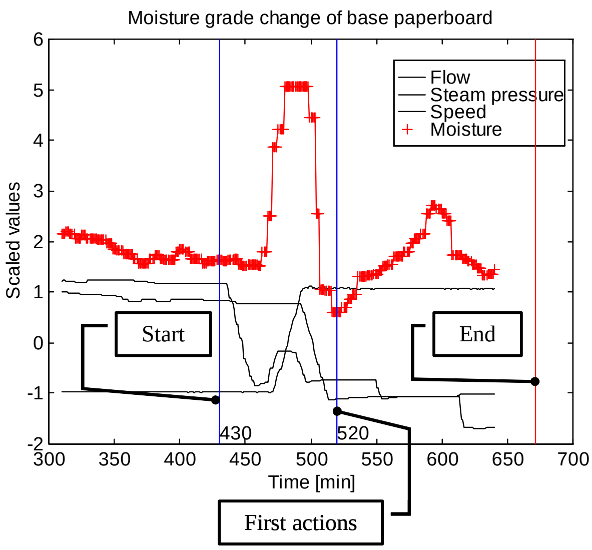

Figure 4.2 Sampling instants and actions of control variables in a grade change as an example for the moisture of base board.

It was also found that by removing the effects of dead time and time constant from all the variables the prediction accuracy of the models was improved greatly. For example the error range decreased from about 1.5 % to 0.75 % just by removing the time effects from variables that were used in the moisture modeling (Viitamäki 2003). The estimation of the dead time was done by calculating the transport delays. Time constant of the drying section multiplied by three was also added to the dead time. Similar approach was also used for basis weight and coater section modeling.

The detailed (off-line) data that are used for the physical modeling are usually made available by the mill. The data include temperatures of web, cylinders, infrared burners, air drying burners and temperatures inside the hood of the drying section of a paper machine. The physical models could use also humidity but the reliability of the measurements is not good enough. The structural data, such as lengths of free draws, cylinder diameters, thickness of the cylinder walls and the existence of cylinder bars must also be collected from the mill.

Selection of variables for the analysis is important because the variables that do not have any correlation with the explained variable may not produce good results. However, PLS is quite insensitive to the data that are not correlated with the output data because for example PLS seeks automatically the variables that have the highest covariance with the output data (Wise and Gallagher 1996). Each grade change file consists of more than 269 variables ranging from the refiners to the reel. The variables were chosen for the modeling both according to à prior knowledge and empirical methods. The most influential variables were chosen by the prior information that was acquired from the paper mill personnel and modeling literature. The list of selected variables and the PLS procedure are given in Appendix A.

The selection model structure for the PLS is the same as the number of principal components. This was done by genetic optimization and using k-fold gross-validation combined with Subspace Information Criterion, SIC (Sugiyama and Ogawa 2001, Appendix E) as the penalty.

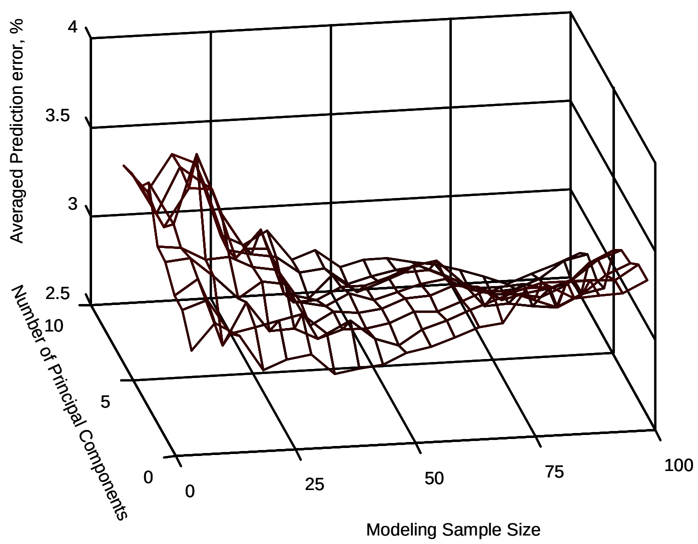

Figure 4.3 Prediction error of a PLS model as a function of principal components and modeling sample size.

Three principal components were found to be the most appropriate number for the PLS modeling in the hybrid models as well as with PLS models in itself. The result is surprisingly low but it is supported by modeling runs with PLS that are presented in Figure 4.3. It can be seen from the figure, that when the sample size is 30, there is not much improvement to be gained even though the number of principal components increased from three. Thus the SIC penalty will give the simplest structure of the model. It can be also seen from the plot that modeling with 30 grade changes will give reasonably good results. The reason for this is that the span of 30 grade changes covers the range of production cycle run with the broad machine. It was also considered important to be able to make accurate predictions quickly after process changes or start of new board grades. Besides, it was confirmed earlier that hybrid models worked well even with sample sizes of 10 grade changes (Viitamäki 2003).

In practice the modeling performance (standard deviation of predicted moisture error) is independent of the index of the grade changes where the modeling samples are extracted. This is shown in Figure 4.4 where the number of principal components of a PLS model is 3 and the modeling sample size is 30. For convenience, the extraction point was chosen to start from the first grade change to the 30th grade change.

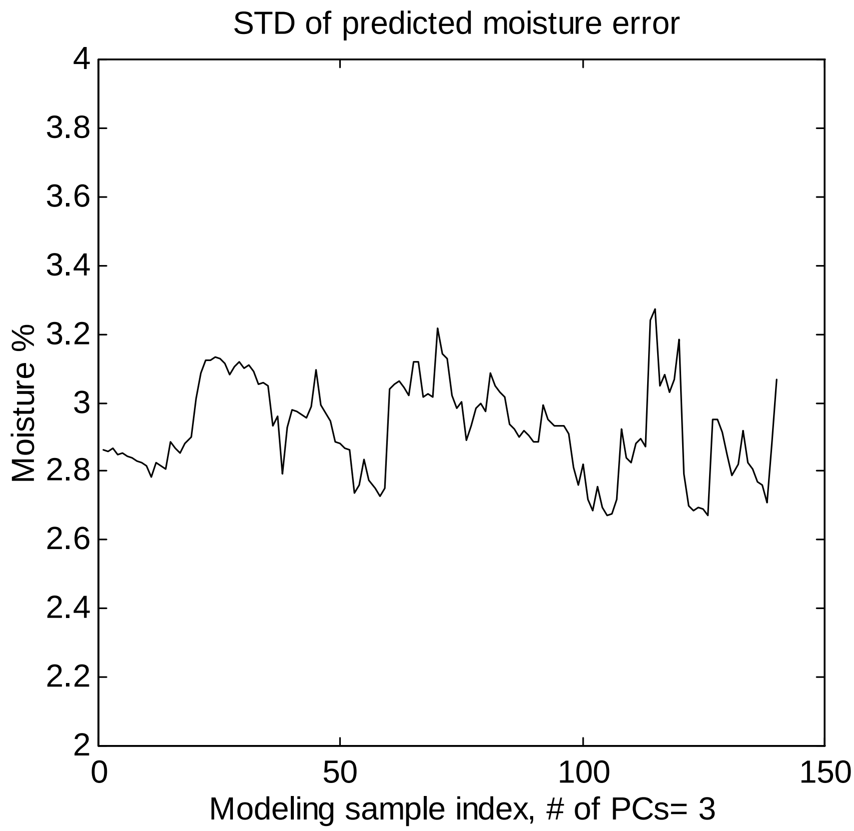

Figure 4.4 Standard deviation of predicted moisture error of PLS model as a function of starting point of 30 modeling samples. Number of primary components is 3.

4.3. Modeling procedure for the grade changes

The hybrid modeling can begin when the model structure of the empirical model is chosen and the physical models built up as presented in the chapter 3 'Modeling of a paper machine for a grade change'. First the data must be divided to input and output variables and also to modeling and test samples. Then the physical modeling a grade change (GC) is done with the detailed (off-line) data and after that with the on-line data. Finally PLS modeling is applied to the error of physical modeling (Figure 4.5).

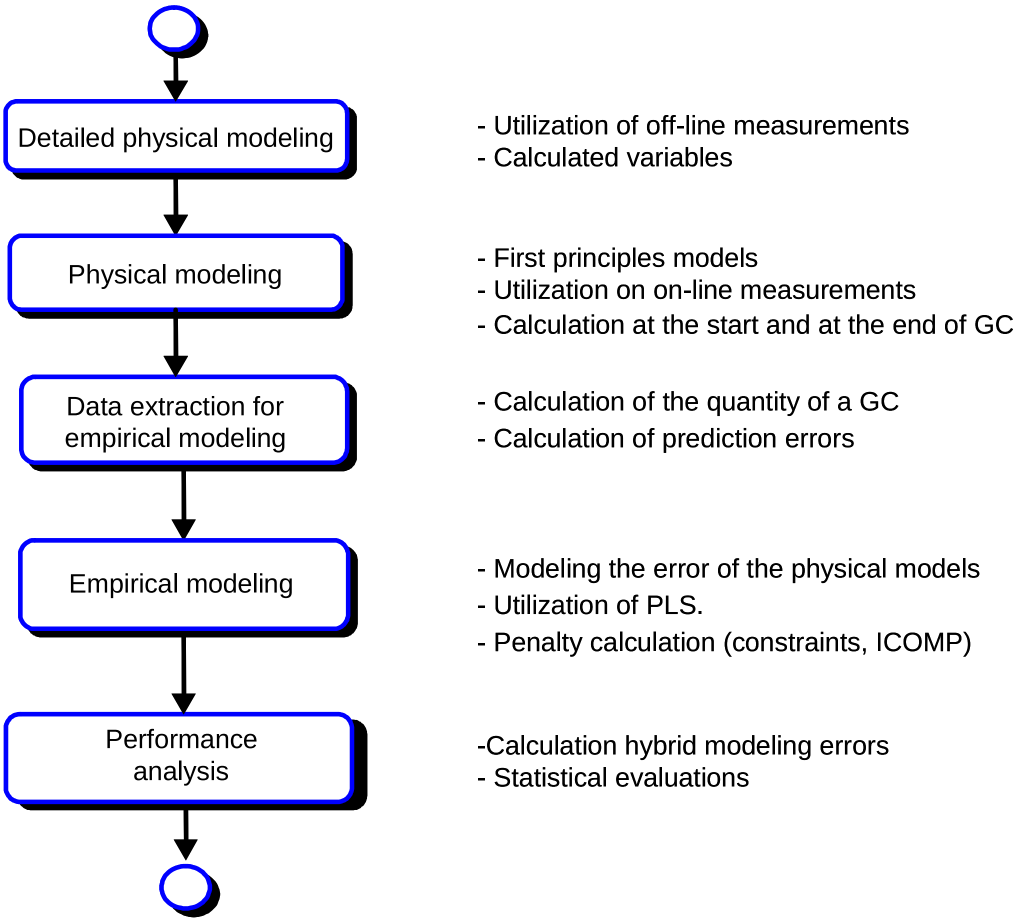

Figure 4.5 Simplified hybrid modeling procedure

The models are tuned with genetic optimization (Figure 4.6). In the optimization and also in the prediction the process is simulated with the physical model at the start and at the first control actions (or at the end grade change) and then the error of the quantity of grade change is calculated. The error, the unknown part is then submitted to empirical modeling with PLS. Finally the performances of the models are validated by the test samples that were not used in the modeling of process.

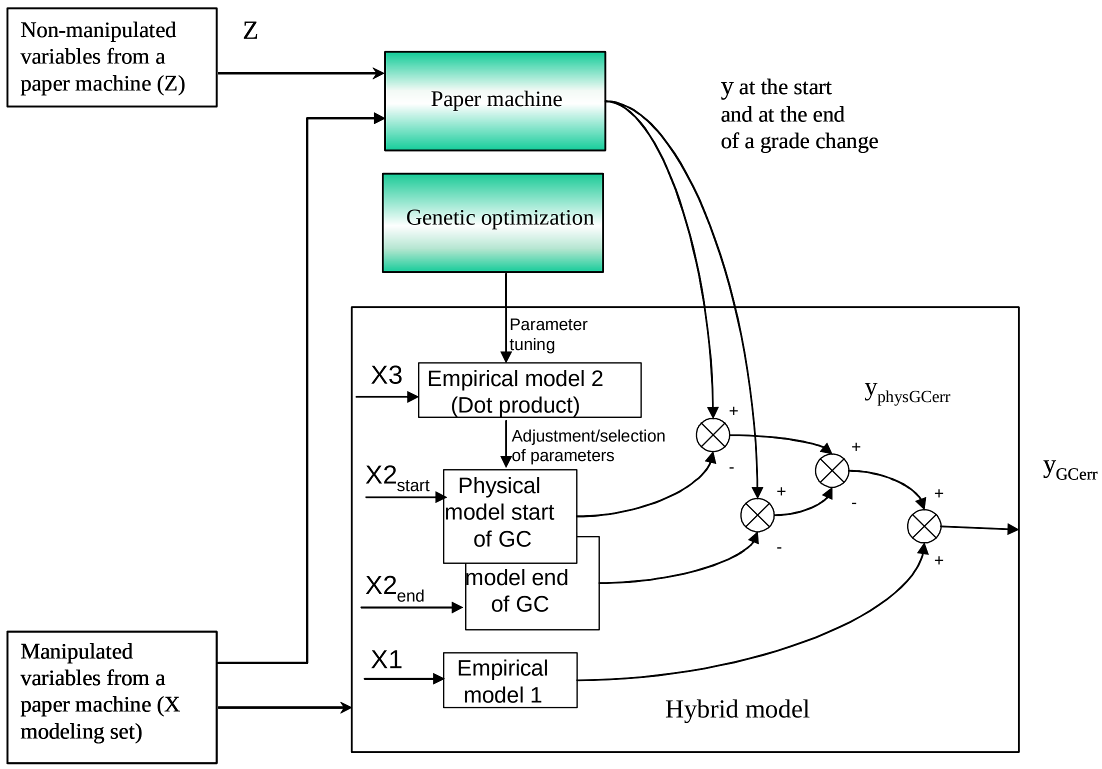

Figure 4.6 Tuning of hybrid model of a grade change. The tuning is performed with the modeling set and separate samples are fed into each model. Genetic algorithm uses a loss function (sum of y_{GCerr} is the empirical risk) to tune the simple physical model. At the same time empirical model 1 (PLS) is tuned to correct the error of the magnitude of the grade change. Z is a collection of variables that are not measured but have influence on the output y. X1 is empirical modeling data. $X2_{start}$ and $X2_{end}$ are data sets for the start and end of grade change. X3 is data for tuning of the physical model.

Genetic algorithms have been used to solve difficult problems in which the objective function is not convex or the problem is otherwise difficult to handle by classical optimization methods. A simple genetic algorithm was first presented by Holland (1975). The form of the algorithm used in the optimization is still basically the same. Only a short introduction on genetic methods is given here because there exists for example a good textbook by Goldberg (1989) and many of other books and articles about the topic.

Genetic algorithms simulate evolution by producing populations and letting only the fittest members to survive. The search for the best solution is diversified through mutation, crossover and selection operations applied to individuals in the population. The selected members reproduce and the iteration is repeated certain number of times so that the predefined termination condition is reached and thus the final generation is born.

The initial population is typically selected randomly and consists of binary coded elements (genes) but the tools allow also the use of non-binary parameters. In mutation ones and zeroes are set or reset randomly with a predefined probability. In crossover the positions adjacent genes are switched with a predefined probability.

The power of genetic search is that it does not get trapped to a local minimum as easily as classical optimization algorithms do. The random search path of a genetic algorithm alleviates the problem of getting results that depend on the initial starting point of the optimization. Genetic optimization can handle a large number of parameters and still find the fittest parameters to the tuning. A genetic algorithm converges slowly and produces usually sub-optimal results. However, genetic optimization is very suitable to be used with the grade change data that consists easily of over 200 variables and a loss function with many local minimums.

Penalization

In order to be able to identify reliably model structures (inference) or to generate predictions, the penalty function of an inference method must contain in addition to lack of fit a term that addresses the model complexity (Cherkassky and Mulier 1998). Complexity means here dependencies or correlation among the parameter estimates (Bozdogan 2000). A generic form of the penalty (empirical risk) function could be the following:

Loss = Lack of fit + Model complexity

The overall penalty of the hybrid model consists of error of the off-line model, error of the physical model with on-line variable, error of PLS part and the information complexity criterion (ICOMP). Each error is a sum of empirical error, penalty of predicting to a wrong direction and penalty of infeasible values as for example moisture below zero, complex values, etc. The empirical error in the PLS model is calculated as k-fold gross-validation. The components are weighted experimentally the most important are penalties that improve to estimate the amount and direction of the change.

An important penalty function is the information complexity criterion (ICOMP, Bozdogan 2000). It gives maximal covariance complexity of the covariance matrix $C_1(\Sigma)$.

$$C_1(\Sigma) = \frac{p}{2}\log\left[\frac{tr(\Sigma)}{p}\right] - \frac{1}{2}\log|\Sigma| = \frac{p}{2}\log\frac{\bar{\lambda}_a}{\bar{\lambda}_g} \tag{1.1}$$

where Σ is the covariance matrix, p is the rank of Σ, $\bar{\lambda}_a$ is the arithmetic mean of the eigenvalues of Σ and $\bar{\lambda}_g$ is the geometric mean of the eigenvalues of Σ: $\bar{\lambda}_a = tr(\Sigma)/p = 1/p\sum_{j=1}^{p}\lambda_j$ and $\bar{\lambda}_g = |\Sigma|^{1/p} = \left(\prod_{j=1}^{p}\lambda_j\right)^{1/p}$.

An important property of $C_1(\Sigma)$ is that it is zero when the covariance matrix is diagonal. That is to say that the variables of the model are independent. Thus $C_1(\Sigma)$ can be thought to measure the amount of dependence and correlation of the samples.

In this work we use a combination of c_p and $C_1(\Sigma)$. Mallows' c_P is a subset predictor and is defined as (Mallows 1973):

$$\sum (y - y_p)^2 / s^2 - n + 2p = RSE_p / s^2 - n + 2p \tag{1.2}$$

where y_p is the predicted value of y from the p regressors.

s^2 is standard deviation is a finite sample estimate of error variance σ^2
n *is the sample size* and RSE_p stands for the residual square after regression of p on the complete set of n.

In addition $C_1(\Sigma)$ will readily compensate for multicollinearity that is common in the measured data.

4.4. Calculation of the results

The results were calculated for the original automation performance (reference values from the collected data), PLS model, simplified physical model, combined physical and empirical model (parallel hybrid model) and extended combined physical and empirical model (series/parallel hybrid model) with ICOMP penalty (Table 4.3).

Table 4.3 Summary of the basic properties of the applied modeling methods.

Modeling method	**Physical part**	**Empirical part**	**Tuning method**
PLS	Not applicable	3 principal components, 36 variables	Number of principal components by SIC with k-fold gross-validation
Hybrid	Simple model as in the literature	3 principal components, 36 variables	Physical part tuned first to detailed data, then to prediction of grade changes. PLS is the same as above.
Hybrid parameter tuning, traditional	Simple model as in the literature	3 principal components, 36 variables	Physical part tuned first to detailed data, then to prediction of grade changes. Model parameters (heat transfer coefficients) tuned with measured data PLS is the same as above.
Hybrid parameter tuning, ICOMP	Simple model as in the literature	3 principal components, 36 variables	Physical part tuned first to detailed data, then to prediction of grade changes. Model parameters (heat transfer coefficients) tuned with measured data. Tuning is done with ICOMP in the loss function. PLS is the same as above.

After the hybrid models were tuned they were used to predict the quantity of grade change by using the validation set of the samples. First the physical models were used to predict the values for example moisture of base board at the start and at the end of the grade change. Then the difference calculated by the outputs of these models were corrected by the PLS model output. The model outputs (y) were then compared with the actual values from the process measurements and for example standard deviations of the prediction errors and other statistics were calculated.

The performance of the original automation, PLS and hybrid models are presented with the help of histograms and standard deviations. Also the percentage of the number grade changes that start to go in the wrong direction (for example moisture increases when it should decrease) is given. The comparison of standard deviations is performed with F-tests.

The used genetic algorithm and the physical models and optimization were run with Matlab (product of the MathWorks, Inc) and the PLS model was developed with the PLS toolbox (Eigenvector Technologies).

The results of these predictions are reported in Chapter 5 ‘Results with hybrid models’.

5. RESULTS WITH HYBRID MODELS

The modeled processes are moisture of board, basis weight, coat moisture and coat weight. The results of the modeling are presented as a standard deviation of prediction error. The modeling approaches contain the results estimated from the collected data (first actions), PLS model and several hybrid model structures. Hybrid modeling showed the best results in most of the cases.

The models must be validated with real data from a process in order to be able to declare the results useful for industrial practice. This is usually neglected in the research work. Typically only two or three selected examples are shown that support the proposed performance of the developed model.

In this research an alternative approach has been taken. The goal was set to validate the prediction performance of the models with a large number of measurements from a real board mill. The data set contains 172 grade changes so that the results will have exceptionally good statistical value compared to the other studies presented in the literature.

The main contribution of this chapter is the report on qualitative and quantitative benefits of using hybrid models in grade changes. The main subject is the presentation of the prediction performance of the models and not the fitting of the models to a large set of grade change data. For the first time an overall approach to the grade change on a board machine from the raw materials to the on-machine coaters is presented. Especially, the results for coat weight and coat moisture grade changes have not been presented before in the literature. An important contribution is also the validation of the results of the predictions of the models against real measurement data from the board machine.

First the results of the modeling of moisture of base board are presented in detail. Then the summary of the results of models of coat moisture, coat weight and basis weight (Figure 5.1) follows.

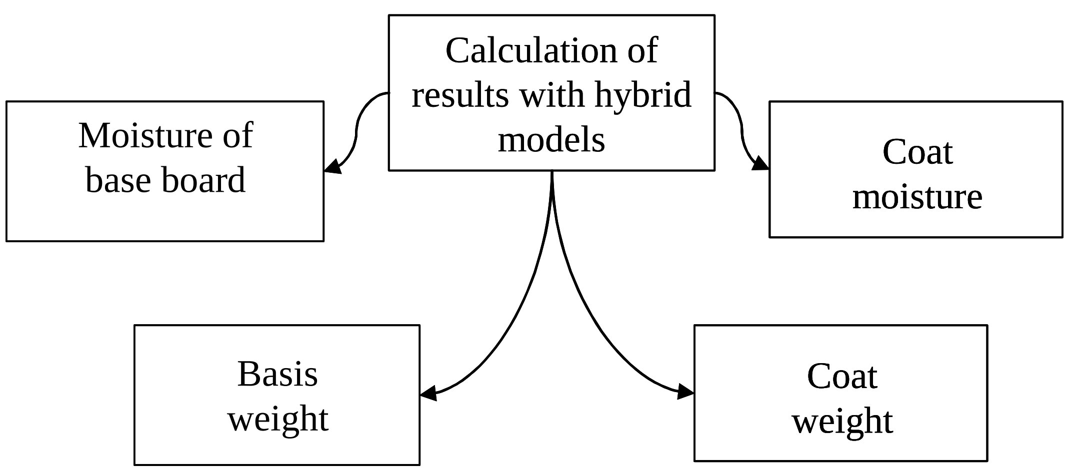

Figure 5.1 Overview of the results in the chapter.

5.1. Moisture of base board

The results are generated with models that use a large number of variables from the board machine. For example, the physical part of the hybrid model uses measurements from the drying section and the empirical model 34 variables from the other sections of the board machine (Figure 5.2). A complete list of variables can be found in the Appendix A and the modeling equations in the Appendix B. In addition to the variables the models have many tuning parameters as described in the Appendixes.

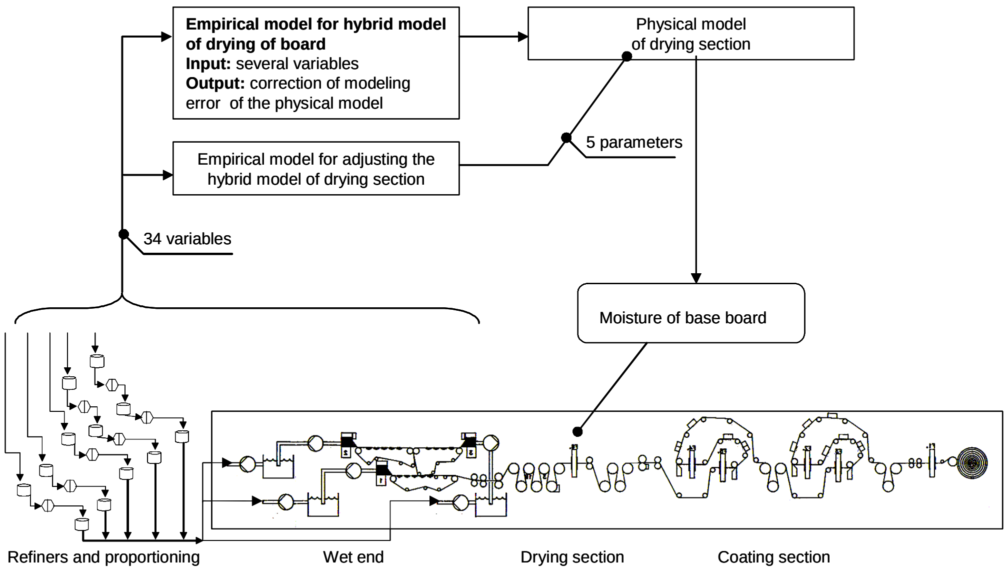

Figure 5.2 Summary of the hybrid modeling of moisture of base board.

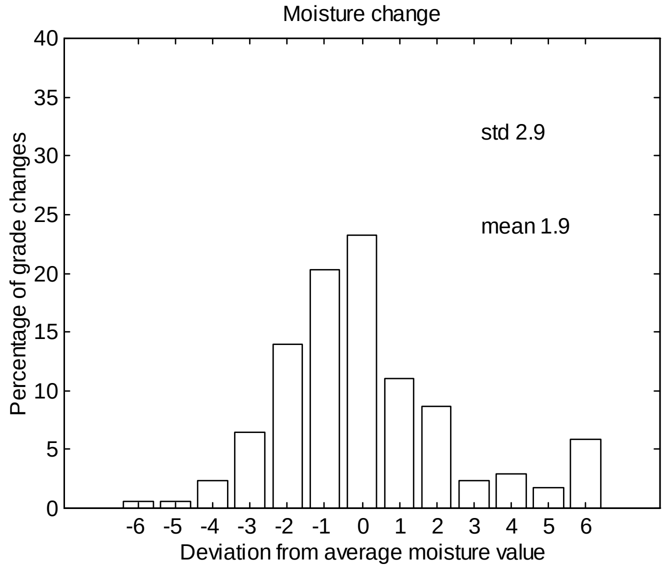

Figure 5.3 The distribution of all 172 moisture changes of base board after the first actions compared to the mean value (1.9 %).

The distribution of all 172 moisture changes to be modeled is presented in Figure 5.3. The changes are calculated as a difference between the beginning of grade change and the response values at the first control actions. The data is almost normally distributed with a longer tail on the right side. However, there should not be problems if robust methods are used.

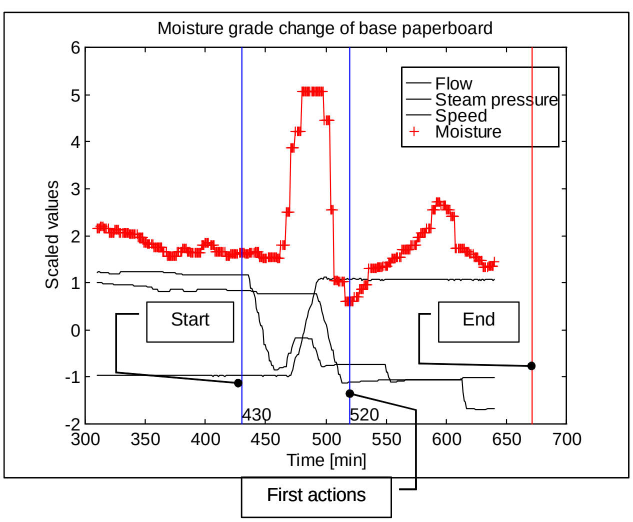

Figure 5.4 The sampling instants for the modeling of moisture of base board.

First the modeling is carried out with the samples taken from the position of the first control actions (combination of the actions of personnel and automation) as shown in Figure 5.4.

The results are presented with two approaches. First, the physical part of the hybrid model is tuned to predict the grade changes and then PLS is added to the model. In the case of ICOMP penalty all the parts of the hybrid model are optimized for prediction at the same time. Then the best model (penalized ICOMP) model is used to predict the moisture at the end of grade changes.

5.1.1. Results with the samples taken from the position of the first control actions

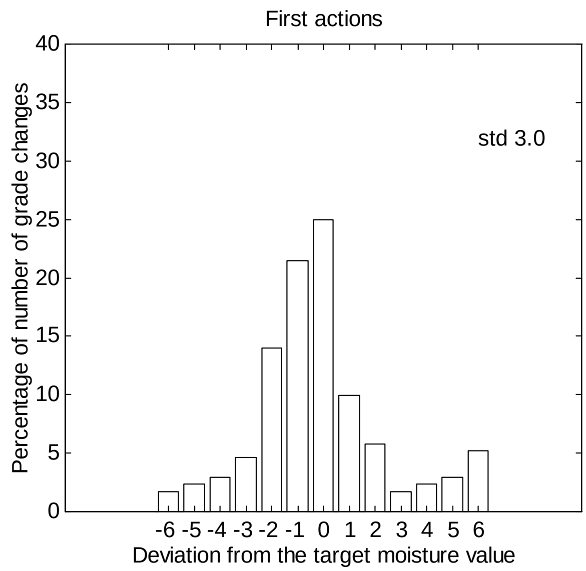

Figure 5.5 Histogram of moisture grade change deviations of first actions compared to the target values the for the moisture of base board.

The standard deviation of moisture error in the first actions case of base board was 3.0 % (Figure 5.5). The standard deviations are calculated from the difference between the moisture values at the end of grade change and the first actions position so that it corresponds to the predictions made with the models.

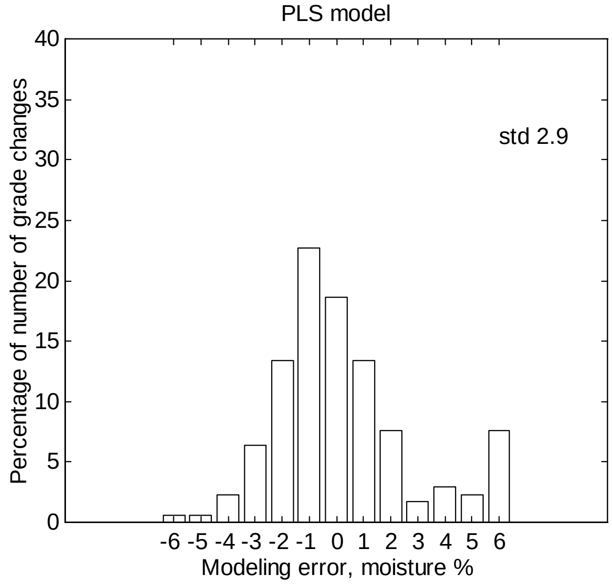

Figure 5.6 Histogram of grade change modeling errors of the PLS model for the moisture of base board.

In the PLS modeling number of principal components is the most important tuning parameter. The optimal number of principal components to be held in the models was found to be 3 with the SIC criterion (Figure 5.6). The standard deviation with the PLS modeling error was 2.9 %.

A simple physical model was first tuned with a genetic algorithm to fit the off-line data as for example moisture of web, temperatures of steam, cylinders and web. Then the physical model was tuned with a help of separate parameters to the data of 30 grade changes and the predictions were made for 142 grade changes. The method is explained in detail in the section 4.3 ‘Modeling procedure for the grade changes’.

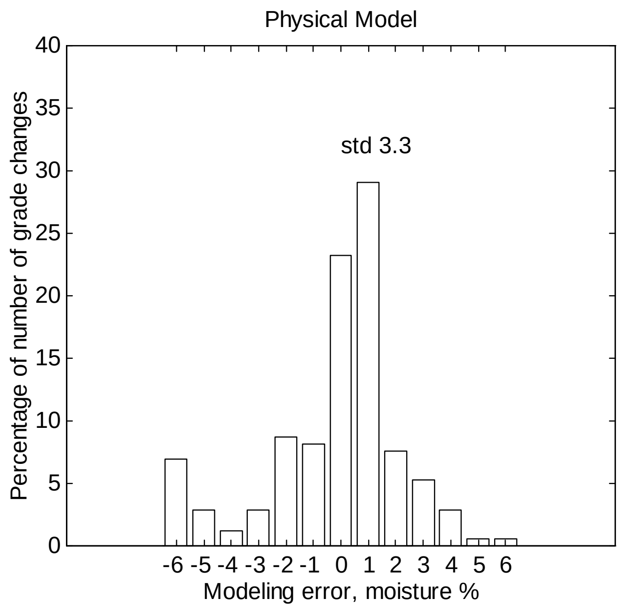

Figure 5.7 Histogram of grade change modeling errors of the simple physical model for the moisture of base board.

The mere physical model gave standard deviation of 3.3 % for the modeling error (Figure 5.7). However, some over 15 % deviations were discovered.

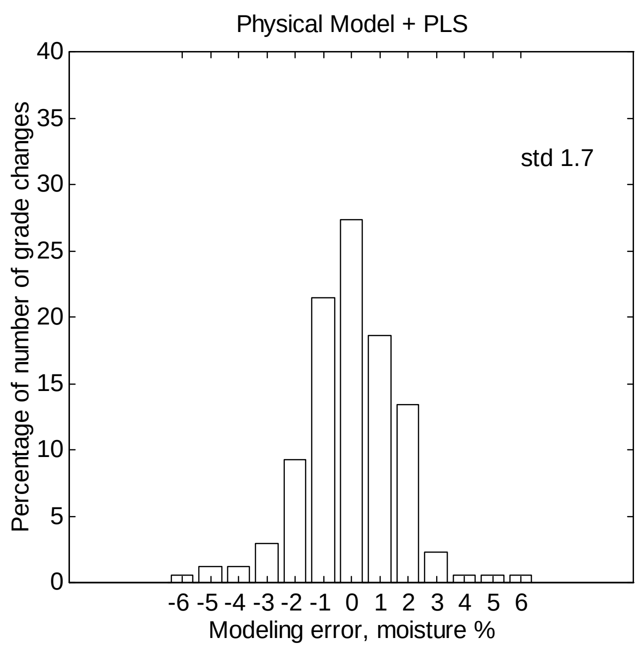

Figure 5.8 Histogram of grade change modeling errors of the simple physical + PLS (hybrid) model for the moisture of base board.

Then the PLS model was added and the hybrid model gave good results. The standard deviation of the modeling error was 1.7 % (Figure 5.8). There are only three values outside 5 % range.

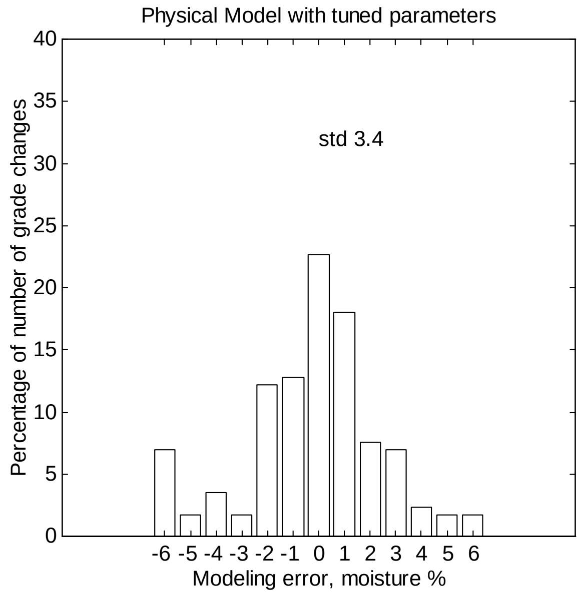

Figure 5.9 Histogram of grade change modeling errors of the physical model with tuned parameters for the moisture of base board.

The hybrid model was then extended with adaptively tunable parameters as explained in the section 4.2. Even though the physical model could have been fitted more accurately with the parameter tuning, the predictive properties did not improve despite the added parameters. The standard deviation of the modeling error for the physical part of the model was 3.4 % (Figure 5.9).

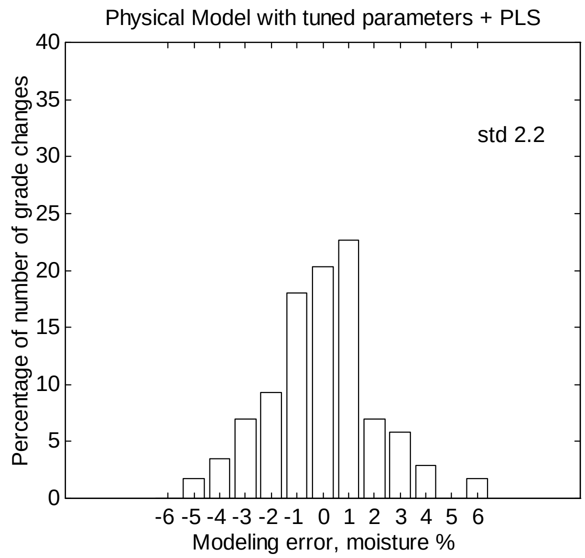

Figure 5.10 Histogram of grade change modeling errors of the hybrid model with tuned parameters with classical nonlinear optimization for the moisture of base board.

The standard deviation for the model error was 2.2 % when PLS model was added to the tuned physical model (Figure 5.10).

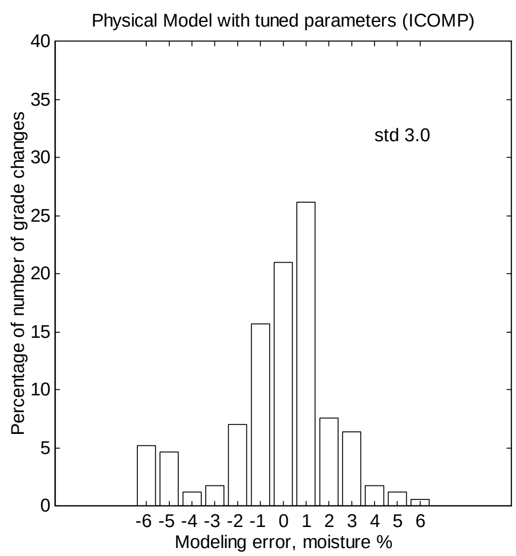

Figure 5.11 Histogram of grade change modeling errors of the physical model with tuned (ICOMP) parameters for the moisture of base board.

Lastly, ICOMP penalizing function was taken into the cost function of genetic optimization. ICOMP penalized tuning was used with the approach where all the parts of the hybrid model were tuned as a combined unit. The parameters of the physical model were tuned so that the weight was on the final moisture error. In the other approaches the physical model was tuned first and the residual moisture error was minimized with PLS. In this approach the standard deviation of the error of the physical model was 3.0

that is a little better than the physical model (3.3 %) that was tuned with more traditional method (Figure 5.11).

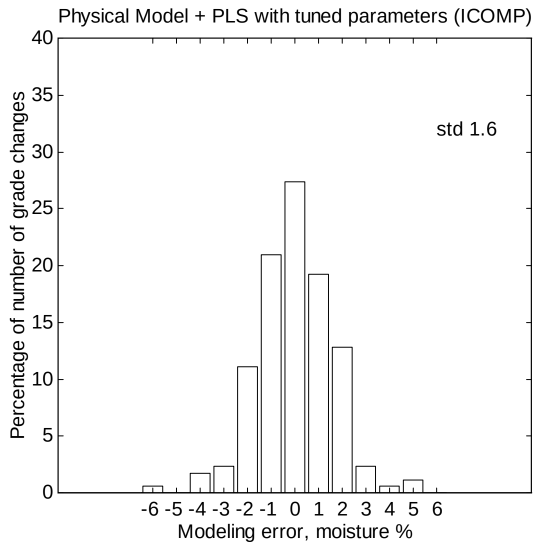

Figure 5.12 Histogram of grade change modeling errors of the hybrid model with tuned (ICOMP) parameters for the moisture of base board.

The corresponding hybrid model gave the standard deviation of 1.6% for the modeling error that is better than in any of the previous models (Figure 5.12). A symmetrical histogram shows also that there are not many large errors.

The results are summarized in Table 5.1. The F-statistics, cumulative distribution function (CDF) show high values 1.76 and 1.83 corresponding ordinary hybrid model and hybrid model with ICOMP. This means that the assumption of equivalence of the standard deviations can be clearly rejected with 95% confidence.

Table 5.1 Comparison of standard deviations (std) of modeling errors of moisture of base board to the first actions case with F-tests. Physical denotes the physical part of the corresponding hybrid model. First actions denotes the response values due to the first control actions done during grade changes.

	Physical or First actions	Hybrid or PLS	Physical vs. First actions	Hybrid or PLS vs. First actions	CDF[1]
Modeling method	**std**	**std**	**F-test**	**F-test**	
First actions	2.99		1.00		
PLS		2.92		1.02	1.29
Hybrid	3.29	1.70	1.10	1.76	1.29
Hybrid param. tuning, traditional	3.40	2.16	1.13	1.39	1.24
Hybrid param. tuning, ICOMP	2.99	1.63	1.00	1.83	1.29

[1)] Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95 % confidence

5.1.2. Prediction of the grade change performance at the end of grade change

Finally the hybrid model with ICOMP parameter tuning model (the best model) was used to predict the moisture of base board at the end of grade change. The model was tuned simultaneously with both the data sampled after the first actions and after the grade change. This method was chosen due to the low excitation of moisture values at the end of grade change (Figure 5.13).

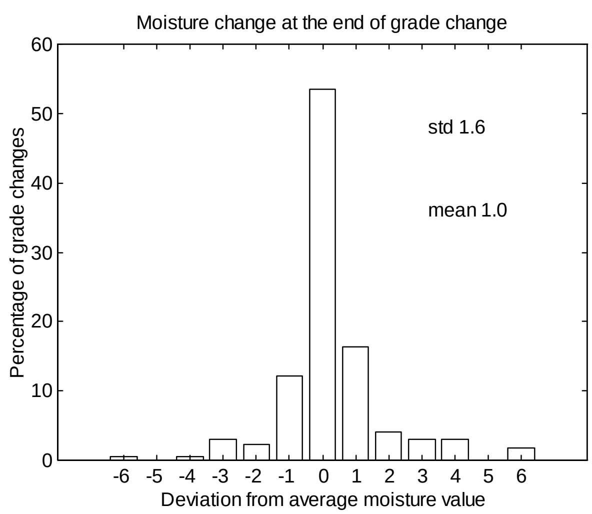

Figure 5.13 The distribution of amount of moisture changes of board from the beginning to the end of grade change.

The standard deviation for the hybrid modeling error with ICOMP parameter tuning model was 1.1% (Figure 5.14). The model performs very well compared to the first actions case as can be seen from the plot of moisture errors (Figure 5.15 and Figure 5.16).

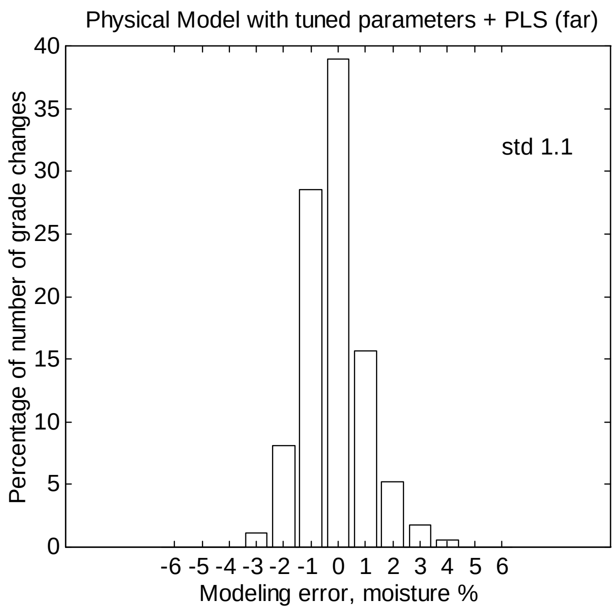

Figure 5.14 Histogram of grade change modeling errors of the hybrid model with tuned (ICOMP) parameters for the moisture of board at the end of grade change.

The modeling errors of hybrid model with ICOMP and the moisture errors at the first actions are plotted grade change by grade change in Figure 5.15 and Figure 5.16. Qualitatively, it can be seen that the modeling error of the hybrid model is quite small.

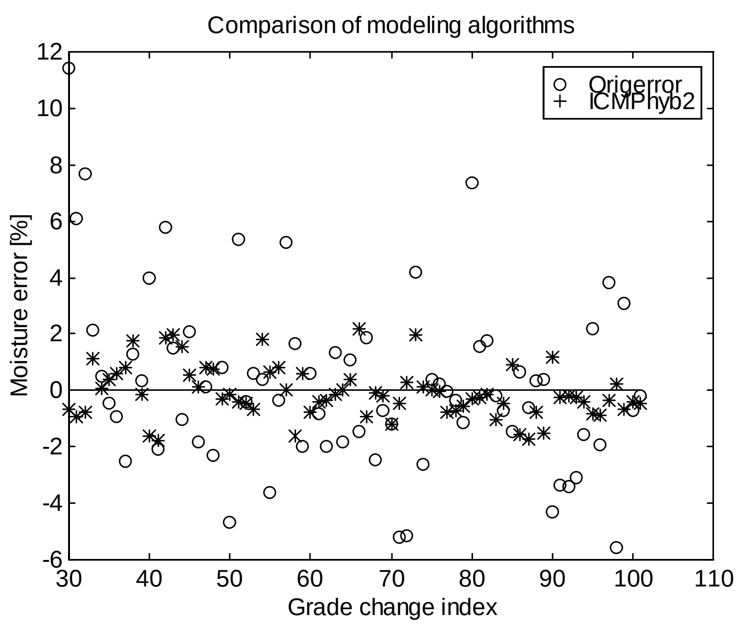

Figure 5.15 Moisture errors of first actions (Origerror) and Hybrid model with parameter tuning with ICOMP (ICMPhyb) at the end of grade change. Considered grade changes are those with indices from 30 to 100.

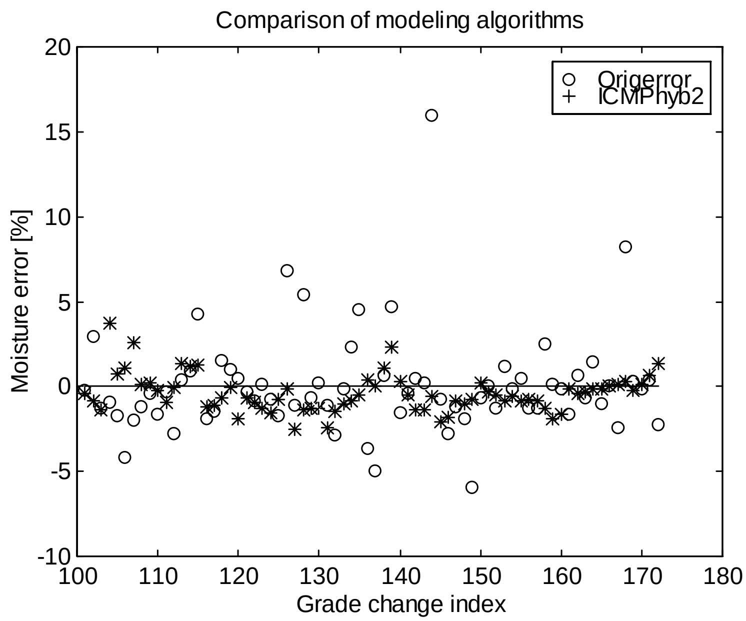

Figure 5.16 Moisture errors of first actions (Origerror) and Hybrid model with parameter tuning with ICOMP (ICMPhyb) at the end of grade change. Considered grade changes are those with indices from 101 to 173.

5.2. Basis weight modeling

The results are generated with models that use a large number of variables from the board machine. For example, the physical part of the hybrid model uses measurements from the drying section and the empirical model 34 variables from the other sections of the board machine (Figure 5.17). Only the gain of the model is adjusted. A complete list of variables can be found in Appendix A.

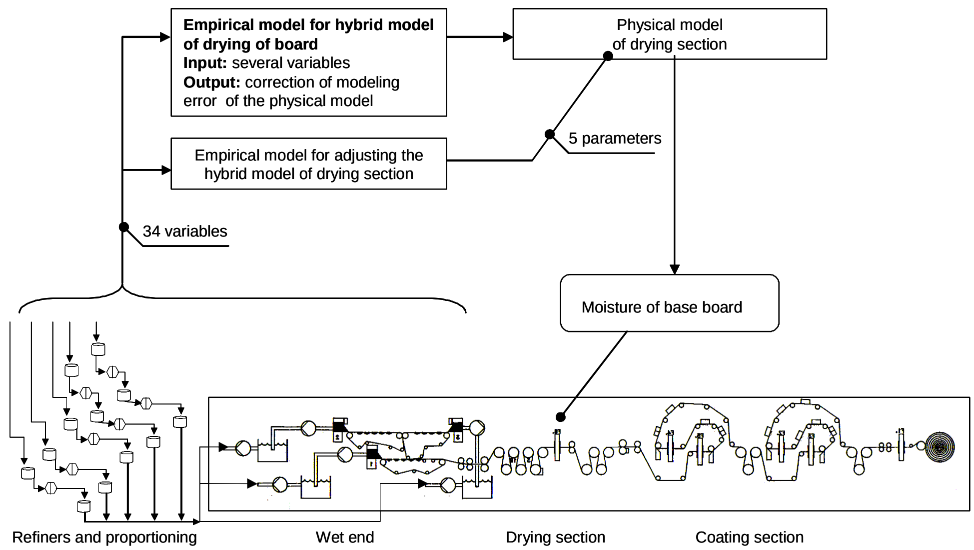

Figure 5.17 Summary of the modeling of basis weight of the board.

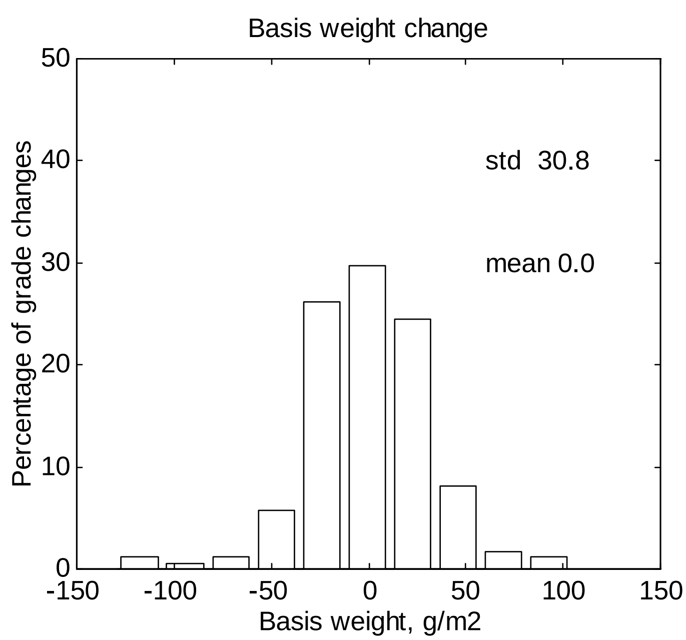

Figure 5.18 The distribution of basis weight changes of base board.

The basis weight modeling was not found very important by the mill personnel. The adjustments during a grade change were considered easier than for the moisture of base board. However, the basis weight changes of paperboard vary from about -120 g/m^2 to 100 g/m^2 which is quite large range (Figure 5.18). It is sometimes necessary to turn off the automatics and to make a large change manually.

In the following the basis weight error after the first actions and the performance of the modeling approaches are presented with the help of histograms and standard deviations.

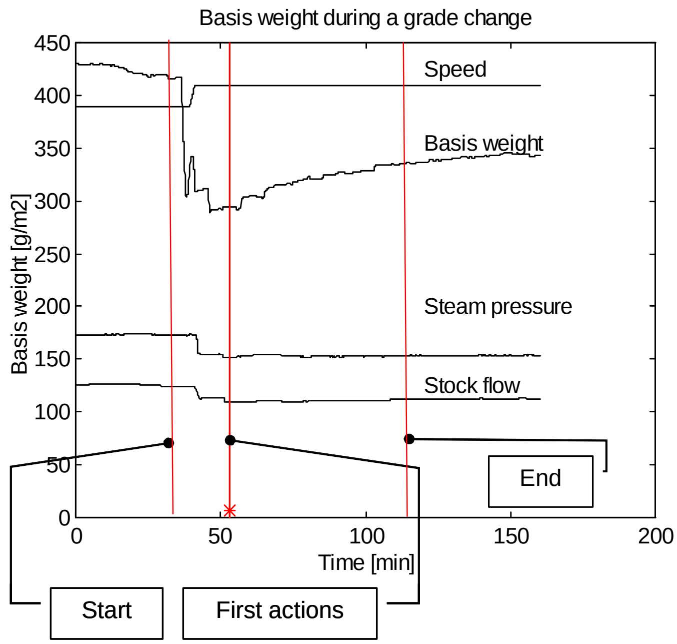

Figure 5.19 Sampling positions for the basis weight modeling.

The sampling is done in the same way as with the moisture of base board: start, first actions and at the end of grade change (Figure 5.19).

Table 5.2 Comparison of standard deviations (std) of modeling methods of basis weight to the first actions case with F-tests.

	Base or First actions	**Hybrid**	**Base or First actions**	**Hybrid or PLS**	
Modeling method	**std**	**std**	**F-test**	**F-test**	**CDF[1]**
First actions	19.67		1.00		
PLS		29.27		1.49	1.29
Hybrid param. tuning, traditional	14.44	12.82	1.36	1.53	1.29

[1)]Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95 % confidence

The results confirm that the basis weight error after the first actions is rather small, Except for the hybrid model, none of the other models could prove to be clearly better than the existing grade change method. The standard deviation for the first actions case is 19.7 g/m^2 that is higher than expected.

The standard deviation of PLS modeling error is high (29 g/m^2) and hybrid modeling error with tuned parameters is on the level 13 g/m^2. The PLS model was tuned with Subspace Information Criterion (SIC) and the resulting number of principal components was one. The tuning was confirmed to be the best by running the modeling with 3 and 7 principal components with standard deviations of 31 g/m^2 and 44 g/m^2 respectively.

5.3. Coat moisture

The results are generated with models that use large amount of variables from the board machine. For example, the physical part of hybrid model uses measurements from the drying section and the empirical model 36 variables from the other sections of the board machine (Figure 5.20). Eight parameters of the physical model are adjusted. A complete list of variables can be found in Appendix A and the modeling equations in Appendix C.

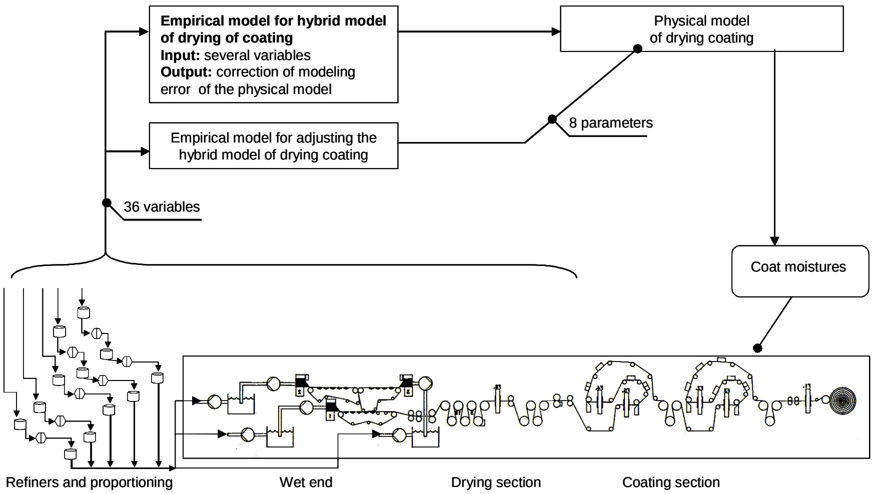

Figure 5.20 Summary of the hybrid modeling of coat moisture.

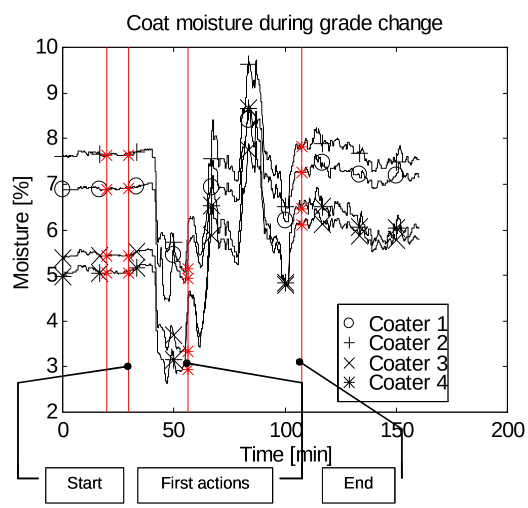

Figure 5.21 Sampling instants for the modeling of coat moisture.

The sampling for the modeling is done at the start, at first actions and at the end of grade change (Figure 5.21).

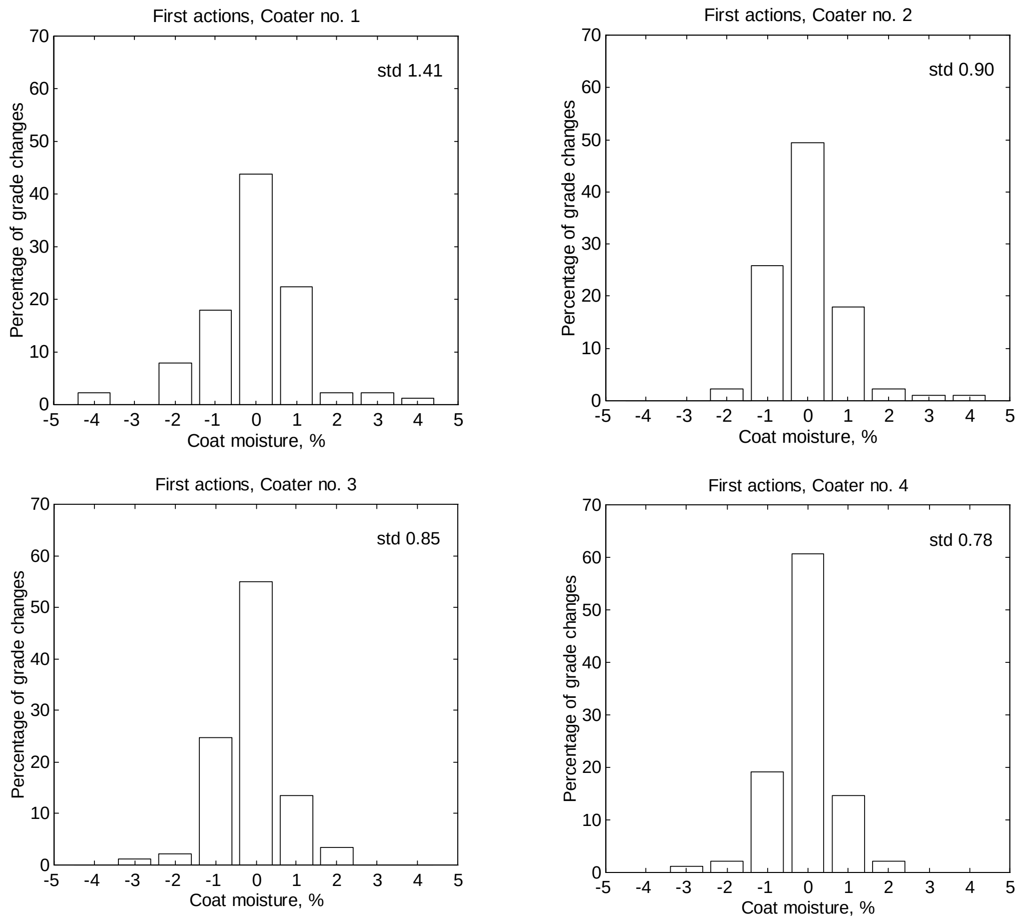

Figure 5.22 Histograms of coat moisture change errors after the fist control actions.

The coat moisture modeling was done with first 17 grade changes out of total number of 89. There were 172 grade changes available in the base paperboard modeling but in the coating studies 83 grade changes were considered unfit for use. The moisture error of the grade changes after the first actions is presented in Figure 5.22. It can be seen that there are not great differences between coaters. The performance of hybrid model with ICOMP tuning is presented with the help of histograms and standard deviations in Figure 5.23.

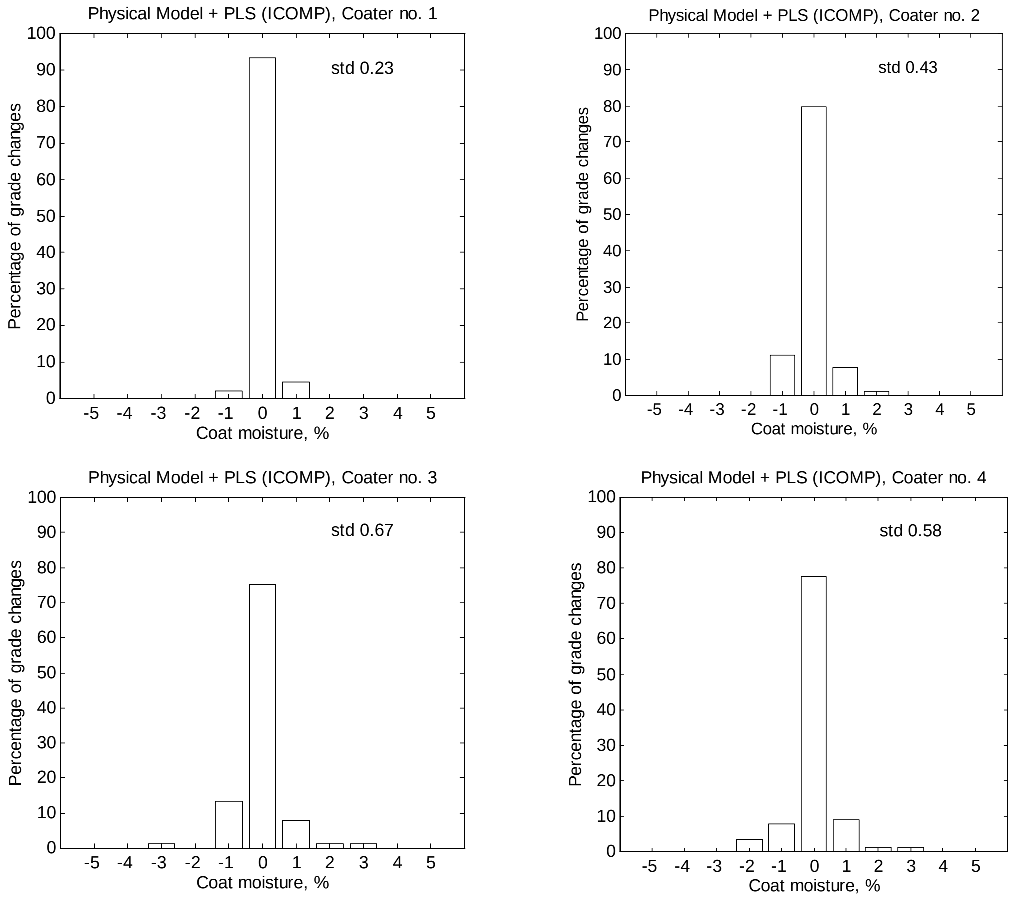

Figure 5.23 Histograms of coat moisture modeling error for the hybrid model with ICOMP tuning.

The hybrid model with the parameters tuned with ICOMP is equal or better than PLS model in the prediction of coat moisture (Table 5.3). The errors of models were generally better than in the first actions case. However, only hybrid model had a lower standard deviation on Coater 3 than in the first actions case.

Table 5.3 Summary of the first actions case, PLS model and the hybrid model of coat moisture with the ICOMP tuning.

Process	**First actions**	**PLS**	**Hybrid ICOMP**
	STD, Coat moisture %	**STD, Coat moisture %**	**STD, Coat moisture %**
Coater 1	1.41	0.22	0.23
Coater 2	0.90	0.41	0.43
Coater 3	0.85	0.92	0.67
Coater 4	0.78	0.57	0.58

5.4. Coat weight

The results are generated with models that use a large amount of variables from the board machine. For example, the physical part of the hybrid model uses measurements from the drying section and the empirical model 36 variables from the other sections of the board machine (Figure 5.24). Nine parameters of the physical model are adjusted. A complete list of variables can be found in Appendix A and the modeling equations in Appendix D.

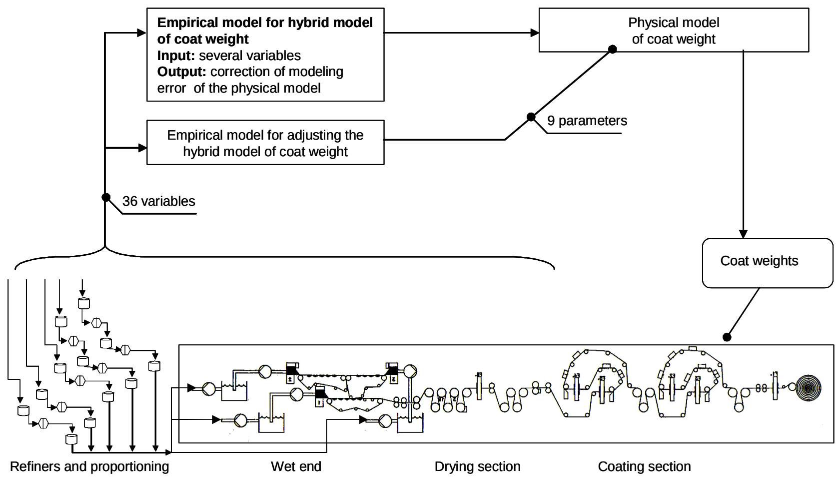

Figure 5.24 Summary of the hybrid modeling of coat weight.

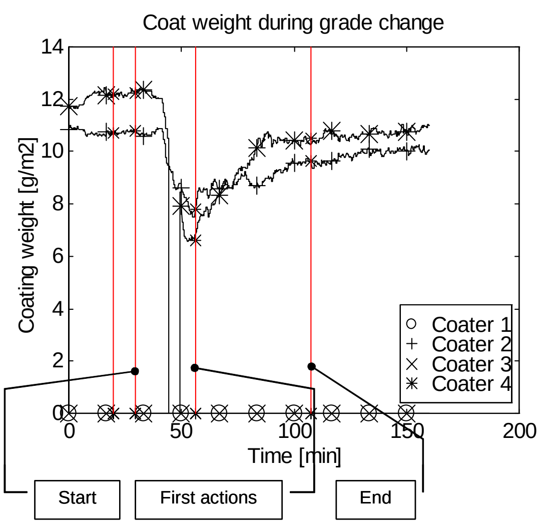

Figure 5.25 Sampling instants of coat weight modeling.

The sampling for the modeling is done at the start, at first actions and at the end of grade change (Figure 5.25).

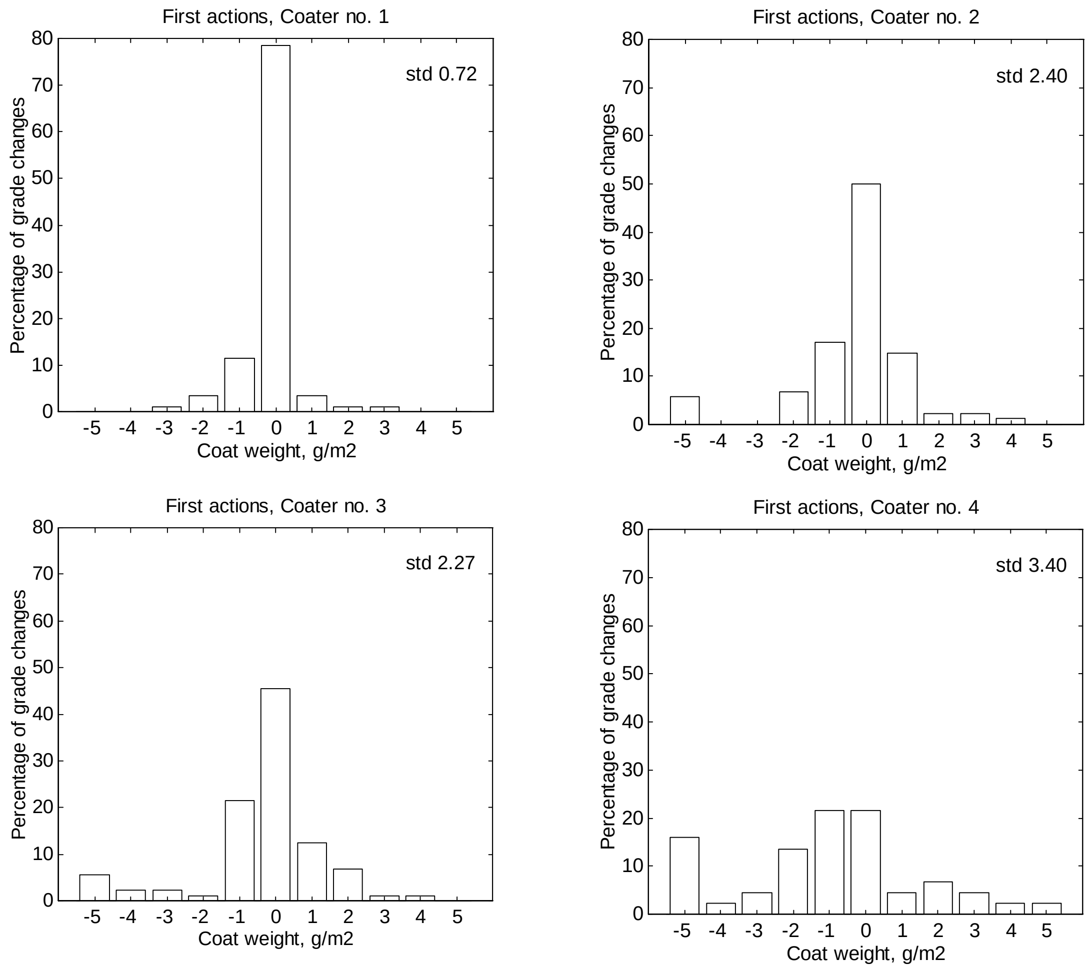

Figure 5.26 Histograms of coat weight change errors on coaters after the first control actions.

The coat weight modeling was done with first 17 grade changes out of total number of 89 as with coat moisture. The errors in the coat weight after the first actions are compared to the final values that are presented in Figure 5.26. It can be seen that there are great differences between coaters 1, 2 and 3 compared to coater 4.

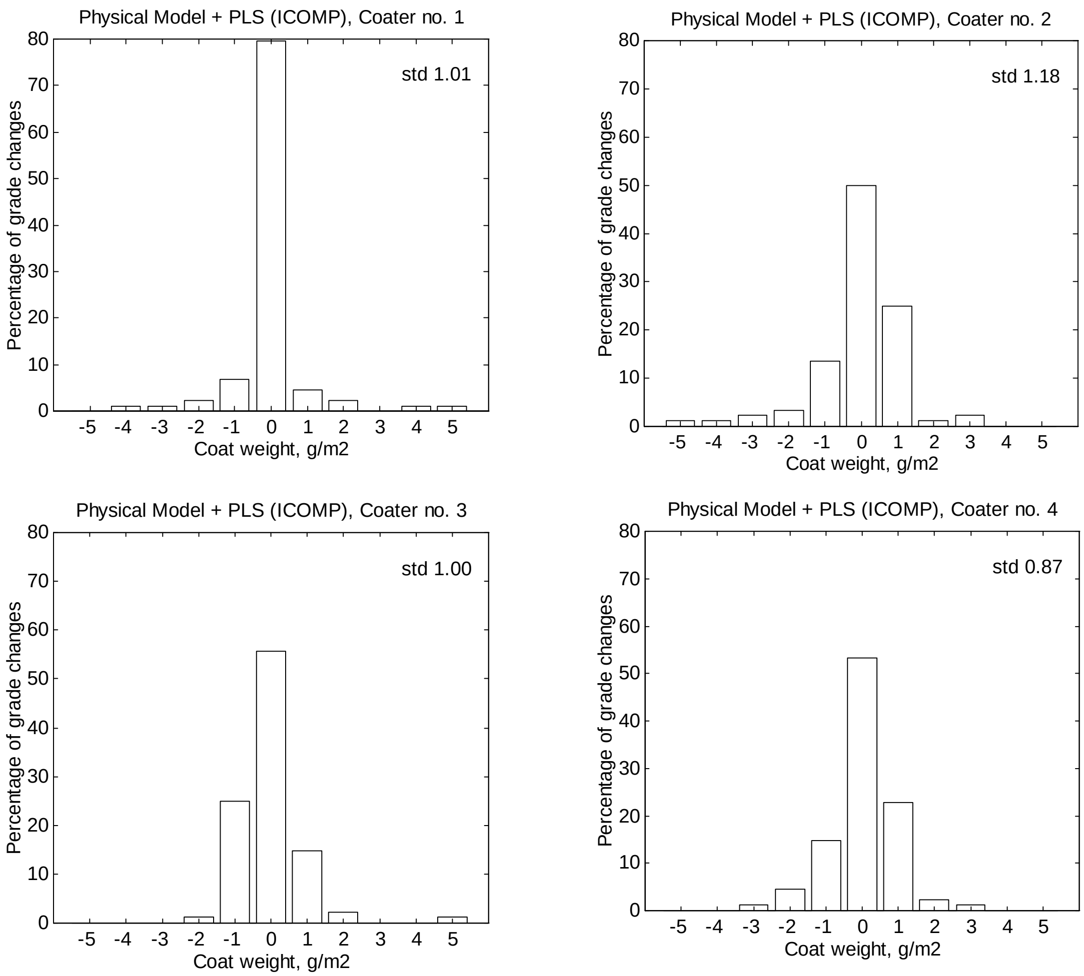

Figure 5.27 Histograms of coat weight change modeling errors on coaters for the hybrid model with ICOMP tuning.

In Figure 5.27 the performance of the hybrid model with ICOMP tuning is presented with the help of histograms and standard deviations. The summary of all the modeling cases is presented in Table 5.4. The hybrid modeling error with ICOMP has the lowest standard deviation of coat weight. Especially, in the case of coater 4, the standard deviation is 0.87 g/m^2 when it is 1.55 g/m^2 with PLS.

Table 5.4 Summary of coat weight PLS model and hybrid model with the ICOMP tuning.

Process	**First actions**	**PLS**	**Hybrid ICOMP**
	STD, Coat weight g/m^2	**STD, Coat weight g/m^2**	**STD, Coat weight g/m^2**
Coater 1	0.72	1.31	1.01
Coater 2	2.40	1.26	1.18
Coater 3	2.27	1.28	1.00
Coater 4	3.40	1.55	0.87

6. DISSCUSSION

In this chapter the prediction accuracy of models is discussed. Especially, the percentage of how much the standard deviations have improved and the percentage of grade changes that have gone to the wrong direction. In addition the duration of grade changes is estimated from the measurements and then an approximate model is used to estimate the duration if models were used in the planning the grade changes. The parameters of the genetic optimization and the loadings of the PLS models are also analyzed.

Comparison of the prediction properties of modeling approaches is done by using data of 172 grade changes that were collected from a real board machine. It is shown that a hybrid model with ICOMP tuning is the best model with 44% improvement compared to the PLS in the standard deviation of prediction errors. The improvement compared to the standard deviation at the first actions is 46%. The result is very promising but it is not comparable to the modeling approaches because the first actions deviations were estimated from the data and the modeling results were done by predicting with the models. The improvement at the end of the grade change can be even 63% compared to the first actions deviations if slice opening is taken into the model.

The performance of the models in a paper mill is different compared to the modeling results. This is due to the human interactions with the automation as well as to the actual duration of the grade change. For example, it is important to achieve operator acceptance for a new approach to the grade change tasks. The operator acceptance is especially sensitive to the response time of the model system or on the number of predictions that go to the wrong direction. If the operators do not accept the system it does not help even if the models were excellent. However, the predictions were made with the model almost 1.5 years forward, when in the real paper mill only the prediction to next grade change is needed.

The discussion of the results is based on the assumption that the real board machine would have the same response as the model. The estimated output for example moisture, depend on many variables that would make it very difficult to estimate the target values. In practice several assumptions had to be made on how to set all the manipulated variables of the paper machine optimally. Testing at mill should be done to be absolutely sure that the results presented in this thesis can be achieved in a board machine. This would be an extensive task and is out of scope of this thesis.

In this chapter first a discussion of prediction performance of models of moisture of base board, basis weight, coat moisture and coat weight is given. In addition to that the parameters of the models are analyzed.

6.1. Discussion about the results of the base board moisture model

The modeling is done with the data sampled from the beginning of the grade change, at the first actions and at the end of grade change. As mentioned in section 5.1, the first actions case denotes the measured response values due to the first control actions taken on the board machine. The error is calculated as a difference to set-point the moisture value. The models were also evaluated at the first actions and the end of grade changes. The analysis of the predictions is given in the following section.

6.1.1. Prediction of moisture of base board after the first control actions

The standard deviation of the moistures at the beginning of grade change is 1.4% which is not very wide (Figure 6.1). However, there exist also large values up to 9%. It was a surprise that it was not possible to tune a model to a perfect fit with several grade change samples. However, the primary goal was not to achieve the prediction of the absolute moisture level but rather the change of moisture.

It was also considered to use local models for example by using grade specific models. However, it was shown earlier that the use of local models did not improve the standard deviation of moisture model significantly (Viitamäki 1998) and will not be discussed any further.

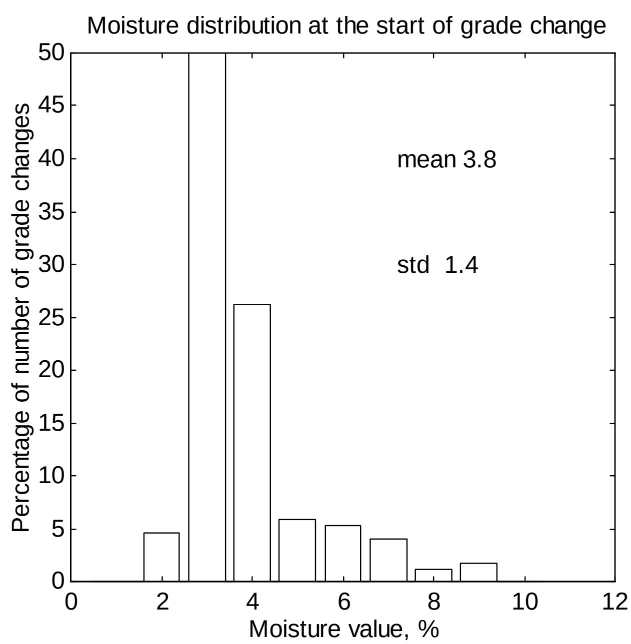

Figure 6.1 Histogram of moisture values at the beginning of grade change.

The results shown in the previous section indicate that the hybrid model with the parameters tuned with ICOMP was the best of the models tested for the prediction of grade change moisture of base board. The hybrid model with tuned parameters with ICOMP included in the loss function of the optimization had f-test value 1.83 (Table 6.1). The value is clearly over the 95% confidence level (CDF 1.29). The ordinary hybrid model is the second best with almost as good performance as the more complex model with ICOMP. The statistical figures are based on predictions of more than 140 grade changes. According to the author's knowledge, there does not exist another study where the performance of the grade change algorithms would have been evaluated as widely as in this thesis.

Table 6.1 Comparison of standard deviations (std) of modeling methods of moisture of base board to the first actions case with f-tests and percentage improvement of hybrid models compared to PLS. Physical denotes the physical part of the corresponding hybrid model. First actions denote the response values due to first control actions done during grade changes.

	Hybrid or PLS vs. First actions improvement of std	**Hybrid or PLS vs. First actions**	**CDF(1**	**Hybrid vs. PLS improvement of std**
Modeling method	%	f-test		%
PLS	2	1.02	1.29	
Hybrid	43	1.76	1.29	42
Hybrid param. tuning, traditional	28	1.39	1.24	26
Hybrid param. tuning, ICOMP	46	1.83	1.29	44

1)Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95% confidence

The improvement of standard deviation of moisture error from 3% to 1.6% is 46% compared to the first actions case. It should be noted that the standard deviations of modeling errors were better than in the first actions case in over 55% of the grade changes. However, these results are not completely comparable due to estimations of first actions data from the measurements. The comparison between PLS and hybrid model is valid because both methods use the same data as an input and the output are compared to the same data. PLS can be considered to simulate a modern regression based grade change automation. It can be seen that the standard deviation of a hybrid model with ICOMP is 44% better than PLS. This shows also that adding a physical model to an empirical model is clearly better than just pure empirical model. Also, a general observation was that the convergence of the optimization was faster with ICOMP than that with a more standard penalty function. However, this issue was not elaborated further.

Murphy and Chen (2000) presented results that claimed 35% improvement of reel moisture range (Table 6.2). Viljamaa et al. (2001) have published results that the fuzzy system based algorithm improved the error of the predicted set points of a paper machine with about 15% in average. The model was optimized for 30 grade changes and then validated for 11 grade changes. However, neither the exact description of the manipulated variables nor the error statistics of the results of the extended use at the paper mill was reported.

Table 6.2. Performance figures of grade change automation from the literature.

Measure	**Initial figure of GC**	**New figure of GC**	**Improv-ement, %**	**Reference**
Reel moisture range of a paper machine	3.55%	2.3%	35	Murphy and Chen (2000)
Target values of a GC			15	Viljamaa et al. (2001)

Hybrid modeling was a success because the standard deviation of prediction errors of the hybrid modeling was significantly smaller than with PLS model. The hybrid model was also significantly better than the ones presented in the literature although the comparison is not totally valid. It must also be noted that the hybrid model has not been tested in the real process use at a board mill. However, the model was able to predict grade changes that were collected during 1.5 years. In practical use at a paper mill the model could be tuned after each new grade change, since only the next grade change needs to be predicted. The weakness of the model is that it is not able to predict absolute values of the dependent variable (moisture) but only the amount of change. However, it predicts the change very well (Figure 6.2).

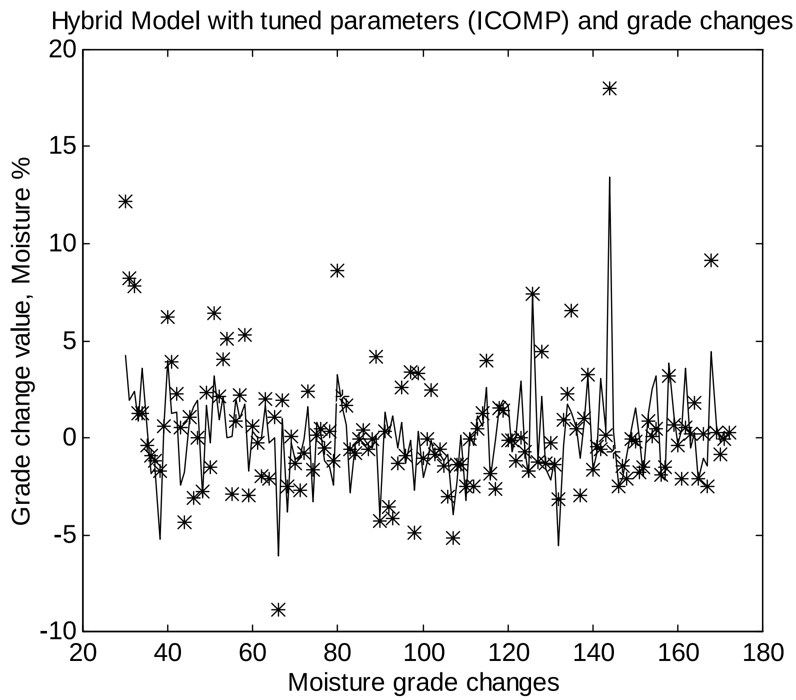

Figure 6.2 Prediction of moisture changes with the hybrid model with tuned (ICOMP) parameters for the moisture of base board (-) and the real measured grade changes (*).

A simplified sensitivity of base board moisture to the most important variables is shown in Figure 6.3. It can be seen from the graph that the most important variable is the machine speed. Basis weight is also very important but it is dependent on the machine speed so that the effects are not separable in reality. The simplified sensitivity is presented to show that the model reacts to its inputs in correct direction.

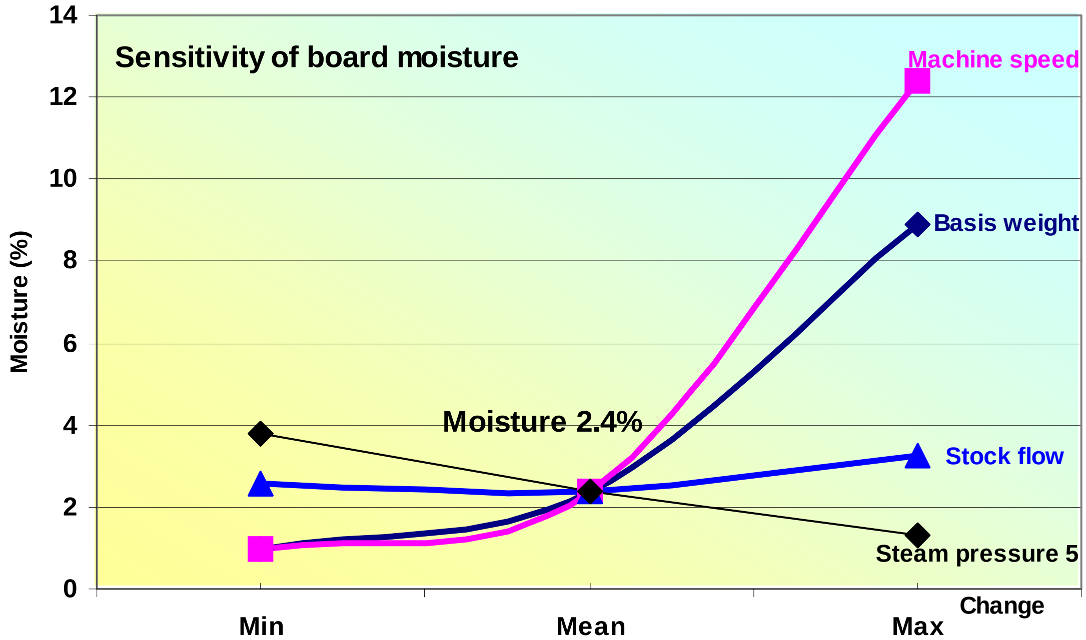

Figure 6.3 Simplified sensitivity of the base board moisture to minimum and maximum values of machine speed, basis weight, stock flow and steam pressure 5 (last steam group).

The prediction performance of the direction of grade changes and comparison of physical parts and hybrid models are given in Table 6.3. The percentage of grade changes that would start to go in the wrong direction was high in the first actions case (44.8%). It should be remembered that this value was calculated by using the samples from the time instant of the response of the process caused by the first control actions.

The lowest percentage of wrong directions in grade changes would have been with the physical part of the hybrid model (16%). In this approach the physical model was tuned first for the best prediction error and to predict the right direction. However, the standard deviation of the physical part alone is high (3.4%). The hybrid model with the ICOMP in the cost function, was the second best with 18.6% of the grade changes pointing to the wrong direction.

Table 6.3 Prediction performance of the direction of grade changes and testing the need of the empirical part (PLS) for the hybrid models for each modeling approach. Physical denotes the physical part of the hybrid model.

	Physical model or First actions	**PLS or Hybrid model**	**Physical model or First actions**	**PLS or Hybrid model**	**F-test of physical vs. hybrid**	**CDF(1)**
Option	**Wrong direction**	**Wrong direction**	**Standard deviation of moisture error**	**Standard deviation of moisture error**		
	%	%	moisture %	moisture %		
First actions	44.8		3.0			
PLS		29.1		2.9		
Hybrid	36	19.8	3.3	1.7	1.76	1.29
Hybrid param. tuning, traditional	16	22	3.4	2.2	1.39	1.24
Hybrid param. tuning, ICOMP	24.4	18.6	3.0	1.6	1.83	1.29

1)Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95% confidence

The PLS part has improved the physical model the most in the ICOMP case even though the physical model had the lowest standard deviation (Table 6.3). All the F-test values between the physical part and the total hybrid models are above CDF reference values which means that PLS has improved the performance of models significantly. This implies that by using hybrid models it is possible to achieve better performance than with just one model.

6.1.2. Prediction of base board moisture at the end of grade change

Finally the hybrid model with ICOMP parameter tuning model (the best model) was used to predict the moisture of base board at the end of grade change. The model was tuned simultaneously with both the data sampled after first actions and at the end of grade changes. The modeling was not performed at the end of a grade change alone due to the low excitation of moisture values (Figure 6.4). Standard distribution of moisture measurements was only 1.6% that is small compared to the 2.9% after the first actions presented Figure 5.1 in the section 5.1.

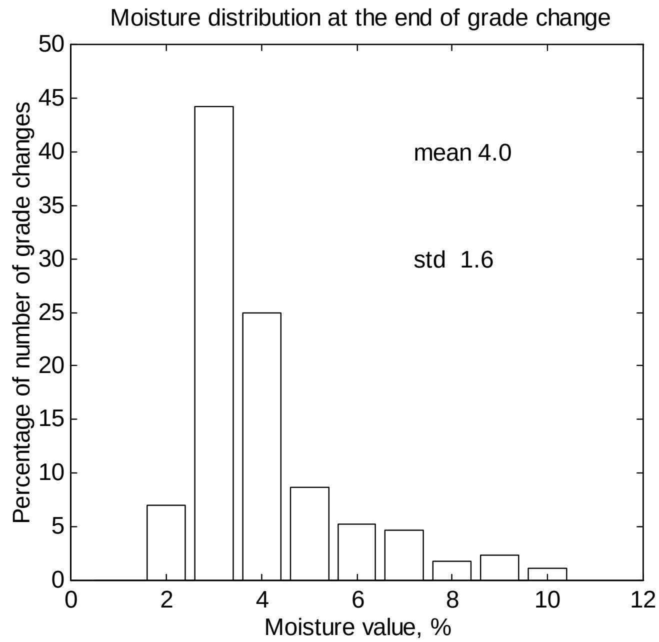

Figure 6.4 Distribution of board moisture at the end of grade change.

The standard deviation for the hybrid model with ICOMP parameter tuning model was 1.1% (Table 6.4). The improvement is 63% which is even better than at the first actions situation. However, the models are not totally comparable due to the addition of the amount of retention aid and the slice opening to the PLS part of the model.

Table 6.4 Comparison of standard deviation (std) of the best modeling method of board moisture to the first actions case with f-tests at the end of grade change.

Option	**Wrong direction**	**Standard deviation of moisture error**	**F-test of physical vs. hybrid**	**CDF[1]**
	%	%		
First actions	44.8	3.0		
Hybrid param. tuning, ICOMP at the end of grade change	38.3	1.1	2.779	1.287

1)Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95% confidence

It was found that the model could not be tuned to predict the board moisture unless the change of slice opening was included in the model. Slice opening cannot typically be adjusted before grade change but it is adjusted manually to comply with the dewatering rate on the wire. For example, the wet-line of the middle-layer is positioned near by the point where the layers of board are pressed together in the wire section. This is why these measurements were excluded from the model at the first actions. This result gives a clear indication that the hybrid model can be used to evaluate also the response of the actions of proportioning and headbox to the moisture. However, this issue was not elaborated. It requires an extensive amount of work and is outside of the scope of this thesis.

6.1.3. Efficiency of moisture grade change of board machine

It is interesting to evaluate the time saved in the grade changes because this would directly show much it is possible to increase the saleable production. This makes it also possible to estimate economic benefits gained trough model assisted grade changes. Of course, it should be kept in mind that in the case of board machine with on-machine coaters the savings potential could not be achieved if all the sections do not perform well.

The duration of grade changes estimated from the measurements is presented in Figure 6.5. The mean grade change time to reach the target (set point value) range within 1% range of moisture is about 38 min and to 0.5% range the time is 56 min. The accuracy of 1% would be enough in most of the cases and the tighter 0.5% range is calculated just to see if there is any difference in the results.

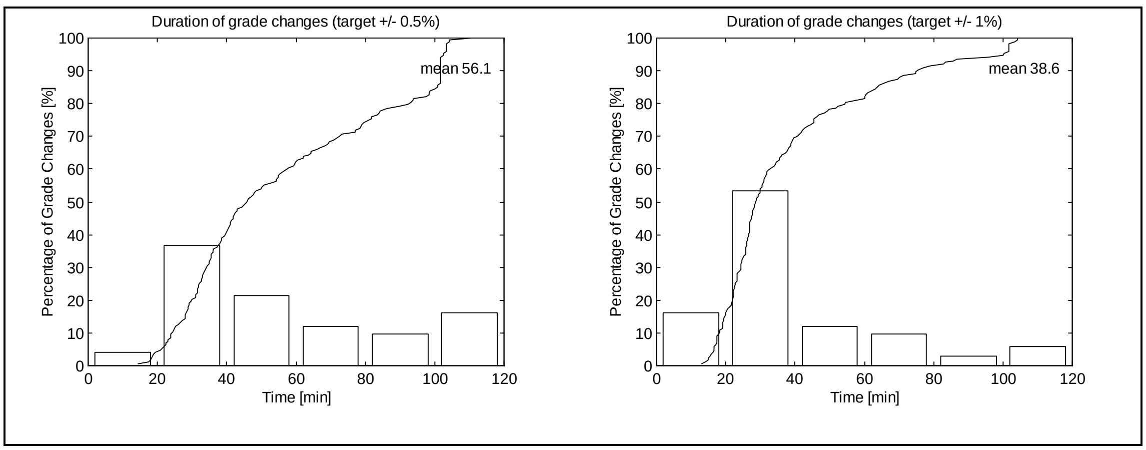

Figure 6.5 Histograms and cumulative graphs of the duration of grade changes on a board machine. The end of grade change is defined here when the moisture [%] has been 10 min inside 0.5 and 1%.

If the developed models were used to estimate the control actions, the duration of a grade change would have been shorter. The resulting duration is estimated with an approximate method. First, it is assumed that the duration of a grade change is dependent on the moisture error of the first grade change actions. Then rules and models are generated from the measurements.

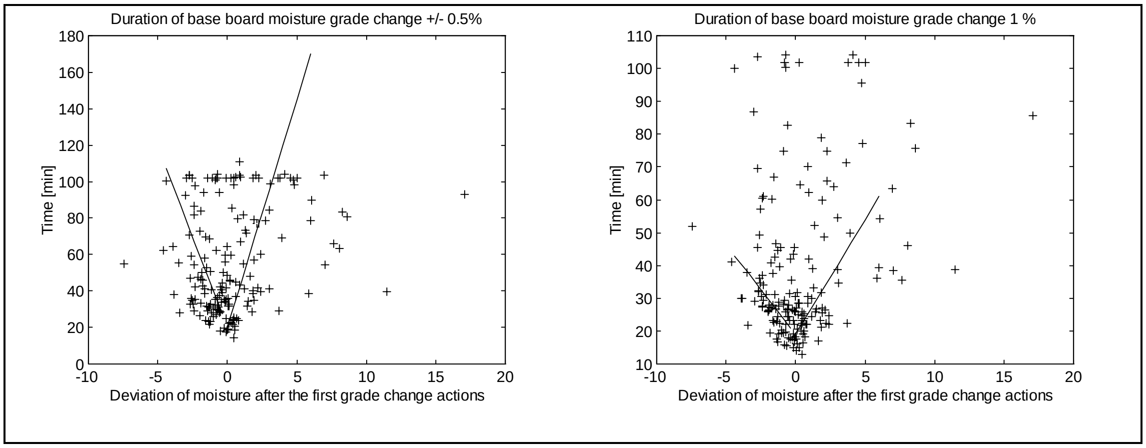

Figure 6.6 Duration of grade change estimated from the measurements as function of moisture errors (limit 0.5 and 1%) of base board. The errors are calculated after the first grade change actions. The lines are fitted separately for the error value below and above zero.

The duration as a function of the moisture error, after the first grade change actions, is presented in Figure 6.6. It is qualitatively obvious that the error is not the only factor that effects the duration of grade change but for the purpose of this practical case a rough estimation is used. Namely, the modeling error can be linked directly to the performance of the models.

The duration of grade change, that was estimated from the measurements, was fitted by adjusting the lines in Figure 6.6 in order give roughly the same mean values as was estimated from the earlier data (Figure 6.5). The rules for the estimation of the grade change duration from the prediction errors of the models are given in Table 6.5.

Table 6.5 Calculation rules to roughly estimate the duration of grade change from the moisture prediction error of models.

Moisture error, ex %	**Duration of grade change, t_{GC} (0.5% range) min**	**Duration of grade change, t_{GC} (1% range) min**
<= -3	100	100
> -3 and < 0	$t_{GC} = -20e_x + 20$	$t_{GC} = -5.5e_x + 19$
>= 0 and < 5	$t_{GC} = 25e_x + 20$	$t_{GC} = 7e_x + 19$
>= 5	100	100

The results from the estimation show that the mean deduction in the duration of a grade change time would be only 9 min (Table 6.6). For PLS this deduction is about 4 min. It is seen from the plot that the largest possible deduction could be 18 min because 20 min is the lowest grade change time. The improvement achieved by the hybrid models is thus 50% of the available range if the acceptance range would be 1%. The estimate is quite conservative because the models are evaluated with stringent constraints. For example modeling was done with only 30 grade changes and then the model was used to predict 142 grade changes. In practice only the next grade change needs to be estimated and the earlier data can be used for modeling.

Table 6.6 The estimated duration of grade changes with modeling methods for the board moisture.

Modeling method	Duration of grade change (0.5% range) min	Duration of grade change (1% range) min
Estimation from the measurements	56	38
PLS model	52	34
Hybrid model	47	29
Hybrid model with ICOMP	47	29

The sales value of the production of 9 min savings per grade change is 1.8 million €/a. The calculation is based on 400 grade changes annually and on the production rate of 30 t/h as estimated from the collected data. The sales price of the board is assumed to be 1000 € /t. This estimate is fictive because it has not been verified in the actual production usage. It is presented only to show that the application of the grade change modeling is economically feasible.

Table 6.7 Performance figures of grade change automation from the literature.

Measure	Initial figure of GC	New figure of GC	Improv-ement, %	Reference
GC duration of a board machine	6.7 min	4.4 min	35	McQuillin and Huizinga (1994)
GC duration of a paper machine	20.4 min	16.6 min	18	Mori et al. (2000)

The deduction of grade change time has been about 4 min in the literature (Table 6.7). Murphy and Chen (2000) reported 35% improvement of a paper machine that previously had a simpler grade change automation in use.

Even though the optimizing controllers can make corrective actions earlier than ordinary controllers, the intrinsic problem with the mismatch of the model gains still remains. McQuillin and Huizinga (1994) reported the results from a replacement of an open-loop supervisory grade change system, originating from year 1982, with a model predictive control. After the replacement, the duration of an average grade change on a board machine decreased from 6.7 min to 4.4 min (34%). It was not reported in detail what was the time period or the procedure that was used for the average values. It was not reported either what was the prediction accuracy of the used impulse models at the end of grade change.

The estimation of the target values of manipulated variables has also been done in Mori et al. (2000). They used a simple physical model for drying of web and basis weight. The physical model was adapted by a drying correction factor to comply the actual moisture at the beginning of grade change and the new moisture at the end of grade change that was predicted. Then also the steam pressures were calculated. Basis weight was calculated by using material balance of the wet end and then the new stock flow at the end of grade change was predicted. Finally, a first-order lag model was included to simulate the model in order to verify the control responses. It was estimated that the duration of a grade change could be decreased by 18% with this method.

6.1.4. Analysis of loadings of the PLS part of hybrid models

The most influential factors in the PLS part of a hybrid model should be the variables that were not used in the physical models. Thus, the factors can be used to analyze effects of a process variable to the dependent variables and also the modeling performance of the physical part of the model.

The loadings of a PLS model can be considered to show the influence of each variable of the model to the dependent variable(s) in principal groups. The first principal group is the most important and then the second group, etc. In the first actions case, the loadings of variables in PLS part of the hybrid model show that most of the weight is on soft-wood and hard-wood stock percentage in top and bottom layer (Table 6.8).

Table 6.8 Loadings of PLS part in the hybrid modeling near the grade change

Principal Component 1	**Loading 1**	**Principal Component 2**	**Loading 2**	**Principal Component 3**	**Loading 3**
Top and bottom -layer soft-wood %	-0.40	Steam Pressure 1b	-0.55	Steam Pressure 1b	0.39
Top and bottom -layer hard-wood %	0.37	Thick stock consistency	0.35	Steam Pressure 1a	0.37
Broke % (middle layer)	-0.37	Steam Pressure 1a	-0.30	Steam Pressure 3	0.32
Specific energy consumption of broke	0.34	Steam Pressure 2	-0.27	Steam Pressure 5	0.27

The broke stock percentage of middle layer and specific energy consumption refining of broke have also high loadings values. This is in good agreement with the initial assumption that the empirical model would supplement the physical model. These variables are not taken into account in the physical model.

It is however interesting that the steam pressures of first cylinders in the drying section (Steam Pressure 1a, 1b and 2) are included in the PLS part. This might indicate that the modeling of the drying of wet web at the beginning of dryer section is not done well enough. In this case however, the reason for the discrepancy was the malfunctioning of steam pressure measurements of the first two steam groups.

At the end of the grade change, the loadings of variables in PLS part of the hybrid model, show large weight on steam pressures, wire speed and production rate (Table 6.9). This means that the physical model could have been tuned more accurately. The physical model was mainly tuned for the first actions case and it obviously cannot model the situation at the end of grade change equally accurately at the same time.

Table 6.9 Loadings of PLS part in the hybrid modeling at the end of grade change

Principal Component 1	Loading 1	Principal Component 2	Loading 2	Principal Component 3	Loading 3
Steam Pressure 2	0.34	Bone dry production rate	0.40	Retention aid (middle layer) change	-0.49
Steam Pressure 1b	0.33	Steam Pressure 2	0.37	Steam Pressure 1a	0.36
Wire speed	-0.32	Steam Pressure 3	0.35	Headbox slice 2	-0.31
Steam Pressure 3	0.31	Mass flow	0.33	Steam Pressure 1b	0.29

The amount of retention aid and the slice opening are known to effect moisture of paper. Thus retention aid change and headbox slice opening are in the third principal component of the model. The dynamic changes take place relatively slowly due to retention and volume of the white water circulation. That is why their effect will take place at the end of the grade change. In the following the duration of the grade changes and the economic effects of the application of hybrid model is estimated.

6.1.5. Analysis of tuning parameters of hybrid models for base board grade change of moisture

In this chapter, a short summary of the results from the tuning of most important parameters of hybrid model is presented. These are the heat transfer coefficient between the cylinder and the web, heat transfer coefficient between the web and air at the free draw and initial moisture ratio at the beginning of the drying section. The importance of each variable is shown as percentage of total sum of parameter values (Table 6.10).

It was known from Wilhelmsson (1995) and also from the experiments of the author that the heat transfer coefficient between cylinder and the web is the most sensitive parameter of the physical part of the hybrid model (α_{CW1}). It can be seen from Table 6.10 that the increase of specific energy consumption of a birch refiner for top or bottom layer will increase also α_{CW1}. This is in good agreement with the common knowledge of drying of paper because refining increases the surface area that is in contact with the drying cylinder. The dependencies of dry basis weight, production rate and broke in the middle layer to the contact heat transfer is probably indirectly related to other variable that are not measured. Also Paltakari (2000) shows in his doctoral thesis that the drying time is proportional to basis weight.

Table 6.10 Percentage weight of the hybrid model tuning parameter K_{sp0} of the heat transfer coefficient between cylinder and web, α_{CW1}.

Variable	Percentage of total sum of parameter values
Top+bottom layer, birch refiner, specific energy consumption	26
Base board dry basis weight	15
Bone dry production rate	-14
Percentage of middle layer, broke stock flow	13

The percentage of broke should increase and not to decrease initial moisture and the evaporation (Table 6.11). May be the inappropriate effect of broke to the heat transfer coefficient between cylinder and the web is just in a wrong place (Table 6.10). This problem may be due to lack of data as for example temperature of web. On the other hand, it is known that if there is much broke in the web the lineal pressure has to be decreased at the press section. The lineal pressures and removal of water in the press section were not included in the model.

Table 6.11 Percentage weight of the hybrid model tuning parameter K_{wa} of the heat transfer coefficient between web and air, α_{wa}.

Variable	Percentage of total sum of parameter values
Percentage of top+bottom layer, birch stock flow	-30
Wire speed	16
Sum of thick stock consistencies	14
Percentage of middle layer, broke stock flow	-13
Top+bottom layer, birch refiner, specific energy consumption	9

The heat transfer coefficient α_{wa} between the web and air at the free draw seems to be inversely proportional on percentage of birch on top or bottom layer and directly proportional to specific energy consumption of birch refining (Table 6.11). This is due to interdependence of the variables via the operation of the process where the specific energy consumption of birch refining is always high when the flow is low. The increase of speed of paper machine creates more turbulence and thus also increases evaporation. However, this was already taken into account in the physical part of the hybrid model. This may mean that the turbulence model should be also tuned. The heat transfer in the drying process depends on the stock mixture and pulp refining. This could explain why it is very difficult to predict even the direction of the moisture change.

The water removal is done on wire and on press section before drying. Typically there is no on-line sensor for the initial moisture before the drying section so that it had to be estimated from the data (Table 6.12). As mentioned earlier, the percentage of birch on top or bottom layer may make the structure on the surface of the web more porous and thus it facilitates the removal of water (Table 6.11). The specific energy consumption of birch refiner for the top or bottom layer and basis weight is known to decrease the initial moisture.

Table 6.12 Percentage weight of the hybrid model tuning parameter Kz0 of the initial moisture ratio at the beginning of the drying section (z_0).

Variable	**Percentage of total sum of parameter values**
Percentage of top+bottom layer, birch stock flow	24
Percentage of middle layer, broke stock flow	-23
Top+bottom layer, birch refiner, specific energy consumption	-19
Broke refiner, specific energy consumption	13
Base board dry basis weight	-9
Percentage of top+bottom layer, pine stock flow	-5

6.1.6. Summary of the modeling results of the board moisture

The conclusion of the results of the modeling of board moisture is that the hybrid model with parameter tuning with ICOMP is the best choice for the prediction from the tested modeling methods. The prediction of the moisture at the end of a grade change could also be performed with a very good accuracy with this model. The modeling with ICOMP in the optimization procedure makes the models more stable and the convergence rate is faster than with other approaches.

One of the findings was that retention aid change and slice opening had effect on the model that predicts the moisture at the end of grade change, but not after the first control actions. It also points out that the prediction of slice opening should be considered in the preparation phase of the grade change by using this model. The heat transfer in the drying process depends on the stock mixture and pulp refining. This could explain why it is very difficult to predict even the direction of the moisture change. This also explains at least partially why similar grade changes cannot be performed with previously used target values such as speed, stock flow and steam pressures.

6.2. Application of models to basis weight changes

Basis weight range has large variation in the board manufacture (Figure 6.7). In the used data the lowest is 113 g/m^2 and the highest 330 g/m^2 with a mean 207 g/m^2 and standard deviation of 51 g/m^2.

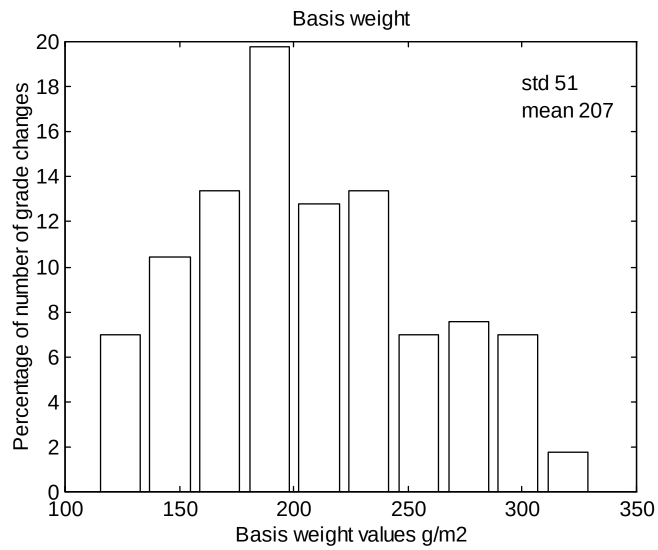

Figure 6.7 Basis weight distribution.

The standard deviation of the basis weight errors of hybrid models is better than in the first actions case (Table 6.13). The improvement was from 20 g/m^2 to 13 g/m^2 that is a 35% improvement. PLS model had much worse standard deviation than in the first actions case.

Basis weight starts to go in the wrong direction only in 5.8% of the grade changes at first actions case. The hybrid model with tuned parameters has also quite a low percentage of grade changes towards the wrong direction (8.1%). There does not exist a literature that would explicitly give a performance of a grade change of basis weight.

Table 6.13 Summary of the performance of the basis weight modeling approaches.

	PLS or Hybrid model	PLS or Hybrid model	F-test	CDF[1]
Option	**Wrong direction**	**Standard deviation**		
	%	**improvement %**		
First actions	5.8			
PLS	41.5	-49	1.49	1.30
Hybrid model	11.6	16	1.24	1.29
Hybrid model with tuned parameters	8.1	35	1.53	1.29

[1] Cumulative distribution function (CDF) value of the F-test statistic with assumption of equal variances is rejected with 95% confidence

The most significant tuning parameters of the basis weight hybrid model computed with genetic optimization are presented in Table 6.14. The output of the simple physical model is multiplied by the sum of the product of variables and factors. These factors can be interpreted as pseudo regression coefficients. The physical meaning of these factors may be related for example to the basis weight through shrinkage or elongation of the web.

Table 6.14 Tuning parameters of the physical part of the basis weight hybrid model from the genetic optimization.

Variable	**Tuning parameter, %**
Steam pressure steam group, 4	10.5
Percentage of top+bottom layer, pine stock flow	7.0
Slice opening, top-layer	6.4
Speed-to-wire speed ratio, middle layer	-6.1
Wire speed	6.0
Slice opening, bottom-layer	-5.9
Steam pressure group, 1B	-5.4
Board moisture	4.7
Thick stock flow, top-layer	-4.3
Slice opening, middle-layer	-4.2

The lower the steam pressure is at the beginning (steam group 1b) and the higher the steam pressure is near the end of the drying section (steam group 4) the larger is the basis weight change than what the physical part of the hybrid model predicts (Table 6.14). If the steam pressure at the beginning of drying section is low then the moisture is there also higher than usually. If there is an increase in the draw forces between the drive groups in the drying section, there may be a larger elongation of the web and thus the change of basis weight is also larger. This rule will only hold when the basis weight is going downwards.

Other elongation related variables are top/bottom-layer hardwood percentage, jet-to-speed ratio and speed. The hardwood fibers are shorter than softwood so that the web may be more readily elongated. Speed difference between different parts of the machine cause also elongation.

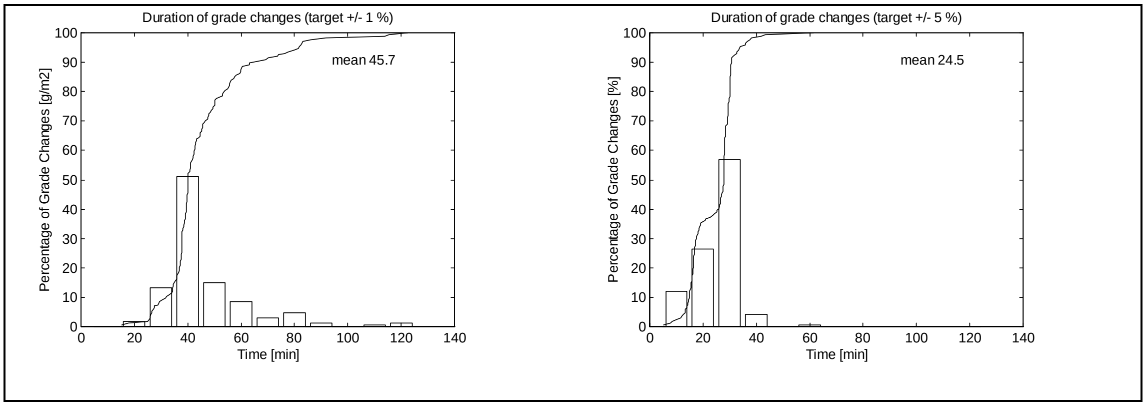

Figure 6.8 Histograms and cumulative graphs of the duration of basis weight grade changes on a board machine. The end of grade change is defined here when the basis weight has been 20 min inside 0.5 and 1% of the basis weight.

The grade change times for the basis weights are 45 min and 24 min for the acceptance ranges 1 and 5% of basis weight (Figure 6.8). The shortest grade change is 15 min (Figure 6.9). It is also assumed that the total grade change time could not decrease significantly by improvement of basis weight change alone because basis weight and board moisture are strongly dependent of each other. The grade change duration depends only a little on the prediction error of the basis weight.

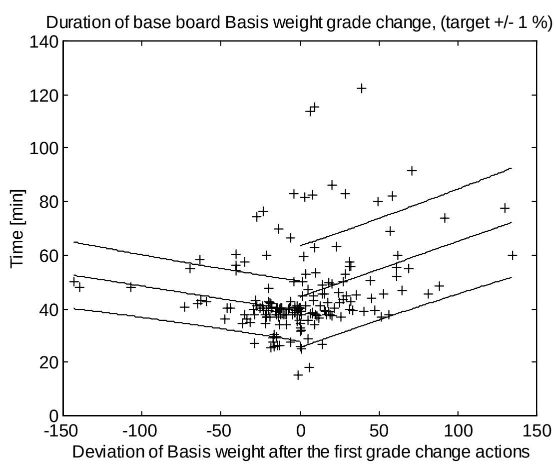

Figure 6.9 Duration of grade change as a function of basis weight errors (limit 1% of basis weight). The errors are calculated at the end of grade change.

Qualitatively it is deduced that there does not exist much potential to improve or shorten the grade change of basis weight because majority of the duration values are inside small area. This is in agreement with the opinion of paper machine operators.

6.3. Discussion of models to coat weight and coat moisture changes

The first two coaters (1 and 2) apply the coating color onto top and bottom side of the base board. The coaters (3 and 4) apply a second coating color layer after that. Thus the drying model will be different in each case. There may also be wetting with water or coating with low concentration color application instead of the usual operation. The models have to be able to handle all these combinations of operation modes.

6.3.1. Prediction of coat moisture

The distribution of coat moistures on each coater is rather similar (Figure 6.10). In that sense there should not be large differences in the modeling accuracy of modeling approaches. PLS and hybrid model on coaters number 1, 2 and 4 had lower standard deviations than measured in the first actions case (in section 5.3). The coater 3 has a much more complicated production mode structure than the other coaters has.

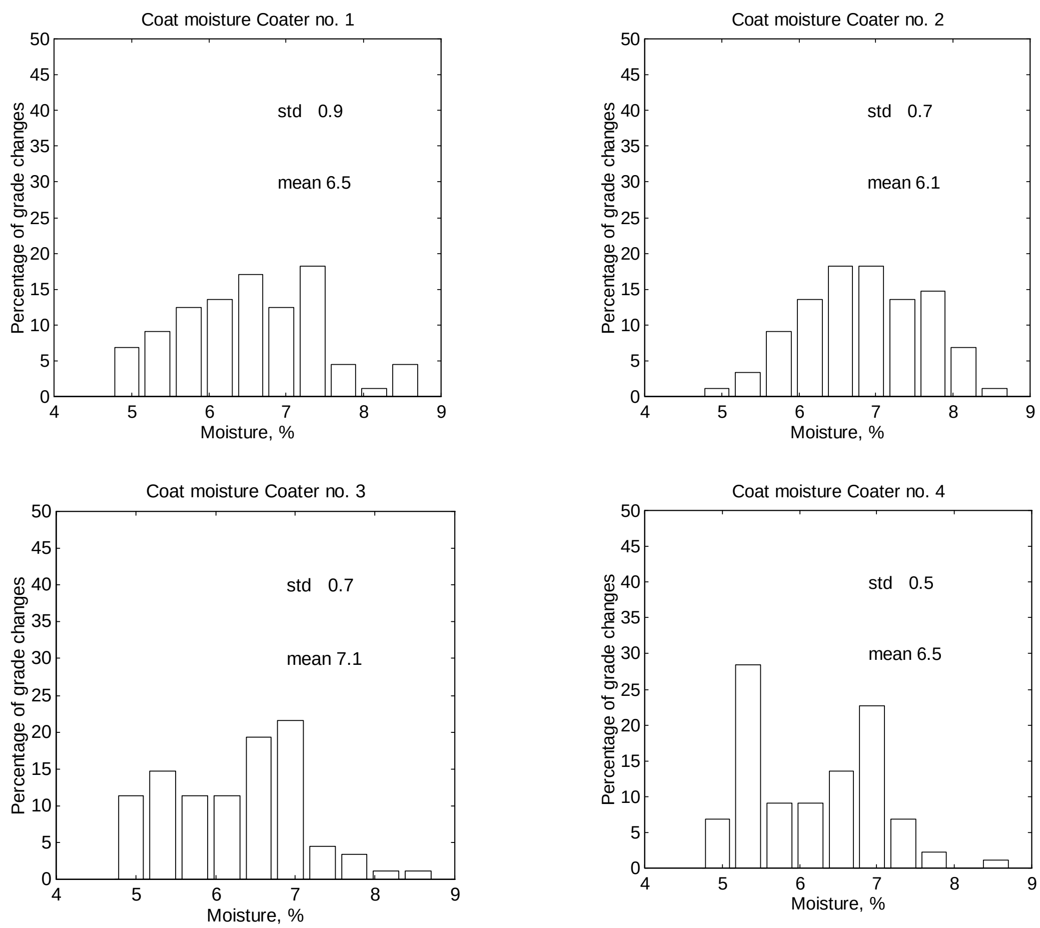

Figure 6.10 Histograms of coat moistures at the beginning of the grade change.

Table 6.15 Percentage of improvement of coat moisture of PLS and hybrid model with ICOMP.

Process	PLS Improvement of moisture std compared to first actions	Hybrid ICOMP Improvement of moisture std compared to first actions	Hybrid ICOMP Improvement of moisture std compared to PLS
	%	%	%
Coater 1	84	84	-5
Coater 2	54	52	-5
Coater 3	-8	21	27
Coater 4	27	26	-2

The standard deviations of the predictions of coat weight and the coat moisture were improved 26 to 84% with the hybrid models on coaters 1, 2 and 4 compared to the ones measured in the first actions case (Table 6.15). The hybrid model could be used for the prediction of coat moisture with good results. However, the performance of the hybrid model was almost equal to PLS except with coater 3. This problem was anticipated already during the tedious tuning of the physical model. Even though, there seems to exist proper physical models, the prediction of coat moisture does not work well enough.

It can be seen that the coater operators are able to adjust the direction of the change equally well with all the coaters (Table 6.16). Models are only better on coaters 1 and 2. This may mean that it might be difficult to get an operator acceptance and to use the model predictions.

Table 6.16 Prediction of grade change direction for coat moisture in the first actions case and with PLS and hybrid ICOMP model.

Process	First actions	PLS	Hybrid ICOMP
	Wrong direction %	**Wrong direction %**	**Wrong direction %**
Coater 1	24.7	2.2	5.6
Coater 2	23.6	10.1	7.9
Coater 3	21.3	30.3	20.2
Coater 4	22.5	24.7	25.8

It should be noted that the predictions in the wrong direction are not significant in the hybrid modeling case. It was calculated that 97% of these moisture errors (wrong direction) were between -0.5% and 0.5% (Figure 6.11).

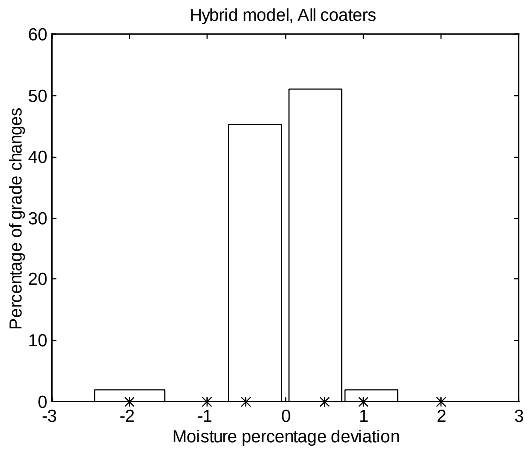

Figure 6.11 Histogram of coat moisture errors of all coaters of grade changes where the predictions were in the wrong direction.

As with the board moisture, the absolute coat moistures could not be predicted well enough from the data. It is surprising that Fisera et al. (1998) could achieve good results with only a physical model. They even mentioned that it was possible to predict evaporation rates or gel points of the coating. Their coater had much on-line instrumentation such as web temperatures so that it was easy to fit the model appropriately and they also used customized model parameters for each grade. However, they did not present any statistical data about the performance of the system.

6.3.2. Prediction of coat weight

The coat weight distributions for coaters 1, 2 and 4 are in the same range from 7 to 11 g/m^2 (Figure 6.12). They have all two modes of coating (no coating and full coating). Coater 3 does have in addition the other modes the light coating in the range from 2 to 4 g/m^2. That is one reason why it is the most difficult to model.

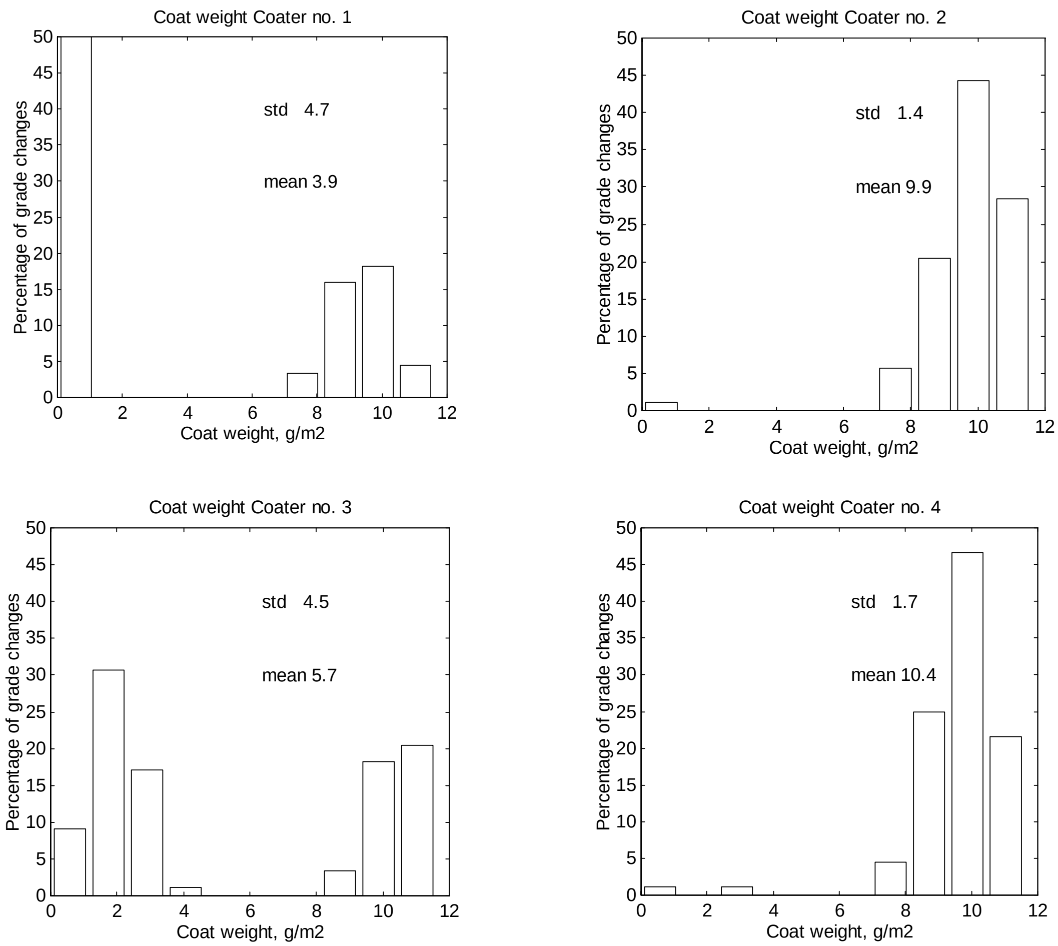

Figure 6.12 Histograms of coat weight at the beginning of grade change.

Table 6.17 Percentage of improvement of coat weight of PLS and hybrid model with ICOMP.

Process	PLS Improvement of weight std compared to first actions	Hybrid ICOMP Improvement of weight std compared to first actions	Hybrid ICOMP Improvement of weight std compared to PLS
	%	%	%
Coater 1	-82	-40	23
Coater 2	48	51	6
Coater 3	44	56	22
Coater 4	54	74	44

The hybrid model could be used for the prediction of coat weight with good results. The surprising result was that none of the models could compete with the values measured at the first actions case on coater 1. There should not be much difference with the coater 2. There is a lack of a proper physical model for coat weight but the modeling of different operation modes seems to compensate the loss.

The prediction of the right direction was much more difficult to the PLS than for the hybrid model (Table 6.18). It is should be noted that only the hybrid model with tuned parameters could predict the direction of change practically equally well as measured at the first actions case.

As a conclusion it can be stated that the hybrid model could be used for the prediction of coat weight with good results. However, the performance of hybrid model was almost equal to PLS with coater 2.

Table 6.18 Prediction of grade change direction for coat weight at the first actions case and with PLS and hybrid ICOMP model.

Process	First actions	PLS	Hybrid ICOMP
	Wrong direction %	Wrong direction %	Wrong direction %
Coater 1	12.5	23.9	11.4
Coater 2	33.3	52.3	37.5
Coater 3	23.9	34.1	21.6
Coater 4	19.3	21.6	13.6

6.3.3. Efficiency of the grade changes on coaters

Grade change in the coating section will always be dependent on the changes done to the base board due to the on-machine configuration of the board machine in question. The base board change must be nearly completed before the grade change on the coating section can start. There are also washing operations, blade changes, etc. that cannot be shortened with the means available by the proposed model assisted approach. The model can be used to the prediction of coat weight or the coat moisture or alternatively by iteration, calculation of target values as for example air dryer temperatures and blade angles.

The duration of grade changes was estimated from the measurements in the same way as the board moisture. The average length of grade change was about 96 min if the target range limit is 0.5% and 38 min if the range is 1% (Figure 6.13). The shortest change was 33 min (in the 1% range).

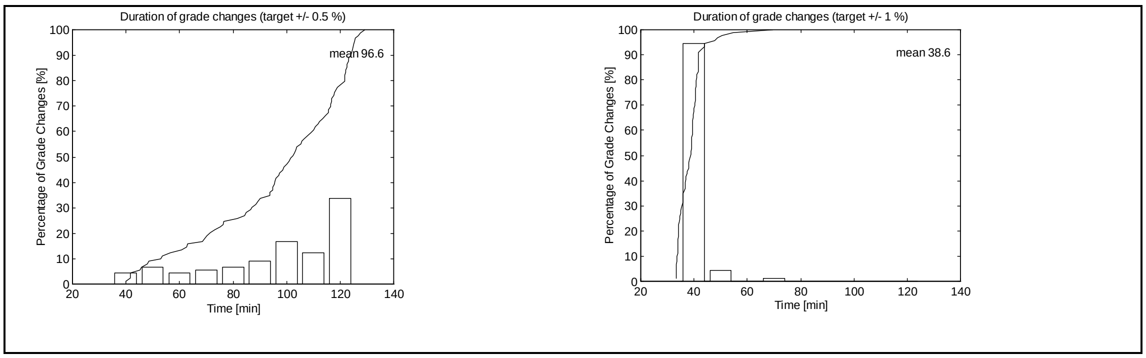

Figure 6.13 Histograms and cumulative graphs of the duration coat moisture grade changes on a board machine. The end of grade change is defined here when the coat moisture [%] has been 20 min inside 0.5 and 1% limit.

It can also be seen that duration of a grade change is not as dependent on the moisture error as in base board case (Figure 6.14). The errors are calculated as a difference compared to moisture at the end of grade change. It is assumed here that the duration of grade changes on the coaters can be decreased in ratio of the deduction of standard deviations. This was found to be roughly the case also in the board moisture. However, it is not probable that this improvement could be added directly to the time saved already with base board change. This is because the changes are done in sequence with one after another.

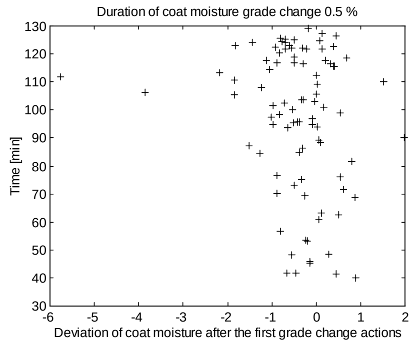

Figure 6.14 Duration of grade change as function of coat moisture errors (limit 0.5%) of base board. The errors are calculated at the end of grade change.

The duration of grade change time with coat weight is 74 min when the acceptance range is 0.5 g/m^2 and 46 min when the range is 1 g/m^2 (Figure 6.15). Coat weight and moisture depend of each other trough process and the coater operation by the personnel of the mill.

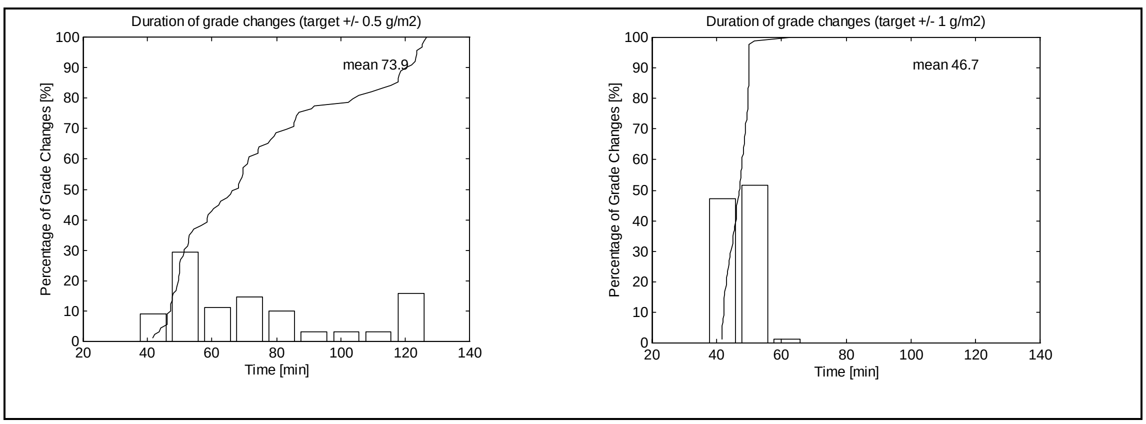

Figure 6.15 Histograms and cumulative graphs of the duration of coat weight grade changes on a board machine. The end of grade change is defined here when the coat weight has been 20 min inside 0.5 and 1 g/m^2 limit.

It can be seen qualitatively from the plot that the grade change duration and the coat weight prediction error are independent of each other (Figure 6.16). The errors are calculated as a difference compared to the coat weight at the end of grade change. The improvement of the standard deviation of the coat weight does not necessary shorten the duration of the grade change. This is due to the fact that there are many other tasks that increase the change time in addition to coat weight error as discussed with coat moisture.

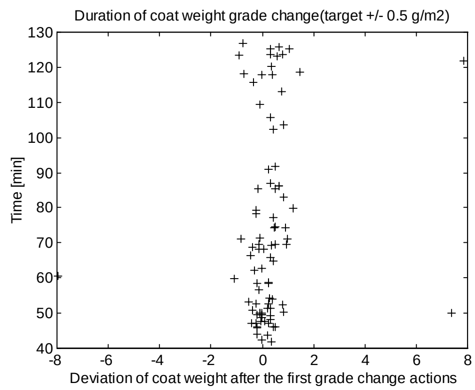

Figure 6.16 Duration of grade change as function of coat weight errors (limit 0.5 g/m^2). The errors are calculated at the end of grade change.

7. CONCLUSIONS

In this thesis a hybrid modeling concept for base board moisture, coat moisture, coat weight and a basis weight grade change from data collection to the selection of the best modeling method is presented.

The tuning of hybrid models was done with a genetic algorithm, because it gives global optimum. Also a hybrid model with tuned parameters was evaluated. In this method selected parameters of physical models were adjusted by a sum of product of tuning parameters from the genetic optimization and selected measurements in a feed-forward fashion.

The tuned parameters for the moisture of base board included for example heat transfer coefficients between steam and cylinder, cylinder and web. In addition to these, also the initial moisture ratio before drying section and the thickness of condensate layer inside drying cylinder, was tuned the same way.

The tuned parameters for the moisture of coating are rate of drainage to the web or coating from coating and heat transfer coefficient in the air-dryers of coating. Similarly the tuned parameters for the coat weight model are blade loading pressure factor, impulse pressure factor, dynamic pressure factor and dewatering coefficient to base board or coating.

The tuning procedure with finite modeling sample size of 30 grade changes, is a challenging task and there were large amount of tunable parameters compared with the number of samples used in the modeling. Especially, Information Complexity Criterion (ICOMP) was used in the loss function of the optimization scheme. It was qualitatively found to speed up the convergence of the optimization as well as to make the model more robust to the variation of modeling sample size. The parameters of models were partly tuned by using leave-one-out prediction error of empirical model (PLS) in the loss function.

The board moisture is the most important of all output variables due to the dominant effect on the total duration of grade change. The results of the modeling studies show that hybrid modeling with ICOMP is the best predictor for the moisture of base board (Table 7.1). The improvement of standard deviations of errors was 46% compared to first actions and 44% compared to PLS. The improvement at the end of grade change can be even 63% better compared with the first actions if slice opening is taken into the model. The improvement with ordinary hybrid model was 43% and with tuned parameters 28%. However, even though the model has many tunable parameters it was as easy to tune as ordinary hybrid model due to help of ICOMP in the loss function.

It was also found that the model that was tuned to predict the moisture after the first control action of grade change could not be used directly to predict the moisture at the end of grade change. This is due to slow dynamic changes taking place in the white water circulation. The amount of retention aid and the opening of the slice of the headbox had to be included in the model in order to achieve proper results.

For the coating applications hybrid modeling or hybrid modeling with tuned parameters performed very well (Table 7.1). However, there was not a significant advantage compared to hybrid with ICOMP. PLS was the best for the moisture of coating except in the third coating unit. However, ICOMP based models were at least equally good and with coater 3 ICOMP was better than PLS.

None of the modeling approaches worked well with coat weight number 1. However, improvement could be achieved with coater 2, 3 and 4. All the models seemed to work equally well with coater 2.

Table 7.1 Summary of the performance of the models.

Modeled variable	Best method	STD improvement compared to first actions %	Hybrid ICOMP STD improvement compared to first actions %	Hybrid ICOMP STD improvement compared PLS %
Moisture of base paper	Hybrid ICOMP	46	46	44
Basis weight	Hybrid param. tuning,	35	not used	not used
Moisture of coat 1	PLS	84	84	-5
Moisture of coat 2	PLS	54	52	-5
Moisture of coat 3	Hybrid model	46	21	27
Moisture of coat 4	PLS	27	26	-2
Coat weight 1	First actions	-	-40	23
Coat weight 2	Hybrid param. tuning,	51	51	6
Coat weight 3	Hybrid param. tuning,	58	56	22
Coat weight 4	Hybrid param. tuning,	77	74	44

The continuation of the research work would be to simplify the model and apply it to the MPC approach. For example, the drying section could be modeled only with five combined drying units. In order to achieve better control of the drying section, it should be possible to have more reliable on-line measurements of the incoming moisture and temperatures inside the drying section than now. There was also an indication from the literature that the physical modeling of coaters could be improved with additional instrumentation.

8. REFERENCES

Äkesson J. and Årzén K.-E. 2002. A Frame Work for Process State Transitions: Grade Changes. Preprints Regelmöte 2002, Lindköping, Sweden, pp. 379-375.

Appel D.W. and Hong S.H. 1969. Condensate Distribution and Its Effects on Heat Transfer in Steam-Heated Dryers. Pulp Paper Magazine of Canada, Vol. 40, No. 2, pp. 66-77.

Banerjee A. and Arkun Y. 1997. Model Predictive Control of Plant Transitions using a New Identification Techniques for interpolating Nonlinear Models. Preprints of ADCHEM'97, Banff, Canada, June 9-11, 1997, IFAC symposium, pp. 547-552.

Booth G.L. 1990. The Coating Machine. In: Pulp and Paper Manufacture. Vol 8.- Coating, Converting, and Speciality Processes. Editor Kocurek M.J. pp. 77-108.

Bozdogan H., 2000. Akaike's Information Criterion and Recent Developments in Information Complexity. Journal of Mathematical Psychology, Vol. 44, No 1, pp. 62-91.

Cherkassky, V. and Mulier, F. 1998. Learning from Data: Concepts, Theory, and Methods. New York: John Wiley & Sons, Inc. (Chapters 1 and 2)

Eklund D.E. 1984. Influence of Blade Geometry and Blade Pressure on the Appearance of a Coated Surface. 1984 Coating Conference, Nashville, TN, USA, May 13-16, TAPPI Press, pp. 37-43.

Eklund D.E. and Kahila S.J. 1978. Die Vorgänge inter dem Schber beim Glättschberstreichen - I. Theorie. Wochenblatt für Papierfabrikation, Vol 106, No. 17, pp. 661-665.

Fisera P., Lee L., Ladak S. and Ghofraniha J. 1998. Advanced Coating Technology Experience. Control Systems'98, Porvoo, Finland, pp. 151-158.

Gartaganis P.A., Cleland A.J. and Wairegi T. 1984. Blade Mechanics of Extended Blade Coaters, Theory and Practice. Tappi Vol. 61, No. 4, pp. 77-81.

Geladi P. and Kowalski B.R. 1986. Partial Least Squares Regression: A tutorial, Anal. Chim. Acta, 185, No. 1, pp. 1-17.

Goldberg D. E. 1989. Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wiley Publishing Company, Inc., 432 p.

Grapentine T. 1997. Managing Multicollinearity. Marketing Research, Fall 1997, pp. 11-21.

Hagberg M. And Isaksson A. J. 1995. Preface to the Special Selection on Benchmarking for Paper Machine MD-control. Control Engineering Practice, Vol. 3, No. 10, pp. 1459-1462.

Harrmann M. and Schulz S. 1990. Convective Drying of Paper Calculated with a New Model of the Paper Structure. Drying Technology, Vol. 8, No. 4, pp. 667-703.

Heikkilä P. 1992. A Study on the Drying Process of Pigment Coated Paper Webs, Ph.D. thesis. Åbo Akademi, Finland, 150 p.

Heikkilä P. and Paltakari J. 2000. Fundamentals of paper drying. In: Drying, Book 9, Part 2, Papermaking Science and Technology, Editor: Niskanen K., Finnish Paper Engineers' Association and TAPPI, Helsinki, Finland, pp. 55-83.

Heikkilä P., Timofeev O. and Kiiskinen H. 2000. Multicylinder dryer. In: Drying, Book 9, Part 2, Papermaking Science and Technology, Editor: Niskanen K., Finnish Paper Engineers' Association and TAPPI, Helsinki, Finland, pp. 84-125.

Holland, J. H. 1975. Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. Ann Arbor, MI, USA University of Michigan Press.

Höskuldsson A. 1988. PLS Regression Method, Journal of Chemometrics, Vol 6, No. 2, pp. 211-334.

Huhtelin T. 1996. Total Production Management - How to implement it, Automation Technology Review 1996, Editor Ranta J., Published by VTT Automation, Espoo Finland, pp. 6-15.

Hyötyniemi H. 1998. Summary: On linear multivariate methods. Collected Papers of the Autumn 1998 Postgraduate Seminar on Multivariate Statistical Methods in Systems Engineering. Ed. Hyötyniemi H. and Koivo H. Helsinki University of Technology, Control Engineering Laboratory, Report 112, 193 p.

Ihalainen H. and Ritala R. 1996. Optimal Grade Changes, Control Systems '96 Preprints, Chateaux Halifax, Halifax, Nova Scotia, Canada, Apr 30-May 2, pp. 213-216.

Johansen T.A. 1994. Operating Regime Based Process Modeling and Identification. Ph.D. Thesis, University of Trondheim, Norway, 224 p.

Johnston R. E. and Kirk L. A. 1970. Sub-Optimum Grade Change Procedures. Transactions of the Symposium: Papermaking Systems and their Control, Editor: Bolam F., The British Paper and Board Maker's Association, London, Vol. 1, pp. 523-538.

Kallela J. and Tuominen L. 1992. Katkoanalyysi kehittämisen välineenä, Paper and Timber, Vol. 74, No. 7, pp. 528-534. (in Finnish).

Karlsson M. 1984. On-line Study and Mathematical Modeling of a Paper Dryer Section. Dr. Thesis, Åbo Akademi.

Kemna A.K. 1993. Identification of Combined Physical and Empirical Models, Ph.D. thesis, University of California Santa Barbara, USA, 191 p.

Koivo H. and Peltonen H. 1993. Prosessimallit ja säätömenetelmät – prosessin ohjattavuus ja muunneltavuus lajinvaihdon kannalta. AEL-INSKO, Finland. (in Finnish).

Kramer M.A., Thompson M.L. and Bhagat P.M. 1992. Embedding Theoretical Models in Neural Networks. Proc. 1992 American Control Conference, pp. 475-479.

Kuni S. and Nordlund J. 1998. Board Coating with Constant Tip Angle Control. 1998 Coating/Papermakers Conference, New Orleans, LA, USA, May 4-6, TAPPI Press, Book 2, pp.777-789.

Kuusisto R., Kosonen M., Shakespeare J. and Huhtelin T. 2002. Multivariable control of paper machine grade changes. Pulp and Paper Canada. Vol. 103, No. 10, October 2002, pp. 28-31.

Lakshiminarayanan S., Shah S.L. and Nandakumar K. 1997. Modeling and Control of Multivariable Processes: Dynamic PLS Approach. AIChE Journal, Vol. 43, No. 9, pp. 2307-2322.

Lampinen M.J. and Ojala K.T. 1993. Mathematical Modeling of Web Drying. Advances in Transport Processes IX, Editors: Mujumdar A.S. and Mashelkar R.A, Elsevier Science Publishers B. V., pp. 271- 347.

Lappalainen J.T.J. 2004. Paperin- ja kartonginvalmistusprosessien mallinnus ja dynaaminen reaaliaikainen simulointi. VTT Publications 518, VTT Technical Research Centre of Finland, Espoo, Finland, 144 p. (in Finnish).

Lehtinen J. 1992. The Heat Pipe Process in Intraweb Heat Transfer in Hot-surface Paper Drying, Proceedings of The Helsinki Symposium on Alternate Methods of Pulp and Paper Drying, June 4-7, Helsinki, Finland, pp. 189-235.

Leiviskä K. and Nyberg T. 1999. Process control in paper mills. In: Process Control, Book 14, Papermaking Science and Technology, Editor: Leiviskä K, Finnish Paper Engineers' Association and TAPPI, Helsinki, Finland, pp. 147-197.

Lindskog P. and Ljung L. 1994. Tools for Semi-Physical Modeling. Preprint of IFAC Symposium on System Identification, Copenhagen, Denmark, July 1994, Volume 3, pp. 237-242.

Luomi S. 1991. Päällysteseoksen applikointi ja päällystemäärän säätö teräpäällystyksessä. Paper and timber Vo. 73, No. 9, pp. 833-839.

MacGregor J.F. and Kourti T. 1995. Statistical Process Control of Multivariate Processes, Control Engineering Practice, 3, No. 3, pp. 403-414.

Mallows C.L. 1973. Some comments on Cp, Technometrics Vol. 15, No 4, pp. 661 - 675.

Mäkinen J., Rajala P. and Nuyan S. 1998. Optimization of Drying of Coated Paper by means of Automation. 1998 Coating/Papermakers Conference, New Orleans, LA, USA, May 4-6, TAPPI Press, Book 1, pp. 159-166.

McQuillin D. and Huizinga P. W. 1994. James River cuts Grade Change Time with Automated, Predictive Controls. Pulp & Paper, September, pp. 143-146.

Meinander P.O. and Olsson L-H. 1998. Compact, Airless, Hydraulic Back Water Circulation with Centrifugal Deaeration. The Second ECOPAPERTECH conference, Helsinki, Finland, June 1-5. pp. 113-123.

Miyanishi T., Iida K. and Iwatsu T. 1988. Dynamic Simulation for Efficient Paper Machine Grade Change. Tappi Journal, Vol. 71, No. 1, pp. 49-56.

Mori Y., Shimitsu H. and Takao K. 2000. Development of a new automatic grade change control system for paper machine. Control Systems, Preprints, Conference, Control Systems 2000 'Quantifying the Benefits of Process Control', p. 231-234.

Murphy T.F. and Chen S.-C. 2000. Fast Grade Change for Papermaking Process. Control Systems, Preprints, Conference, Control Systems 2000 'Quantifying the Benefits of Process Control', p. 189-192.

Nederveen C.J., van Schaik-van Hoek A.L. and Dijkstra J.J.F.M. 1991. Present Theories on Multi-Cylinder Paper Drying, Proceedings of The Helsinki Symposium on Alternate Methods of Pulp and Paper Drying, June 4-7, Helsinki, Finland, pp. 23-41.

Nuyan S., Fu C. and Bale S. 1997. Coater Start-up Optimization, 1997 TAPPI Advanced Coating Fundamentals Symposium. Philadelphia, PA, USA, May 9-10, 1997. pp. 149-157.

Ohshima M., Hashimoto I, Yoneyama T., Takeda M. and Gotoh F. 1994. Grade Transition Control for an Impact Copolymerization Reactor. Preprints of ADCHEM’94, Kyoto, Japan, May 25-27, 1994, IFAC symposium, pp. 507-512.

Ojala K. T. 1993. Studies on Infrared Drying of Paper, Use of Integrating Spheres in FTIR Measurements, and Heat and Mass Transfer inside Paper. Ph.D. thesis. Helsinki University of Technology, Espoo, Finland.

Paltakari J. 1995. Koelaite ja menetelmä paperin kuivatusteknisten parametrien määrittämiseksi. Lic. Thesis. Helsinki University of Technology, Espoo, Finland.

Paltakari J. 2000. Internal and External Factors Affecting the Paper Drying Process. Doctoral thesis. Helsinki University of Technology, Espoo, Finland.

Pekkarinen T. Kaunonen A. and Paavola J. 1999. New Approach to Wet End Management. Paper and Timber, Vol. 81, No. 1. pp. 40-44.

Psichogios D.C. and Ungar L.H. 1992. Process Modeling using Structured Neural Networks. Proc. 1992 American Control Conference, pp. 1917-1921.

Ranta J., Ollus M. and Leppänen A. 1992. Information Technology and Structural Change in the Paper and Pulp Industry, Computers in Industry, 20, pp. 255-269.

Roihuvuo, J. 1986. Paperikoneen kuivatusosan ja sen säätötapojen dynaaminen mallintaminen ja simulointi, Masters thesis, Tampere University of Technology, Finland , 84 p. (in Finnish).

Smail M., Koivo H., Huhtelin T. ja Kuusisto R. 1998. Dynamic Modelling of Paper

Machine from Grade Change Data, Control Systems'98, Porvoo, Finland, pp. 79-86.

Smook G.A. 1992. Handbook for pulp and paper technologist, Angus Wilde Publications, Canada, 419 p.

Soininen M. 1991. Modeling of Web Drying, Proceedings of The Helsinki Symposium on Alternate Methods of Pulp and Paper Drying, June 4-7, Helsinki, Finland, pp. 7-22.

Soininen M., Karlsson, M., Paltakari, J. 1991. Kuivatusosan simulointimallin kehittäminen paperikoneen käyttäjän tarpeisiin, RAINA- seminaari 1991 no 6 (in Finnish).

Sorsa T., Koivo H.N. and Korhonen R. 1992. Application of Neural Networks in the Detection of Breaks in a Paper Machine. IFAC Symposium: On-line Fault Detection and Supervision in the Chemical Process Industries, Newark, Delaware, USA, April 22-24, pp. 162-167.

Sugiyama M. and Ogawa H. 2001. Subspace Information Criterion for Model Selection. Neural Computation Vol. 13, No. 8, pp. 1863-1889.

Sun D. and Kosanovich K. A. 1997. Transition Control for Time-dalayed Systems. Proceedings of the American Control Conference, Albuquerque, New Mexico, USA, June 1997, pp.3210-3214.

Tessier P., Broderick G, Desrochers C. And Brussière S. 1998. Refiner Pulp Prediction and Control using PLS Transforms. Control Systems'98, Porvoo, Finland, pp. 160-167.

Thompson M.I. and Kramer M.A. 1994. Modeling Chemical Processes using Prior Knowledge and Neural Networks. AIChE Journal Vol. 40, No. 8, pp. 1328-1340.

Välisuo H. 1997. Managing Grade Changes and Other Transitions in Paper-board Production, CD ROM, ISBN 952-5183-07-6, Automation 97, Finnish Society of Automation, Helsinki, Finland, 23-25.9.1997.

Välisuo H., Ventä O., Smolander A., Viitamäki P, Laukkanen I, Niemenmaa A., and Juslin K. 1996. Managing Grade Changes in Paper Production by using Modern Process Control Techniques, Automation Technology Review 1996, Editor Ranta J., Published by VTT Automation, Espoo Finland, pp. 16-30.

Viitamäki P. 1993a. Grade Change on a Paper Machine, Automation Days -93, Finnish Society of Automation, 11-13.5.1993, Helsinki, Finland, pp. 241-243, (in Finnish).

Viitamäki P. 1993b. Grade Change on a Paper Machine, Proceedings of the 12th International Conference on Production Research, 16-20 August, 1993, Lappeenranta, Finland, pp. 587-588.

Viitamäki P. 2001. Hybrid Modeling of Moisture in Paper Machine Grade Changes. Pulp & Paper Canada, Vol. 102, No. 7, pp. T193-196.

Viitamäki P. 2003. Hybrid modeling of paper machine grade changes. Paperi ja Puu, Vol. 85, No. 1, pp. 33-36.

Viitamäki P., Välisuo H. and Ventä O. 1995. Information Technology Based Grade Change in the Process Industry, Automation Days, Finnish Society of Automation, Helsinki, Finland, 3-5.5.1995, pp. 355-357, (in Finnish).

Viljamaa P., Peltonen H. And Koivo H.N. 2001. Estimation of Target Values for Grade Changes in Paper Machine. Industrial Applications of Soft Computing. Editor Kauko Leiviskä, Physica- Verlag, Germany. pp. 211-220.

Wilhelmsson B. 1995. An Experimental and Theoretical Study of Multi-Cylinder Paper Drying, Ph.D. thesis. Lund University, Sweden, 172 p.

Wilson J.A. and Zorzetto L.F.M. 1997. A Generalized Approach to Process State Estimation using Hybrid Artificial Neural Network/Mechanistic Models. Computers in Chemical Engineering, Vol. 21, No. 9, pp. 951-963.

Wise B.M. and Gallagher N.B. 1996. PLS_Toolbox for use with Matlab™, Eigenvector Technologies, WA, USA, 172p.

APPENDIX A: LIST OF VARIABLES AND PARAMETERS

In this appendix the list of variables that used for the modeling of moisture, basis weight, coat moisture and coat weight.

Table 8.2. The scope of collected variables from the refiners to the calanders

Name
Top+bottom layer, birch refiner, specific energy consumption
Top+bottom layer, birch refiner, power
Etc…
Broke refiner, specific energy consumption
Broke refiner, power
Top+bottom layer, birch stock flow
Top+bottom layer, pine stock flow
Middle layer, birch, stock flow
Middle layer, pine stock flow
Middle layer, broke stock flow
Top+bottom layer, birch, refining consistency
Top+bottom layer, pine refining consistency
Stock starch top+bottom layer
Stock starch, white water, 1.layer
Neutral size, headbox,3.layer
Retention agent, 1-layer
Middle layer headbox consistency
Middle layer headbox slice opening
Middle layer headbox pressure
Middle layer headbox jet-to-wire ratio
Top layer-wire speed
1-press, lineal pressure …
4-press, lineal pressure
Steam group, 1A, measurement
Steam group, 1A, setpoint
Etc….
Steam group, 5 ,measurement
Steam group, 5, setpoint
Steam group, 5, controller output
Steam group, 7 low cylinder
Steam group, 8.1 lower cylinder pressure
Condensate, total
Machine running, web broken
Break at wet pressing
Break at 1,2 drying group
Break at 3,4 drying group
Break after size press
Break at 1. Calander

Selection of variable with PLS loadings

PLS loadings were especially useful in order to consider the significance of the variables (Table 8.3). In addition to previously selected variables, calculated descriptors were included in the analysis. For example estimated dry basis weight (calculated from stock consistencies, stock flows, machine speed and machine width) and dry production rate were chosen for further analysis. The genetic variable selection algorithms from the PLS Toolbox were also applied to select variables (Wise and Gallagher 1996) and it produced almost the same set as was assembled by hand.

The variables with the highest absolute values of loadings of manipulated variables in the three first principle components are shown in (Table 8.3). The grouping done by loadings can sometimes be interpreted to have a physical meaning as for example the one in the first primary component could be called 'Drying effort'. The grouping changes if the number of variables is modified and the naming presented here is of course subjective and has been given in order to give an interpretation of each principal group.

Table 8.3. The most important variables sorted by the loadings of the first three principal components (pc).

Drying effort	**pc 1 loadings**	**Amount of Water**	**pc 2 loadings**	**Evaporation Resistance**	**pc 3 loadings**
Steam Pressure change 3	0.214	Moisture Content	-0.253	Top+bottom layer softwood %	0.260
Steam Pressure change 4	0.214	Base moisture %	-0.226	top+bottom layer hardwood % change	0.248
Steam Pressure change 5	0.213	Bone dry production rate	-0.224	Top+bottom layer hardwood %	-0.247
Steam Pressure change 3	-0.204	Mass flow change	-0.220	Broke % (middle layer)	0.232
Steam Pressure 4	-0.199	Production rate change	-0.219	Hardwood % (middle layer)	-0.228
Steam Pressure 5	-0.199	Base moisture setpoint	-0.218	Wire speed change	-0.220
Bone dry production rate	0.197	Basis weight	-0.218	Basis weight change	0.219
Wet sizing change	0.195	Wire speed	0.218	Dry basis weight change	0.219
Broke % change(middle layer)	0.190	Wire speed change	-0.217	Steam Pressure change 1	0.210
Steam Pressure 2	-0.190	Dry basis weight	-0.209	Wet sizing %	0.200

The selection of variables by using PLS loadings of variables is an iterative process (Figure 8.17). First PLS modeling is applied to the initial set of variables. Cross-validation should be executed in order to discover the optimum number of latent variables as instructed in the PLS Toolbox manual (Wise and Gallagher 1996). Then the variable loadings and variables are sorted in descending order according to absolute values of loadings in each primary component. Finally the set of variables are selected according to the loadings and the prior knowledge.

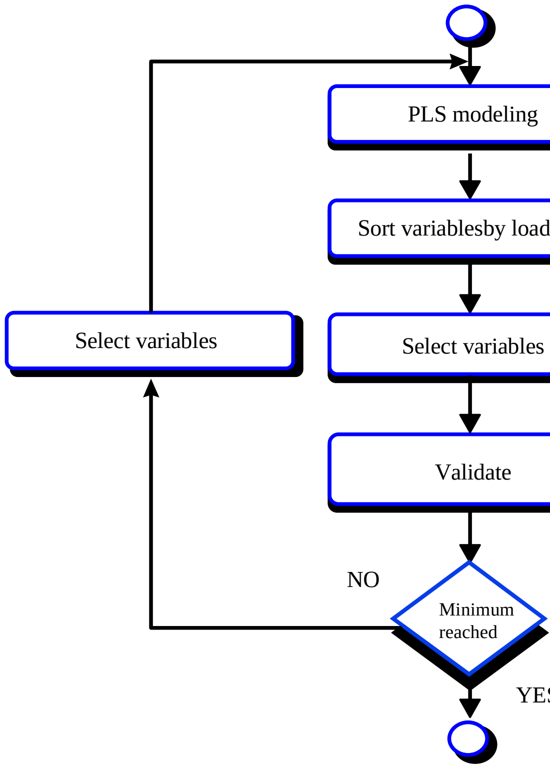

Figure 8.17. Selection of variables by using PLS loadings

Table 8.4. List of the selected process variables for the adaptive tuning of parameters of the simple physical moisture model of base board.

Name	Comments
Base board moisture	
Base board dry basis weight	Calculated from basis weight and board moisture
Wire speed	
Total sum of flows to the headbox	
Bone dry production rate	
Percentage of top+bottom layer, pine stock flow	Percentage based on total flows
Percentage of top+bottom layer, birch stock flow	Percentage based on total flows
Percentage of middle layer, broke stock flow	Percentage based on total flows
Sum of thick stock consistencies	Summation of the consistency of each layer
Broke refiner, specific energy consumption	
Top+bottom layer, birch refiner, specific energy consumption	
Top+bottom layer, pine refiner, specific energy consumption	
Middle layer, birch refiner, specific energy consumption	
Middle layer, pine refiner, specific energy consumption	
Retention agent, total	Summation of the proportioning of each layer
Steam pressure group, 1A	
Steam pressure group, 1B	
Steam pressure steam group, 2	
Steam pressure steam group, 3	
Steam pressure steam group, 4	
Steam pressure steam group, 5	
Top layer headbox slice opening	
Headbox pressure, top layer	
Headbox pressure, middle layer	
Headbox pressure, bottom layer	
Slice opening, top-layer	
Slice opening, middle-layer	
Slice opening, bottom-layer	
Thick stock flow, top-layer	
Thick stock flow, middle-layer	
Thick stock flow, bottom-layer	
Speed-to-wire ratio, top layer	
Speed-to-wire ratio, middle layer	
Speed-to-wire ratio, bottom layer	

Table 8.5. List of adaptively tuned parameters of the hybrid model of board moisture.

Name
K_{sp0} parameter of the heat transfer coefficient between cylinder and the web (α_{CW1})
K_{wa} parameter of the heat transfer coefficient between the web and air at the free draw (α_{wa})
K_{co} parameter of the heat transfer coefficient between condensate and cylinder (α_c)
K_d parameter of the condensate thickness (d_c)
K_{z0} parameter of the initial moisture ratio at the beginning of the drying section (z0)

Table 8.6. List of variables that are used for the adaptive tuning of the simple physical models of the coat moisture and coat weight.

Name	Comments
Base board moisture (before coaters)	
Base board dry basis weight (before coaters)	Calculated from the basis weight and moisture
Wire speed	
Top layer headbox jet-to-wire ratio	
Middle layer headbox jet-to-wire ratio	
Bottom layer headbox jet-to-wire ratio	
Bone dry production rate	
Percentage of top+bottom layer, pine stock flow	Percentage based on total flows
Percentage of top+bottom layer, birch stock flow	Percentage based on total flows
Percentage of middle layer, broke stock flow	Percentage based on total flows
Top+bottom layer, birch refiner, specific energy consumption	
Top+bottom layer, pine refiner, specific energy consumption	
Soft calander a pressure	
Soft calander b pressure	
Soft calander a temperature	
Soft calander b temperature	
Amount of surface sizing	$c_s q_s/v$ where c_s and q_s are concentration and flow of sizing and v is the machine speed
Coat dry basis weight, coater1 (before coating 1)	Calculated from the coat weight and the coat moisture
Coat dry basis weight, coater2 (before coating 2)	Calculated from the coat weight and the coat moisture
Coat dry basis weight, coater3 (before coating 3)	Calculated from the coat weight and the coat moisture
Coat dry basis weight, coater4 (before coating 4)	Calculated from the coat weight and the coat moisture
Coat moisture, coater1 (before coating 1)	
Coat moisture, coater2 (before coating 2)	
Coat moisture, coater3 (before coating 3)	
Coat moisture, coater4 (before coating 4)	
Burning air 1 used	Binary
Burning air 2 used	Binary
Burning air 3 used	Binary
Burning air 4 used	Binary
burning air 5 used	Binary
Burning air 6 used	Binary
Coating blade 1 running time	
Coating blade 2 running time	
Coating blade 3 running time	
Coating blade 4 running time	

Table 8.7. List of adaptively tuned parameters with the process variables in the hybrid model of coat moisture.

Name	Comments
K_{co} parameter of the heat transfer coefficient between condensate and cylinder (α_c)	
Kc_{wd} parameter of drainage coefficient from the coating color to the web	All coater units
$K\lambda$ parameter of convective heat transfer coefficient of the impingement air in the air drying of coating	All coater units

Table 8.8. List of adaptively tuned parameters with the process variables in the hybrid model of coat weight.

Name	**Comments**
K_{cd} parameter of the dewatering coefficient to base board or coating	All coater units
K_{Fz} parameter of the blade loading pressure factor for each blade	Coater units with beveled blades
K_{Fi} parameter of the blade impulse pressure factor	Coater units with low angle blades

APPENDIX B: MODELS OF DRYING OF PAPER

The most important heat transfer coefficients are paper web contact with cylinder α_{cw}, a condensate heat transfer coefficient α_{sc} and heat (mass) transfer coefficient from the surface of the web α_{wa}. The heat transfer coefficient through cylinder cell wall α_c is assumed to be constant although it is susceptible to dirt and rust that change it. The overall heat transfer coefficient α_{all} can be calculated with the equation

$$\frac{1}{\alpha_{all}} = \frac{1}{\alpha_{sc}} + \frac{1}{\alpha_c} + \frac{1}{\alpha_{cw}} \tag{1.1}$$

The total heat flow from steam to the web is the calculated with

$$q_{tot} = \alpha_{all}(T_s - T_w) \tag{1.2}$$

where T_w is the web temperature and T_s is steam temperature estimated from steam pressure with a known approximation $T_s = 100\sqrt[4]{(P_s + P_a)/100)}$ where P_s is steam pressure (Pa) and P_a is ambient air pressure (101.325 Pa)

The temperatures of cylinders T_c at the web contact can be calculated to be in average

$$T_c = T_s - \frac{q_{tot}}{1/(1/\alpha_{sc} + 1/\alpha_c)} \tag{1.3}$$

It is assumed that about 10% of the heat is loss via the heads of the cylinders or some other way (Ojala 1993) and this is taken into account when calculating the change in the web temperature during the contact with the cylinder

$$\Delta T_w = t_c(q_{tot} - q_{ev} - q_{lost})/(W_{odbw}C_z) \tag{1.4}$$

where t_c time of contact with the cylinder, q_{tot} heat transferred to the web from steam, q_{ev} heat lost due to the evaporation of water, q_{lost} heat losses, W_{odbw} oven dry basis weight and C_z density of web.

When the web moisture is calculated the evaporation from the web surface is calculated. This means that the initial temperature and moisture of the web must be known or estimated before this model can be used. The evaporation and heat transfer coefficients are presented in the following chapters.

Evaporation from the surface of paper web

There exists several different theories of contact drying of a paper web. A fairly recent review of the theories is in Nederveen *& al* (1991). However, a very thorough representation of the theories and modeling methods of the drying of web is discussed in the new book by Finnish Paper Engineer's Association (Heikkilä and Paltakari 2000, Heikkilä et. al. 2000).

The driving force of evaporation is assumed to be a combination of several mechanisms. The most important is assumed to be Stefan diffusion, where the average pore diameter is essentially higher than the free travel length of a water molecule and the partial pressure of the water vapor is essentially below the total pressure (Heikkilä 1992). When the average pore diameter is below the free travel length of a water molecule then it is question about Knudsen diffusion. Thus the movement of molecules is controlled mainly by the collisions with the pore walls. The driving force is assumed to be partial of total pressure gradient (Heikkilä 1992).

Other approaches include enthalpy-difference approach by Soininen (1991), Darcy-flow induced by a pressure gradient by Lehtinen (Nederveen *& al* 1991), thermodynamical surface energy and vapor or gas pressure as described by Lampinen & Ojala (1993) and laminar (Hagen-Poiseuille) flow, when vapor partial pressure is close to or equal with the total pressure. The driving pressure is then the total pressure gradient inside the porous material (Heikkilä 1992).

A more recent theory considers the mechanism as a heat pipe that has been proposed by Lehtinen (1992). Also it should be remembered that actual physical reformations as shrinkage may cause additional vapor transport (Harrmann and Schulz 1990).

Many of the theories above will lead to models with numerous parameters that are difficult or impossible to estimate from the drying process. However, it has been shown in Nederveen & al. (1991) that almost all the models give the same evaporation rate. That is why the simplest of the models (Stefan diffusion) was chosen as the approach taken in this thesis. Stefan diffusion can be modeled as a descending front model with a modified linear Stefan equation.

$$\frac{\dot{m}_h}{A} = K_{kc1} C \alpha_{wa} K_{kc2} K (p_p - p_a) \tag{1.5}$$

where $\frac{\dot{m}_h}{A}$ is the evaporation rate per area [kg/s/m^2], α_{wa} is the heat transfer coefficient, C is an initial tuning parameter, K_{kc1} is tuning parameter for the hybrid model, p_a is partial vapor pressure in the saturated air and p_p is partial vapor pressure on the web surface and K is the initial diffusion resistance of dry layer below critical moisture point (Heikkilä 1992) and K_{kc2} is the corresponding tuning parameter for the hybrid model.

When the moisture ratio of the web has reached a certain value (critical value, x_{cri}) the evaporation will change to a falling rate zone. It is modeled as a descending front model with a modified linear Stefan equation.

$$\frac{\dot{m}_h}{A} = \frac{K_{kc1} C \alpha_{wa} K_{kc2} K}{K_{kc1} C \alpha_{wa} + K_{kc2} K} (p_p - p_a) \tag{1.6}$$

where $\frac{\dot{m}_h}{A}$ is the evaporation rate per area [kg/s/m^2], α_{wa} is the heat transfer coefficient, C (7.03*10-4 kgH_2O °C/W/s) is an initial tuning parameter, K_{kc1} is tuning parameter for the hybrid model, p_a is partial vapor pressure in the saturated air and p_p is partial vapor pressure on the web surface and K (0.2) is the initial diffusion resistance of dry layer below critical moisture point (Heikkilä 1992) and K_{kc2} is the corresponding tuning parameter for the hybrid model.

The initial values for the heat transfer coefficient, α_{wa} (W/m$^{2\circ}$C) from the web to the air at the free draw is (Karlsson 1984)

$$\alpha_{wa} = K_{wa} 5.3 v^{0.46} \tag{1.7}$$

where K_{wa} is the tuning parameter of the hybrid model and v is the machine speed.

Partial vapor pressure in the evaporation plane (p_p) in the previous equations can be calculated with the help of relative humidity (φ) and Antoine's equation (Soininen *& al.* 1991).

$$p_p = p_0 \varphi \tag{1.8}$$

where p_0 is vapor partial pressure for free water.

Antoine's equation gives p_0 as a function of temperature.

$$p_0 = 10^{(5.127 - \frac{1690}{T})} \tag{1.9}$$

Because a paper web is a hygroscopic material the vapor partial pressure is a function of local moisture, z and temperature inside the web, T' (Heikkilä and Paltakari 2000). The relative humidity $\varphi(z,T')$ is formulated as a function of moisture and temperature.

$$\varphi(z,T') = 1 - e^{-mz^n} \tag{1.10}$$

For example, m and n are for fine paper according to Paltakari (1995).

$$\begin{aligned} m &= a + bT' = K_{w1} 285.65 + K_{w2} 1.670 T' / {}^oC \\ n &= c + dT' = K_{w3} 2.49 - K_{w4} 0.020 T' / {}^oC \end{aligned} \tag{1.11}$$

The conditions inside the hood (temperature, humidity, turbulence, etc.) have a great effect on the evaporation. However, there does not exist online measurements that are reliable enough to be used in the modeling, because for example moisture ratio measurement drifts due to fouling. These conditions are taken into account by utilizing a special measurements done in the paper machine earlier.

Heat of sorption can be calculated with Clausius-Clayperon law:

$$\Delta h_s = -R_v \left[\frac{d(\ln \varphi)}{d(\ln 1/T)} \right]_{X=const} \tag{1.12}$$

When equations (1.11) and (1.12) are combined we get (Heikkilä 1992).

$$\Delta h_s = -R_v \frac{1-\varphi}{\varphi} 0.10085 z^{1.877} T^{1.0585} \tag{1.13}$$

Paper web contact with cylinder

Paper web contact heat transfer coefficient with cylinder surface α_{cw} has been found to be a function of several variables. For example paper moisture, web tension, paper surface smoothness, thermal conductivity of web, use of press roll and air or steam film accumulation between the web and dryer surface have been reported to be among the most important factors (Heikkilä and Paltakari 2000).

Moisture is one the most significant variables, because there is a direct contact from cylinder to water when there exist water on the surface of the web. The heat transfer coefficient between cylinder and the web α_{cw} becomes smaller, when the moisture gradually decreases from the contact surface due to diminishing of the heat conductivity and the contact surface area. The following equation for the heat transfer coefficient (α_{cw}) is achieved by fitting a nonlinear function to the graph originally presented by Appel and Hong (1969) and used also in Roihuvuo (1986):

$$\alpha_{CW1} = K_{sp0}(54.7z^{0.25} + K_{sp1}102.5z^{0.33} + K_{sp2}9.18z^{0.5} + K_{sp3}66.6) \tag{1.14}$$

where z is the moisture ratio of the web, K_{sp0}- K_{sp3} are tuning parameters.

This is not a physical model but it is put in the same group because it quite widely accepted model and there does not exits a better simple model.

Condensate heat transfer coefficient

The properties of the condensate layer on the inside surface of the cylinder mainly determines the amount of heat that is transferred to cylinders. Especially hydrodynamics, distribution around the cylinder and thickness of the condensate layer are the most significant factors for the modeling of the heat transfer coefficient from steam to cylinders. The hydrodynamics of the condensate layer are effected by machine speed, cylinder diameter and spoiler bars installed inside cylinder. For the details of condensate flow the reader is referred to a recent study by Wilhelmsson (1995).

Heikkilä (1992) used the following empirical equations for the condensate heat transfer coefficient:

$$\begin{aligned} \alpha_c &= K_{c0}\left(\frac{685}{K_d d_c} + \frac{10^6}{275 + K_{c1}0.675v^{2.79} + K_{c2}0.0486K_d d_c v^{3.39}}\right) \\ \alpha_{cb} &= K_{c3}\alpha_c(5700 + 60v)/6000 \end{aligned} \tag{1.15}$$

where v is machine speed (m/min), K_{c0} - K_{c03} and K_d are tuning parameters of the hybrid model, d_c is the condensate thickness (mm) and α_{cb} is the correction for condensate heat transfer coefficient with cylinder bars.

APPENDIX C: MODELS OF DRYING OF COATING

Drainage of liquid of the coating color into the web

The moisture of the web is increased during the coating due to drainage of liquid of the coating color as explained in the modeling of coating according to Lucas-Washburn theory (Heikkilä 1992). The amount of liquid that is drained into the web is calculated from the the amount of deposited coating by dividing with the moisture ratio of the coating.

$$\frac{m_{wd}}{A} = \frac{\sqrt{K_{cwd} c_d (100 - X_c) / v}}{x_{cc}} \tag{1.16}$$

where m_{wd} / A is drained liquid weight per unit area, c_d is the drainage coefficient, K_{cwd} the corresponding parameter of the hybrid modeling, X_c is moisture percentage of the coating color, x_{cc} is the moisture ratio of the coating color and v is the machine speed (inversely proportional to time of dewatering).

The models are very simple, but they satisfy the requirements that there exist only a minimum amount of unknown parameters and most of the information is available as measurements from the coater section. Similar models have been tried to give insight about the drying phenomena on a coater (Fisera et al. 1998).The initial parameters of the models are taken from the literature and then fine tuned with separate parameters in the optimization like in the paper drying.

IR drying of coating

IR burners have been extensively modeled by Ojala (1993). The IR emitter's radiation spectrum, the absorption properties of dried surface and the heat losses define how much heat is transferred to the web. Energy is lost for example with flue gas escaping the emitter.

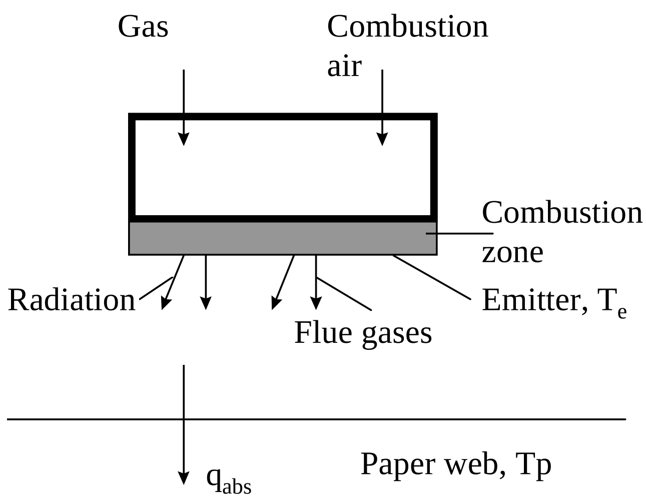

Figure 8.18. A schematic diagram of a gas burner

In practice the spectrums are not known on-line so that a simplified approach must be taken. equation for the calculation of the radiative heat transfer rate (q_{abs}) is given in Heikkilä (1992):

$$q_{abs} = K_\eta \eta_{abs} \frac{P_{input} / w}{I_{eff}} \tag{1.17}$$

where, P_{input} is the input power to the emitter, w is unit width, I_{eff}

is the length of the emitter in machine direction, η_{abs} is the overall radiation efficiency and K_η is the corresponding tuning parameter of the hybrid model.

Moisture is assumed to follow the modified Stefan diffusion equation the same way as in the paper web. The evaporation is assumed to be similar to the cylinder drying due to higher turbulence conditions that is reviewed in the air drying of coating chapter.

Air drying of coating

Air drying is the phase where most of the evaporation takes place. Thus it is the most decisive section when considering the final moisture. Heikkilä (1992) studied the effect of impingement velocity of different air dryer nozzles on heat transfer. He found the following equation of convective heat transfer coefficient to fit to the air drying very well:

$$\alpha_{conv} \approx K_\lambda \lambda \nu^{-0.75} \Pr^{1/3} \tag{1.18}$$

where ν is kinematic viscosity, Pr is Prandtl number, λ is thermal conductivity and K_λ is the corresponding tuning parameter of the hybrid model.

It is assumed that the impingement air temperature is higher than the web surface. Thus the vapor is heated to the temperature of the turbulent bulk flow (T_f) when it diffuses from the web surface through the laminar film (Figure 8.19). Laminar film temperature can be calculated by $T_f \approx (T_a+T_s)/2$ or more accurately

$$T_f \approx T_a - \frac{\alpha_{conv}(T_a - T_s)}{\frac{\dot{m}_a}{A} c_{pa}} \tag{1.19}$$

where $\dot{m}_a / A$ is the specific air flow rate per m^2 of web, c_{pa} is specific heat of the impinged air, T_a is temperature of the air, T_f is laminar film temperature and T_s is the temperature of the coating surface (Figure 8.19).

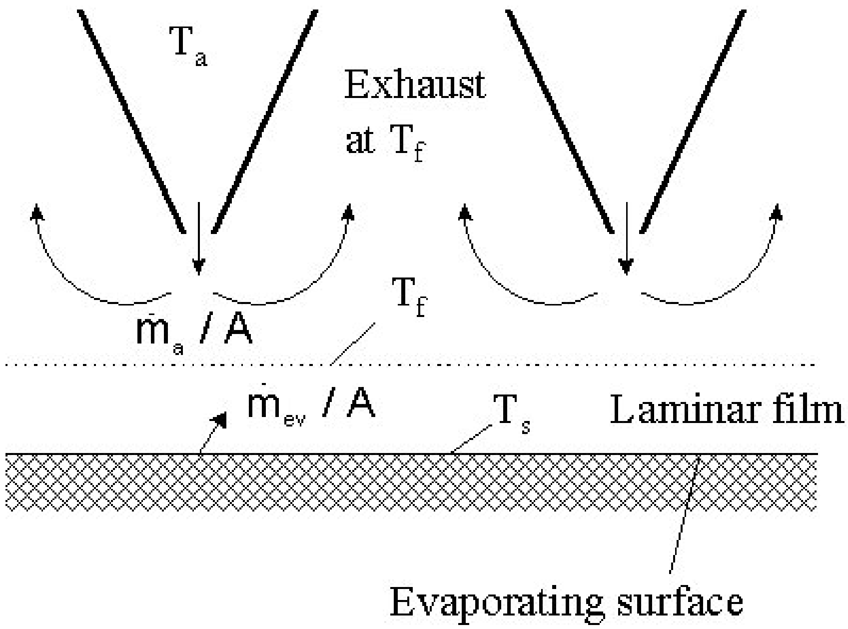

Figure 8.19. The laminar boundary film.

APPENDIX D: MODELS OF COAT WEIGHT

First a static layer of coating is formed due to dewatering according to Lucas-Washburn theory (Heikkilä (1992). It can be stated loosely that the thickness of a coating is proportional to a square root of application solids content and a square root of drainage time according to equation

$$\frac{m_d}{A} = \sqrt{K_{cd} c_d (100 - X_c) / v} \qquad (1.20)$$

where $\dot{m}_d / A$ is drained coating weight per unit area, c_d is the drainage coefficient, K_{cd} the corresponding parameter of the hybrid modeling, X_c is moisture percentage of the coating color and v is the machine speed (inversely proportional to time of dewatering).

Coating will start forming immediately when the coating color is applied to the surface of the web (Figure 8.20).

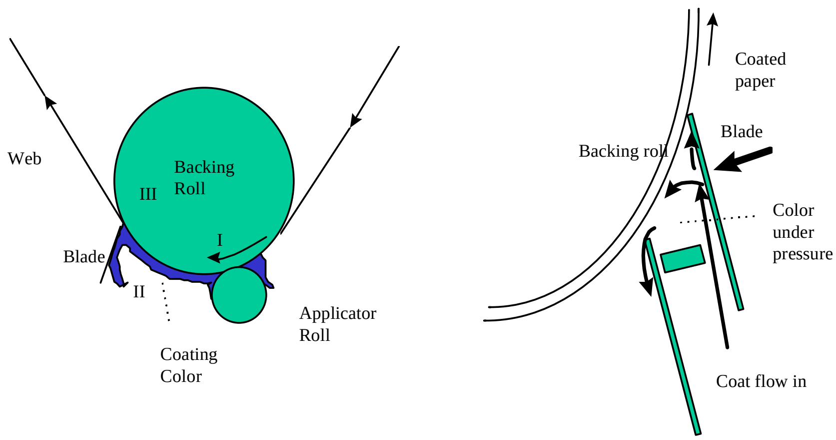

Figure 8.20. Typical conventional and short dwell coater.

Kuni and Nordlund (1998) showed in their experimental research by non-linear regression that the equation proposed by Gartaganis et al. (1978) is basically true. The equations (1.21) are presented also by Booth (1990) and the last equation is the simplified equation for the hybrid modeling.

$$CW_b = \frac{2}{3} b \sqrt{\frac{\eta c_b v^3}{F_z \sin(2\alpha)}} = \sqrt{\frac{K_{Fz} v^3}{F_z \sin(2\alpha)}} \qquad (1.21)$$

where CW_b is coat weight, b is the blade trim (length), η is the viscosity of the color, v is the machine speed, c_b is the blade thickness and F_z the pressure on the blade, α is the bevel angle and K_{Fz} is the tuning parameter of the hybrid model

All the coefficients that are not known are assumed to be contained in the hybrid modeling parameter, K_{Fz}.

The Gartaganis equations (1.21) are for a beveled blade coaters. The corresponding equations for a low angle blade (Booth 1990) are the following:

$$CW_{la} = \frac{2\sqrt{2}}{3} bR\theta \sqrt{\frac{\eta L^3 v^3}{Et^3\delta}} = \frac{2\sqrt{2}}{3} b \sqrt{\frac{\eta v^3 R\theta}{F_i}} = \sqrt{\frac{K_{Fi} v^3}{F_i}} \tag{1.22}$$

where CW_{la} is coat weight, b is the blade trim (length), η is the viscosity of the color, R is backing roll radius, θ is the blade contact angle, L is blade extension (the distance from the blade holder to the blade tip). t is blade thickness (caliber), E is the elastic modulus of the blade, F_i the pressure on the blade and K_{Fi} is the tuning parameter of the hybrid model.

All the coefficients that are not known are assumed to be contained in the hybrid modeling parameter, K_{Fi}.

Eklund (1984) presented impulse force (F_i) and hydrodynamic force (H_z) equations that have proven to be quite widely accepted force balance representations. According to Eklund and Kahila (1978), hydrodynamic force (H_z) that is based on the lubrication theory, is effective only at the blade entrance caused by the coating flow that is deflected away from the blade nip. The equations for the forces are the following:

$$H_z = \frac{6\mu V}{\tan^2(\alpha)}(\ln(1+r) - \frac{2r}{2+r}) \tag{1.23}$$

$$F_0 = \left[F_z - (F_i + H_z)\right]\cos(\alpha) \tag{1.24}$$

where

F_0 = compressive force towards the web

F_i = impulse force

F_z = mechanical force at the blade tip

H_z = hydrodynamic force

$\dot{m}$ = mass flow rate of the coating

V = web speed

r = (h1/h2)-1 and h1 is the coating thickness approaching the blade nip and h2 is the blade nip gap

μ = simple shear viscosity in the blade nip

α = blade angle

The difference to the beveled blade is that in the low angle coater the blade is bent. The tip angle is usually less than 15^{o} (Kuni and Nordlund 1998). The blade is not in contact with the web because the hydrodynamic forces are stronger than the mechanical force due to low blade angle (Figure 8.21). Because the blade bends under the influence of high dynamic forces the blade angle decreases when the mechanical force is increased. Small changes in the blade angle cause large response in the dynamic force (Eklund 1984). It can be assumed that the equations for the forces acting on the blade remain the same as in the beveled blade coating.

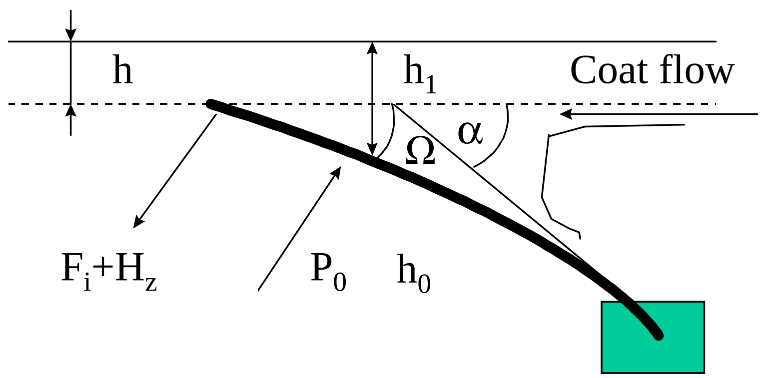

Figure 8.21. Forces in low angle blade coating.

APPENDIX E: SIC

CV and c_p are subspace selection criteria where typically the trade-off between the lack of fit and model complexity is evaluated. The model complexity here is usually defined as the number of free parameters as in AIC. An extension to these is Subspace Information Criteria (SIC), (Sugiyama and Ogawa 2001).

$$SIC = \left\| \hat{\Theta}_S - \hat{\Theta}_U \right\|^2 - \hat{\sigma}^2 tr(X_0 X_0^T) + \hat{\sigma}^2 tr(X_S X_S^T) \qquad (1.25)$$

$\hat{\Theta}$ is estimated model parameter, $\hat{\Theta} = Xy$

X is pseudo inverse of data matrix A, $X = (A^T A)^{-1} A^T$

$\hat{\sigma}^2$ is estimate of variance, $\hat{\sigma}^2 = \dfrac{\left\| AXy - y \right\|^2}{M - tr(AX)}$

M is the number of training samples in the subset.

Subscript S denotes the values estimated with subset of samples.

Subscript U denotes the values estimated with large number of samples or unbiased values.

Subscript 0 denotes difference between the values of training samples and the large sample, $X_0 = X_S - X_U$.

In SIC the complexity is measured with and that are numerical estimates of the number of free parameters.

In SIC the complexity is measured with and that are numerical estimates of the number of free parameters.

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