Process modelling in pulp and paper manufacture

Application studies with aspects of energy efficiency and product quality

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Environmental and Energy Systems

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4. Performance of neural networks and feature selection algorithms on board strength predictions.
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5. Potential energy improvements in a multiple-effect evaporation system: case studies of heat recovery.
   Daniel Ekbåge and Lars Nilsson.
   Peer-reviewed article
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Results from this work have also been presented at the Fundamental Mechanical Pulp Research Seminar Jyväskylä, Finland, on June 13–14 2017 in the following extended abstract:

Trial measurements in a CTMP-process to perform time-series analysis of refining conditions and estimated pulp properties.
Daniel Ekbåge, Lars Nilsson, Helena Håkansson.

Authors’ contributions to the enclosed papers:

Paper 1: Scrutiny of the specific process and extraction of data. Planning and performing of mill trial measurements. Literature review, data analysis and presentation of results.

Paper 2: Scrutiny of the specific process and extraction of data. Planning of experiment and execution of handsheet preparations and measurements. Literature review, process and laboratory data analysis and presentation of results.

Paper 3: Scrutiny of the specific process and extraction of data. Planning of machine trial. Extraction of paperboard samples from the reels. Literature review, process and laboratory data analysis and presentation of results.

Paper 4: Scrutiny of the specific process and extraction of data. Literature review, process and laboratory data analysis and presentation of results.

Paper 5: Scrutiny of the specific process and extraction of data. Literature review, data analysis and presentation of results.

List of abbreviations and variables

$A(z)$	Autoregressive polynomial
ARMA	Auto regressive moving average
$C(z)$	Moving average polynomial
CD	Cross direction
CP	Heat capacity flowrate
CPS	Cyber-physical system
CSF	Canadian standard freeness
CTMP	Chemi-thermomechanical pulp
DCS	Distributed control system
DT	Differential temperature change
ERP	Enterprise resource planning
F	Mass flow of weak liquor
FR	Feed rate
GCC	Grand composite curve
h_F	Enthalpy of weak liquor
h_K	Enthalpy of condensate
h_L	Enthalpy of thick liquor
H_S	Enthalpy of inlet steam
HU-LP	Minimum hot utility for low-pressure steam
HU-MP	Minimum hot utility for medium-pressure steam
HU-TOTAL	Minimum total hot utility
H_V	Enthalpy of secondary steam
K	Mass flow of condensate
k	Lag
L	Mass flow of thick liquor
MD	Machine direction
MEE	Multiple effect evaporator
MIW	Manufacturing information warehouse system
ML	Motor load
$\widehat{m}_y$	Estimation of sample mean
N	Number of data points
PLC	Programmable logic controller
Q	Heat load
QCS	Quality control system
$Q_{ev,cold,i}$	Boiling liquor-side heat load
$Q_{ev,hot,i}$	Condensing steam-side heat load
$Rxx[k]$	Autocovariance
S	Mass flow of inlet steam
SE	Specific energy

SEC	Specific electricity consumption
t	Index of data point
T_S	Supply temperature
T_T	Target temperature
V	Mass flow of secondary steam
y_t	Measured variable
z^{-1}	Unit delay operator
ΔH	Enthalpy change

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1 Abstract

The manufacture of pulp and paper is an energy intensive process configured of several unit processes that shape a network of flows of wood chips, chemical pulp, mechanical pulp, board and other important components. Improved energy efficiency supports sustainability of the process and the products. With the purpose of monitoring and controlling, information from multiple process and quality variables is continuously collected in the process data system. The data may contain information about underlying patterns and variability, and using statistical and multivariate data analysis can create valuable insights into how reduced variations and predictions of certain properties can be accomplished.

This thesis investigates the application of mathematical models for processes and products. These models can be used to increase the knowledge of the process characteristics and for quality predictions, to support process optimization and improved product quality.

Based on process data from a board machine including the stock preparation process, an evaporation system and a CTMP plant, process models have been developed with the aims of quality predictions, improved energy efficiency and reduced process variability.

Through application of modelling and simulation techniques a range of models were developed in several case studies. These techniques included both mechanistic and statistical models and were demonstrated using Pinch to study energy recovery in the evaporation plant, time series and multiple linear regression modelling for predictions in the CTMP process, flowsheet modelling of stock preparation dynamics and neural networks for board quality predictions. The process models that were developed in the case studies demonstrated how these methods can be applied to predict important properties, study systematic variations and improve the energy efficiency by describing the opportunities and limitations associated with these techniques.

2 Introduction

The purpose of this chapter is to briefly guide the reader through industrialization from a historical perspective and describe the idea of value creation in this thesis. Concepts of energy and resource efficiency as well as key performance indicators are introduced in the context of pulp and paper manufacturing. The final part of the chapter describes the general objective and the specific objectives of each paper.

2.1 Background

2.1.1 Industrialization—from mechanization to digitalization

As described by Drath and Horch (2014), the first industrial revolution was initiated during the end of the 18th century through deployment of mechanization and steam engines. Approximately 100 years later, the second industrial revolution took place in the context of electrification and was materialized via continuous production lines, division of labor and conveyor belts. These developments had a huge effect on improving productivity. The third industrial revolution originated from digitalization during the latter part of the 1960s. By applying programmable logic controllers, digital programming of automation systems was possible and led to highly flexible and efficient automation systems (Drath & Horch, 2014). There are numerous articles describing Industry 4.0 as a conceptualized vision of what potentially lies ahead in industrial development.

Industry 4.0-related theory building and research are currently limited due to the absence of a unified definition, and the scientific community is observing an "announced" revolution (Culot et al., in press). The technical basis for Industry 4.0 is the new combination of internet technologies and industry (Drath & Horch, 2014) and has been interpreted as an application of the cyber-physical system (CPS) concept. CPS refers to the next generation of systems with integrated computational and physical capabilities, which is a prerequisite for future technology development (R. Baheti & Gill, 2011). The concept of CPS and Industry 4.0 are closely related. CPS requires following three levels (Figure 1): (1) physical objects, (2) network infrastructure containing data models of the physical objects and (3) services that are based on the available data (Drath & Horch, 2014).

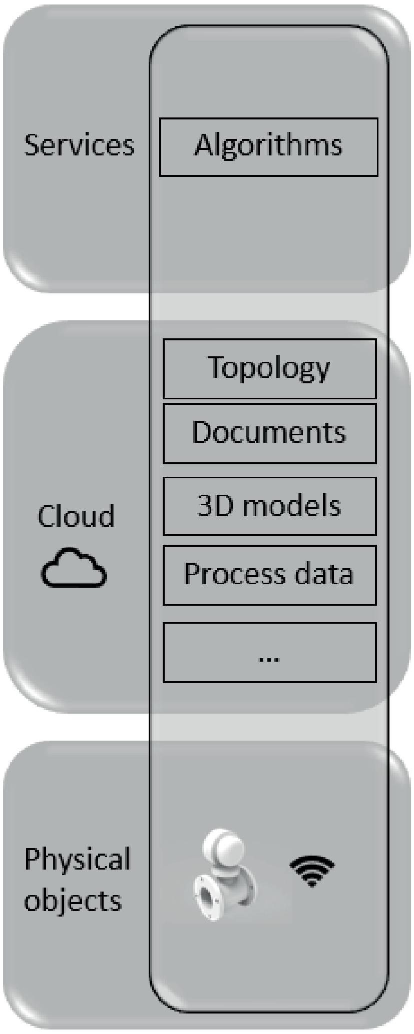

Figure 1. Levels of a CPS, based on Drath and Horch (2014).

Industrial conceptualization of this could be connections between products and components that enable data communication through giving each product and component identities in the data network. Along with these communications, systems could also be virtually integrated, and simulations and algorithms could be applied for optimization purposes. In all, this generates new services, business models and more specific products (Drath & Horch, 2014).

The ministry of enterprise and innovation is a ministry within the government of Sweden and has communicated a strategy for new industrialization. This is referred to as smart industry and underlines that digitalization of the industrial manufacturing processes, products and transformation of big data is crucial for the competitiveness of future industry. Sweden has lost some competitive strengths in a global perspective and should compete by applying digital and sustainable production combined with new products, which are features recognized to have potential for the new industrialization (Ministry of enterprise and innovation of Sweden, 2016). However, a recent survey of Swedish manufacturing companies revealed that the potential of digitalization is recognized as positive, but there is a substantial lack of implementation of Industry 4.0 concepts (Sundberg et al., 2019). A significant number of Swedish manufacturing companies are still at the initial step of digitalization, which is a long-term process, and need to resolve obstacles like insufficient knowledge and competence to move forward (Machado et al., 2019).

A substantial basis for this thesis was the idea of using the process data that is generated at the mill to create value. If the data can be applied in algorithms and computational systems in a constructive matter, new value combined with increased knowledge can be achieved. Value creation from data can be oriented towards both the process and the products being produced by supporting decision-making, increasing understanding of the process and the product and improving performance from several aspects.

2.1.2 Energy and resource efficiency

Manufacturing industries can measure their performance at different levels depending, naturally, on the focus area. A high-level system would include the entire production unit, whereas at lower levels specific unit processes would probably be of interest. Ideally, the information provided by the performance measurements is then handled in a decision-making process to make potential changes and improvements. One way of considering performance is by determining efficiency, the meaning of which differs according to the discipline of interest. Huysman *et al.* (2015) argues that efficiency can be characterized by two different levels: Level 1 and Level 2. Level 1 is defined as the ratio of the benefits to the flows inventoried, and Level 2 is the ratio of the benefits to the environmental impacts. Natural resources are extracted from the environment, and when they enter the production system they are transformed into industrial resources such as energy carriers, chemical building blocks and semi-finished products. It is, therefore, the products and services generated in the production system that are the useful outputs or benefits (Huysman *et al.,* 2015). The levels form a part of a systemized framework that enables resource efficiency indicators to be positioned and provides better insight into what exactly is being indicated. The various types of indicators include resource, efficiency, perspective (system level), scale of economy, completeness at resource level, quantification metrics used and the method used to determine the environmental impact (Huysman et al., 2015).

The European Commission has provided documentation within the domain of both energy and resource efficiency. The EU's (European Union) target for energy efficiency implies a 20% reduction (Broberg Viklund, 2015; European Commission, 2015) in the use of primary energy by implementing energy-efficient measures.

An annual energy savings target of at least 0.8% has been outlined for the period 2021–2030 by the European Commission (European Commission, 2018).

Stora Enso, which was the company that sourced the production and laboratory data in this thesis, is a global company that provides renewable solutions in consumer packaging materials, biomaterials, wood constructions and paper. Stora Enso has an established target, which is aligned with the European Commission's directive for energy efficiency, of 0.8% annual energy savings to 2030.

As of today, there is no existing accepted definition for '*resource efficiency*' (Huysman *et al.,* 2015). In 2011 the European Commission launched a resource efficiency roadmap in Europe. The highlighted benefits of improved resource efficiency were greater productivity (by improving business competitiveness and reducing costs), growth and job creation, reduced carbon emissions and macroeconomic stability (European Commission, 2011). In addition, resource efficiency stimulates technological innovation and benefits consumers via more sustainable products (European Commission, 2017). Two of the definitions given are "*Resource efficiency means using the Earth's limited resources in a sustainable manner*" and "*is a way to deliver more with less*" (European Commission, 2011).

Resources, according to the roadmap, are inputs to the economy; some examples of these are minerals, metals, fuels, timber, water, air, land and sea. The trends in resource efficiency, measured in mass of material, are not sufficient to reduce the intensity of material use in the economy of the European Union, and this is explained by an economical growth rate that is higher than the annual rate of improvement of resource efficiency (European Commission, 2011). Dahlström and Ekins (2005) describe resource efficiency as a dimensionless ratio of two variables, defined as a "*basic ratio of two resource variables of the same kind*". Aligned with this definition, they argue that material efficiency is the ratio of the useful output of material to its input, and that energy efficiency is the ratio of the useful output of energy to its input. Moreover, the engineering definition of efficiency is consistent with these definitions of resource efficiency (Dahlström & Ekins, 2005). Although resource efficiency is consistent with engineering efficiency and the economic concept of efficiency (the ratio of economic outputs to its inputs), there is a fundamental difference: engineering efficiencies are always less than 1, and the economic efficiencies for a profitable company are larger than 1 (Dahlström & Ekins, 2005). Di Maio et al. (2017) argue that the unit of resource efficiency is important when it is measured, since it affects acceptance by policy makers and the direction of "green" policies. Common approaches of resource efficiency are based on mass, and most of the methodologies measure the environmental burden of the resource in relation to the value of the output (Di Maio *et al.*, 2017).

2.1.3 Economic efficiency

Another important factor regarding the efficiency of a pulp and paper mill is the cost related to the manufacturing process. Yin (1999), who studied the production efficiency and cost competitiveness of multiple pulp mills, states that economic efficiency may mean the proficiency with which producers achieve their economical goal and can involve aspects of achieving maximum profit or production at a minimal cost. The mill data used consisted of six input factors: fiber, energy, operating labor, salaried supervision, materials and chemicals. Based on a time series from an integrated Nordic printing paper mill in order to analyze profit, Hämäläinen and Tapaninen (2010) conclude that unplanned stoppages and breakdowns increase the cost of manufacturing by lowering the available production time and that the mill's profits correlate strongly with logistic costs and paper prices. Larger delivery volumes also make higher profits possible (Hämäläinen & Tapaninen, 2010).

2.1.4 Energy efficiency in the pulp and paper industry

The pulp and paper (P&P) industry has developed over a relatively extended period of time. P&P can be considered as an energy-intensive business; the manufacturing process is rather complex with respect to the large number of energy and mass transfer unit operations involved in its multiple sub-processes. In order to study the potential for making improvements in the use of energy in a P&P mill, it is critical to understand these operations not only from an energy perspective on a detailed level but also in combination with surrounding processes. The dominating energy carriers are biofuel and electrical energy. The manufacturing process of pulp and paper consumes substantial quantities of thermal energy in the form of steam that is generated in the recovery boiler. To make the process profitable, as well as to improve efficiency, backpressure turbines are usually installed to produce electrical energy as well as pressure-reduced steam.

The Swedish Energy Agency works with a sustainable energy system. One significant program was the PFE ("*Programmet för* *energieffektivisering i energiintensiv industri*”). Its primary purpose was to increase the efficiency of energy used in energy-intensive Swedish manufacturing industries, and it was based on a tax incentive. To be able to utilize PFE, companies needed to fulfill requirements regarding energy intensity, use electrical energy in the process and be judged as being able to implement the conditions of the program. Studying the results per industry, it was reported that P&P was the major contributor to the improvements made in efficiency. At the same time, P&P was the sector that consumed the most electrical energy of the participating companies. The PFE report also states that energy audits can be used if energy usage or applicable measures are subjects of interest. Energy audits provide a general picture and give perspective to the energy usage in the company, and they can make it easier to identify positions where efficiency measures can be implemented in both short- and long-term perspectives (Swedish Energy Agency, 2011, 2016).

A study carried out to evaluate energy-saving potentials in the German P&P industry concluded that the areas of greatest influence were heat recovery in the paper mill and the use of innovative, highly efficient methods for drying the paper (Fleiter et al., 2012). The potential for energy use savings was found to be limited if it was assumed that current paper production processes could not be subjected to radical changes. Furthermore, it was suggested that further savings could be possible if the system boundaries were extended.

Implementation of energy-efficient industrial improvements depends on several factors. Studies indicate that cost-effective energy efficiency measures are, however, not always implemented (Thollander & Ottosson, 2007), thus indicating the possible presence of barriers. It was concluded that the greatest barriers were technical risks (such as production interruptions and related costs), priorities, organizational aspects and technology inappropriate for the mill in question. Company-specific barriers were also found to be important; one of the biggest driving forces for energy efficiency was found to be its connection with the reduction in costs that resulted from lower energy usage. Further driving forces identified were ambitious personnel and a long-term energy strategy.

The energy efficiency gap is explained by market barriers, and a solution suggested for addressing these barriers is the use of policy instruments. Studies that were based on interviews with energy managers to study utilization of excess heat concluded that heat recovery is generally referred to as the supply of district heating, that there is a need to look for innovative recovery solutions and that policies are required for solutions to be implemented (Broberg Viklund, 2015).

2.1.5 Pinch methodology: general description

The amount of excess heat available in a P&P mill can be estimated by Pinch analysis (Olsson, 2009). The main outputs used in Pinch methodology are, in general, a composite curve and a grand composite curve (GCC). The data thus obtained can be useful for studying the hot and cold utilities (heating and cooling duties) of a system. The method starts by identifying all the hot and cold streams in the system being analyzed, and these all have a start temperature and a target temperature, combined with the heat load of the individual stream. The heat load that corresponds to the enthalpy change can be calculated according to (Kemp, 2007)

$$Q = \int_{T_S}^{T_T} CPdT = CP(T_T - T_S) = \Delta H \qquad (1)$$

Adding heat loads or heat capacity flow rates to all the streams in the system over any given temperature range allows for a single composite of the hot and cold streams, respectively, to be established. Combining the hot and cold streams in a temperature vs heat flow diagram provides a graph of the composite curves (Figure 2), and by studying the point of the smallest distance between the two curves the pinch point can then be identified. If there is an imbalance in the system (as shown in Figure 2), there are demands of cooling and heating, which are referred to as the cooling duty and heating duty. These must be supplied by external heating and cooling (Kemp, 2007), which is also known as the utility requirement.

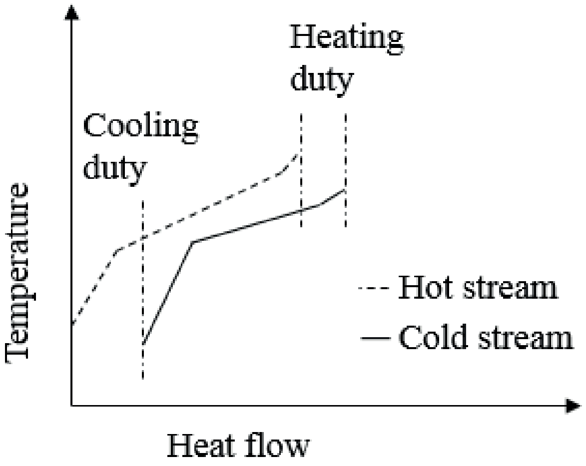

Figure 2. Sketch of composite curves, adapted from (Kemp, 2007).

In order to optimize the heat exchange within each temperature interval, the hot and cold streams need to be modified to ensure there is at least a minimum distance between them. This modification is referred to as shifted temperatures, which involves shifting the cold and hot streams in opposite directions and makes the composite curves just touch at the Pinch Point. The GCC (Figure 3) can be generated by plotting the net heat flow (utility requirement) against the shifted temperature, and it represents the difference between the accessible heat in the hot streams and the heat required by the cold streams (relative to the Pinch Point, at a given shifted temperature) (Kemp, 2007). The GCC is also useful when studying the integration of one specific sub-process (the extracted process) and all other hot and cold streams (the background processes).

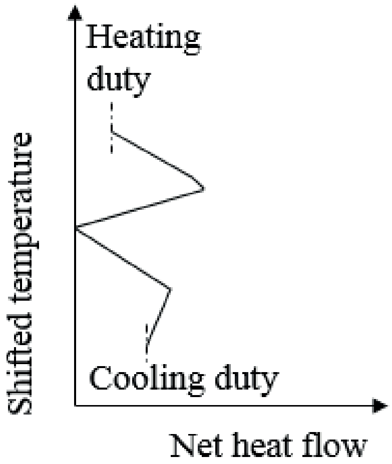

Figure 3. Sketch of a grand composite curve (GCC), adapted from (Kemp, 2007).

2.1.6 Pinch analysis: model mill approach

Several reports describe a methodology that has been used to analyze systems from an energy perspective in model mills. Model mills have been used to study energy efficiency aspects in FRAM (Future Resource Adapted Pulp Mill), a research program with the aim of investigating how pulp and paper production can reduce its impact on the environment (Olsson & Berntsson, 2009). FRAM includes two model mills representing a Scandinavian pulp mill, and it was found that the potential for savings in the consumption of steam was good in the kraft pulp mill models that were developed.

Algehed and Berntsson (2003) performed a study on re-designing evaporation plants using medium-pressure steam and subsequent delivery of low-pressure steam to the steam network. Their results showed that the designs had great potential for savings in the usage of live steam, and that additional waste water may be evaporated without increasing the total demand of live steam. The results also found indications that the demand for low-pressure steam in the rest of the process was less important when it came to savings in the use of live steam.

It was concluded that the potential for process-integrated evaporation was higher in the mill with lower water usage since it had more excess heat available for process-integrated evaporation (Axelsson et al., 2006).

2.1.7 Mill energy audits

An energy audit is a survey and analyzes the energy flows in a process, with the goal of identifying potential areas in which energy may be conserved.

Within energy management, an energy audit is important as it enables systematic work to be carried out so that decisions can be made; one of its objectives is to balance energy inputs with usage (Pareshkumar & Purnanad, 2014).

Audits are applied in the Swedish P&P sector, where the main driving force is to reduce energy usage, related costs and environmental impact. The audit is generally executed at the mill, and the relevant process, or sub-processes, are quantified in terms of energy flows. The results of the energy flows can be analyzed individually as well as benchmarked against other similar processes. In some cases, energy audits are conducted annually; they may also be supported by monthly energy reports, which would show potential changes in the energy flows.

2.1.8 Simulation models

A way of studying critical parameters and design changes in processes is by the use of simulation models. There are several commercial simulators available on the market for constructing simulation models. Such simulators are basically computer software that provides tools for designing a model and analysis via a graphical user interface. The main structure of the model can include process streams that connect blocks representing physical changes in the process. Mass and energy balances can then be calculated based on the model.

Olsson (2009) states that simulation models are often not published because companies do not want to reveal too much information to their competitors. The models reported represent different evaporator configurations and include dynamical assessments as well as mass and heat balances.

2.1.9 Statistical quality control

As outlined by Jaehn (1992), there are several key performance indicators that are being monitored at the mill. These are not limited to quality measurements, such as laboratory test data and rejected rolls, but also include different production processes measured via, for instance, production rate and process downtime. All these measurements are affected by variability, and problems might occur if it is difficult to determine whether the situation has actually deteriorated or if the change in monitored conditions is within normally expected variation. To handle this decision-related issue there are statistical methods that discriminate between random variability and variability that can be traced to differences in materials, operating conditions, measurement methods or operators (Figure 4). Statistical control is a crucial strategy to improve quality and productivity at the mill and means that the process is in a state of being stable and, at same time, random. A common metric for representing variability is the standard deviation, often labelled sigma, and given a normal distribution it can be plotted in combination with the measurements (these plots are called control charts) to help separate random variability from the variability that originates from the sources given in Figure 4 (Jaehn, 1992).

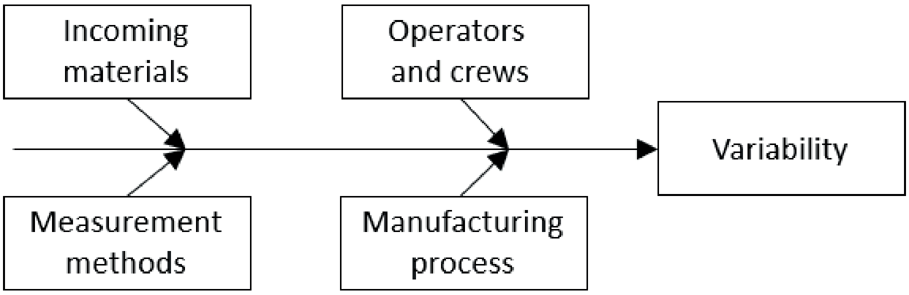

Figure 4. Ishikawa cause and effect diagram, based on Jaehn (1992).

2.1.10 Motivation and selection of case studies

The unit processes selected in this thesis were different in terms of energy source. The evaporation system had significantly high consumption of steam, and the CTMP process utilized a significant portion of the total electrical energy used in the entire mill. An additional aspect was to study the process and the properties of the pulp in terms of systematic variations. The CTMP process can account for about one-third of the total usage of electrical energy in a specific integrated mill. Combining this fact with the variability that results from the raw material and process disturbances, CTMP was selected as one of the cases to be studied. Literature studying the CTMP process often explores a combination of energy and pulp properties and how these relationships depend on different material and process conditions. In a specific CTMP study, C. Sandberg and Berg (2015) describe one definition of refining energy efficiency as "*the increase in tensile index that is achieved with a certain specific energy, i.e. Nm/g per MWh/adt*". Nelsson (2016) suggests a definition of electric energy efficiency as being "*the specific electric energy demand to produce pulp with a certain sheet tensile index and with similar (±5%) values for light scattering coefficient and fiber length*".

During the course of this thesis, "following" the CTMP stream from the CTMP plant through the stock preparation process and to the board machine was implemented to study relationships between this pulp, the process and the final board product with the purpose of increasing the understanding of quality and energy performance. This approach then narrowed down study to production losses during transient conditions, and an important part of the work was the correlation between refining variables, such as specific electricity consumption in the stock preparation process, and dry-end properties of the board.

In a kraft pulp mill the evaporation plant is usually the process with the highest steam demand, and, in many cases, this plant represents 30–35% of the demand for steam in the complete mill (Olsson, 2009). Axelsson *et al.* (2006) also list the evaporation plant as being the major steam consumer in a pulp mill. Improvements in energy efficiency achieved through either the operation or design (or both) of the evaporator is of interest to the industry (Khanam & Mohanty, 2011). Based on both the level of steam consumption and the presence of warm condensate flows at the specific mill studied, the evaporation plant was selected for one case study. The steam economy can be represented by the ratio of the consumption of steam (which can be at different pressure levels) to the difference between the input (low dry content level) and output (high dry content level) of black liquor. The specific process also had a CTMP liquor flow routed to the evaporation plant connecting these systems.

2.2 Objective

The general objective of this thesis is to increase knowledge of how process modelling techniques can be applied to study aspects of energy efficiency and quality in pulp and paper manufacturing. The modelling applications are oriented towards quality-related predictions aligned with reduced process variability and improved energy utilization through process integration. An essential part of this thesis is the study on how process and quality data can be used to create value through mathematical modelling.

The analyses were conducted on process data from an integrated full-scale pulp and paper mill, and the work was based on the development of mechanistic and statistical models. Three unit processes were studied: (1) the CTMP plant, with focus placed on the conical disc refiner and the properties of the pulp measured subsequent to the latency chest; (2) the evaporation system comprising a multiple effect evaporator and (3) the board machine including stock preparation.

2.2.1 Objective of Paper 1

The process of refining wood chips includes mechanical treatment, whereby they are defibrated and fibrillated between discs with a short clearance. The fibers are exposed to different collision and friction types in the refiner, which uses a considerable amount of energy (Salmén et al., 2009). The relationship between the refining conditions and the quality of the pulp was the primary focus in paper 1; hence, data recordings from both the process and the pulp were included.

A widely used indication of pulp quality is freeness (Tervaskanto et al., 2009), which is a measure of the rate at which a dilute suspension may be drained (TAPPI, 2017).

When a change is made to the refiner settings, the time needed to remove latency causes a delay before the pulp produced can be measured. Quality control in a CTMP mill is challenging since it is characterized by requirements of high freeness and low shive content (Tervaskanto *et al.,* 2009). These two aspects jointly require that freeness be predicted and thereby have the potential to reduce the usage of both energy and raw material by accelerating the response and reducing variability.

The main aim of the CTMP study case was to investigate systematic variations in order to predict pulp quality by using a dynamic model. The secondary aim was to increase knowledge of the time-varying characteristics in the CTMP process.

2.2.2 Objective of Paper 2

This study mainly focused on applying multiple linear regression models to predict z-direction strengths of laboratory handsheets, based on both fiber morphology measurements and process data. It was of interest to investigate predictions of the strength properties upstream in the refining process; therefore, pulp was extracted from a position after the CD refiner and from the accept pulp, which is the final product in the CTMP plant. An important feature of this study was the addition of UV and IR lights to include crill in the pulp measurements, which is a form of light attenuation, in terms of analyzing if this measurement could improve the model.

2.2.3 Objective of Paper 3

The system boundaries of this study were the board machine and the stock preparation process. From literature studies and interviews with mill personnel some knowledge gaps were found regarding board properties during grade changes, reduced chest volumes in the stock preparation to facilitate faster grade changes and process variability. Based on outlined gaps, the objective of this study was to increase the understanding of material properties development during a grade change trial, consistency variations for lowered chest levels and cross-correlations between stock preparation and dry-end measurements. On top of these data-driven approaches the goal was also to develop a dynamic model to simulate pulp consistency transients.

2.2.4 Objective of Paper 4

The objective of this study was to increase the understanding of predictions of board strength properties based on supervised machine learning algorithms. Feature selection techniques and the structures of neural networks were investigated with the goal of identifying the best neuron structure and most important process variables.

2.2.5 Objective of Paper 5

Converting wood chips into pulp in a cooking plant involves lignin, hemicellulose and some of the cellulose being dissolved in the cooking liquor. These materials, in combination with the inorganic components of the cooking liquor, generate a component generally referred to as black liquor. The main functionality of the evaporation plant is to increase the dry solids content of the black liquor by evaporating the water (Parvianen et al., 2008).

The primary objective of this evaporation case study was to quantify the amount of excess energy present in the evaporation system (designed for black liquor and CTMP liquor) and then analyze a series of energy recovery cases. Three case studies were defined; these focused on increasing energy efficiency in the evaporation system in terms of estimating the potential reduction in the consumption of steam. Developing scripts based on Pinch methodology allowed Grand Composite Curves to be constructed and were used to theoretically evaluate the improved energy efficiency in specific case studies.

2.3 Research questions

The following research questions were addressed in the papers:

1. Does the CTMP process and pulp data entail application of a dynamic freeness model?
2. In the context of CTMP strength predictions, do multiple regression models increase performance with the addition of UV and IR lights to the pulp measurements?
3. Do extensive laboratory measurements of board quality during transient conditions correlate to board machine and stock preparation measurements?
4. What is the influence of different structures in neural networks on the predictive performance of board strength models?
5. What are the implications of energy efficiency in the evaporation system through recovery of condensates?

3 Process description

This chapter provides insight into the pulp and paper manufacturing process. General descriptions of the selected unit processes are given followed by specific information about the studied mill.

3.1 From wood chips to pulp

The key element in pulp manufacturing is wood, which is a renewable material. Following the flow of raw material in a simplified diagram, the mill is fed with wood logs and chips that are treated in several steps prior to entering the system and generating the output, i.e., pulp. A typical mill can be designed using a number of different unit processes that are required to manufacture the pulp, which starts with the handling of logs and saw mill chips. These can be prepared from two separate incoming material flows: one is the debarking and chipping process, which removes the bark from the logs and then cuts them into chips on-site, and the second material flow is pre-cut chips delivered from a saw mill (Figure 5).

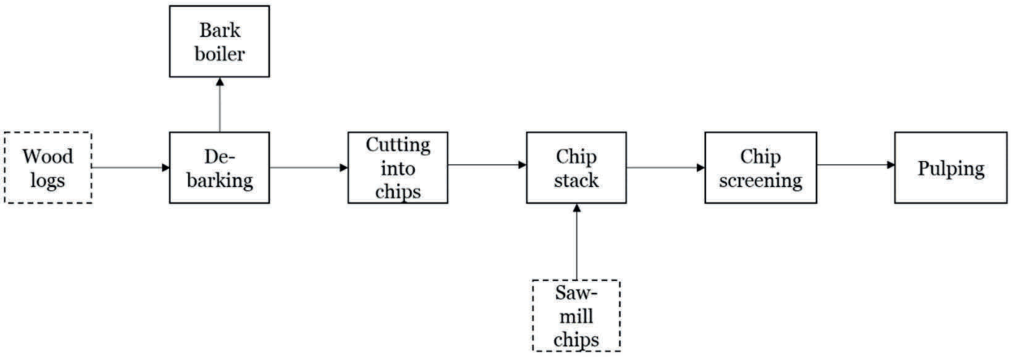

Figure 5. Simplified flow diagram of the path taken by wood, from the initial step to the pulping process.

The logs are debarked so that the pulp produced is as clean as possible. Bark residues can also impact the consumption of chemicals in the pulping process; moreover, bark provides the mill with a biofuel that can either replace, or reduce the consumption of, fossil fuels (Kassberg, 1998c).

The debarking process takes place in a rotating metal drum that mainly applies mechanical loads to the wood to remove the bark (Figure 6).

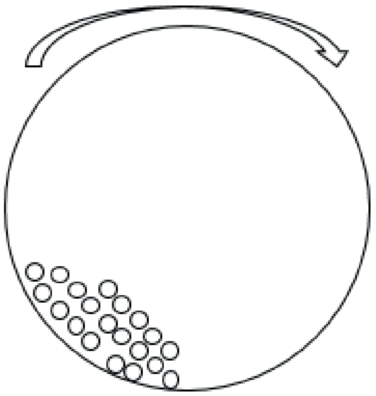

Figure 6. Debarking drum, adapted from (Kassberg, 1998c).

The level of debarking can be controlled for the duration the logs are inside the drum by adjusting the rotational speed of the drum. Following debarking, the logs are cut by rotating knives (Figure 7) into smaller pieces called wood chips (Kassberg, 1998c).

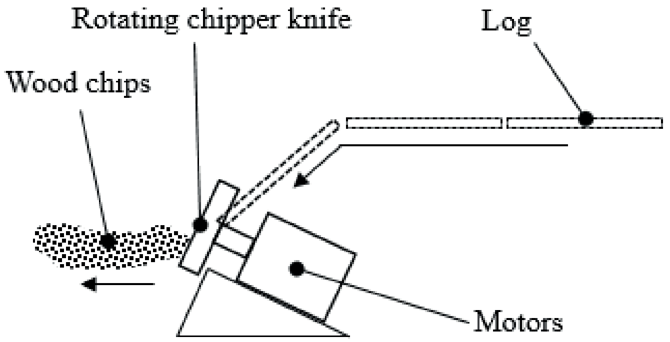

Figure 7. Wood chipper, adapted from (Kassberg, 1998c).

Cutting reduces the size of the wood, which makes it easier to absorb water, chemicals and heat. The refining process requires that the chips pass through a narrow gap in the refiner, so the wood must be in the form of small chips. Subsequent to the cutting process, both sawmill chips and mill-cut chips are stored in large stacks in the woodyard. The function of chip screening (Figure 5) is to increase the production quality by either accepting or rejecting the chips based on their size (Kassberg, 1998c).

Wood has a chemical composition of cellulose, hemicellulose, lignin and extractives; for spruce, this composition is normally 42, 28, 27 and 3%, respectively (Kassberg, 1998c). The structure of the components in wood can be simplified into a picture of a cellulose skeleton surrounded by hemicelluloses that act as a matrix, and lignin functions as an encrusting material (Sjostrom, 1993).
Based on species, wood used for pulping purposes can be divided into softwood (e.g., spruce and pine) and hardwood (e.g., birch and eucalyptus). The density of wood is also reflected in its differentiation. The wood species used highly affects the quality of pulp; its properties can also vary depending on the impact of environmental factors, along with the age of the tree and its growth pattern.
There are two main pulping processes presently employed by the pulp and paper industry: mechanical pulping and chemical pulping. The yield, which is an important factor in measuring production efficiency, differs significantly between the processes; that of mechanical pulping, which is a high-yield process, is typically around 97%, but with added chemicals and elevated temperatures, this lowers to about 90% (Kassberg, 1998b). For chemical pulps made of softwood that are bleached to a kappa number (a metric for the remaining content of lignin) of 20–25, the resulting yield is approximately 45% (Kassberg, 1998a).

Spruce is a softwood favorable for mechanical pulping due to its fiber properties, low content of extractives and high initial brightness. With respect to structure and chemical composition, hardwood is more complex compared to softwood. Mechanical pulps originating from hardwood have poor strength but, on the other hand, have good light-scattering and sheet surface properties (Varhimo et al., 2009). In general, softwood has significantly longer fibers than those of hardwood and also has a higher content of lignin, which is retained when chips are processed in the mechanical pulping process.

In the chemical pulping process, lignin is dissolved chemically during the cooking sequence, thereby causing the fibers to separate from each other (Kassberg, 1998a). When wood chips are converted into pulp in the cooking plant, the lignin, hemicellulose and some of the cellulose dissolve in the cooking liquor. These materials, in combination with the inorganic components of the cooking liquor, generate the component called black liquor (Parvianen *et al.,* 2008). This liquor, in turn, is streamed to the chemical recovery process in order to recover the cooking chemicals and the energy content of the wood substances (Kassberg, 1998a).

3.2 Energy flows in the mill

The raw material and energy flows in a pulp and paper mill are relatively high and critical parameters that impact production costs, energy demands and the environment. Energy (electricity and fuel costs, excluding capital cost) in the European pulp and paper industry in 2009 accounted, on average, for 21% of the total manufacturing cost (Suhr *et al.,* 2015).

Energy, in the form of electrical power and heat, is required to produce pulp and paper. The heat that exits the boiler is in the form of high-pressure steam, and it is the driving force for the turbo generator that generates electrical power. Steam is also extracted from the turbine typically at two reduced pressure levels known as medium-pressure and low-pressure steam. Prior to the reduction in pressure, the steam has too high a pressure level to be used in the manufacturing processes. The medium- and low-pressure steams are used for multiple heating purposes in the mill.

Heating is required in the evaporation plant to increase the heating value of the black liquor and to heat the drying section of the paper machine (or pulp dryer, in the case of a non-integrated pulp mill) to evaporate the water from the pulp or the paper web. Heat is also required in the chemical pulping process to increase the temperature of the cooking liquor and to heat the wood chips, pulp fibers, chemicals and water to the temperatures required in the various processes. Electrical power is used to run the chip refiners (in the mechanical pulping process) and the drives for the pulp and paper machinery, pumps and compressors as well as for beating and refining the pulps (Suhr *et al.,* 2015).

3.3 Pulp properties and their relationship to the final product

Mechanical pulp comprises a mixture of fibers, fragments of fibers and fines. The relevance of two specific aspects of quality can be highlighted for the case of paper products: First, relevant for printing papers, is good opacity (i.e., a high light-scattering coefficient at a given strength) and secondly, relevant for boards, is high bulk at a given tensile index. The bulk provides favorable properties for product applications such as the middle layer in boxboard or in specific tissue products. One unfavorable property of pulp with a significant lignin content is the yellowing effect caused by ultraviolet radiation. Also, mechanical pulps are not the best option for end products with high strength requirements, such as sack paper and liner products (Höglund, 2007).

Mechanical pulp is mixed with chemical pulp for several product applications. Addition of the latter, which contains more flexible fibers, results in an increase in the sheet bonding strength. In comparing sheet properties of mechanical and chemical pulps respectively, the advantages of sheets made from mechanical pulp are twofold: a higher bulk at a given tensile index and a higher opacity (Höglund, 2007).

CTMP is often applied in the middle layer(s) in liquid packaging and multilayer packaging boards. This board structure gives products a high stiffness and bulk and good dimensionality. It also means that the grammage can be lower than a comparable board product made from chemical pulp (Lindholm et al., 2009).

Mechanical pulp is used in the middle layers of folding boxboard products to give not only the highest possible bulk but also give back and top plies the lowest possible grammages, which, in turn, lowers the cost of raw materials. A minimum number of fines for a sufficient bond strength is reached when stiff fibers are combined with well-bonding fines. When well-bonding fines are combined with a middle fraction, the increase in Scott bond (a method for measuring the internal bond strength) versus bulk is greater than that when combined with long fibers (Heikkurinen et al., 2009).

3.4 General description of the mechanical pulping process

The mechanical pulping process in the vicinity of the primary refiner involves some critical steps. These can be outlined in sequence as follows:

1) Lignin softening: the major mechanism in the pre-treatment of wood chips;
2) Refining: converting the wood chips into pulp in the refining zones (in the refiner);
3) Steam separation: the fiber accelerator (cyclone) separates the fibers from the steam;
4) Latency removal: takes place in the latency chest and mainly reduces the curl index of the fibers.

One common pulp measurement that is made, based on material samples extracted subsequent to Step 4, is known as freeness. The procedure for measuring the freeness of pulp (Canadian standard method) was developed originally to control the manufacture of ground wood. The idea behind freeness is that it measures the rate at which a dilute suspension may be drained, and it is related to the swelling of fibers and surface conditions (TAPPI, 2017). This resistance to drainage is described in Höglund (2007) as "the lower the freeness, the more difficult the pulp is to dewater". Schopper-Riegler is another method, often used for chemical pulps, for determining the drainability of a pulp suspension in water.

In Step 1, elevated temperature and chemicals are important. The manufacture of CTMP includes adding chemicals to the chips prior to preheating, causing lignin sulfonation and reducing the temperature at which lignin softens (Höglund, 2007). If wood chips are refined at temperatures below the lignin glass transition temperature, they would be incompletely softened, and the remaining fibers would have a high modulus. The lignin will be hard and glassy-like, developing crack propagations within the cell wall in the transverse direction and also generating fractures (of fibers) perpendicular to the fiber axis. The fracture characteristics will be more brittle compared to those occurring at higher temperatures. Increasing the temperature through the lignin glass transition region allows the remaining lignin (the majority is in the middle lamella, which consists of about 70% lignin) to soften; a bigger proportion of the cracks will be generated along the tangential and fiber directions instead, leading to less fiber damage (Irvine, 1985).

Step 2 is the process step in which substantial amounts of electricity are consumed to power the rotating disc in the refiner, which causes mechanical loading on the wood chips and develops the CTMP properties.

The quality of the fibers and the refiner power are functions of stock consistency and feed rate, type of stock, rotational speed and plate gap (Zand & Wu, 1984). The energy input to the mechanical processing of the fibers controls the final quality of the pulp (Höglund, 2007). Step 2 is a fast process, and the residence time of fibers in the refining zone is therefore limited: it can be as short as around 0.5 seconds (Murton & Duffy, 2005). Refining is a process of compression and decompression loading, resulting in separation and fibrillation of individual fibers aligned with creation of fines. A negative feature of mechanical pulps is the high energy demand, and within thermomechanical pulping one way to reduce this is by enzymatic treatment prior certain refining stages (Viikari et al., 2000).

Step 3 separates the major parts of the two-phase flow of fibers and steam. The steam is directed to the energy recovery department and the fibers to the latency chest. The rotational speed of the device and the velocity of the fibers are related to the degree of purification of the outgoing steam and the capacity.

Step 4 involves a chest of large volume that exposes the diluted pulp to an elevated temperature, whilst being agitated mechanically, for a specific residence time.

Fiber curl is initiated during high-consistency refining conditions; it is removed at disintegration temperatures above 50 °C but remains at low temperatures (Page et al., 1985).

This process, called latency removal, concerns the straightening and deflocculation of fibers (Gao et al., 2016). Deformed fibers increase both the curl index and freeness (Page *et al.,* 1985). Latency removal causes the fiber to straighten and can be observed in the reduced freeness of the pulp (Höglund, 2007). The freeness value is reduced as the temperature within a specific range is increased (Figure 8).

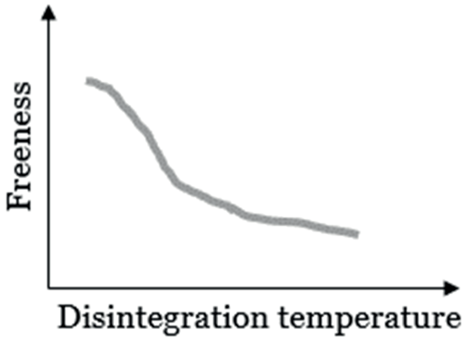

Figure 8. Freeness as a function of the disintegration temperature, simplified and adapted from (Höglund, 2007).

Mechanical pulping is affected by disturbances originating from, for example, the raw wood material and process conditions, which cause variability in the end product. Shahriari and Feng (2011) studied the impact of the variability of raw materials on the quality of the product and energy efficiency in a thermomechanical pulping process. Their results showed that controlling the raw material variability supported reduced process variability, and this can result in improved energy efficiency and quality indexes.

Christer Sandberg et al. (2018) studied the impact of full-scale production on increased softening through chip pre-treatment with sodium sulfite and increased refining intensity. By comparing two double-disc refiners: one with two low shive periphery segments (referred to as standard) and one equipped with a low shive periphery segment combined with a feeding periphery segment, they observed a reduction of specific electricity consumption of 19%, given the application of chip pre-treatment and feeding segments. The outcome of that specific trial involved higher production and similar pulp properties and was compared to refining conditions with standard segments and no pre-treatment. By studying wood chip with no pre-treatment, they observed that the feeding segments reduced the energy usage with 8%, and this was accomplished at increased refining intensity and production rate. Their study also puts focus on the inclusion of pulp properties in an attempt to improve the energy efficiency.

3.5 Description of the specific CTMP process used in this study

The specific CTMP process studied here comprise a primary conical disc (CD) refiner of type RGP-82CD. A simplified diagram of the process is shown in Figure 9, which displays the flow of wood chips from the preheater to the latency chest. Prior to the preheater, the wood chips are mixed with a dose of chemicals, and, once in it, they are exposed to an elevated temperature.

The main reason for adding chemicals and heat is to soften the wood before it enters the refining process. The chips remain for a certain retention time (a number of minutes) in the preheater, which is much longer than that in the refiner (a few seconds or less). After the refiner step, the two-phase flow of pulp and steam (Figure 9) enters a blow line which is routed to a cyclone (fiber accelerator) that separates the steam from the pulp. The pulp then flows into the latency chest for latency removal.

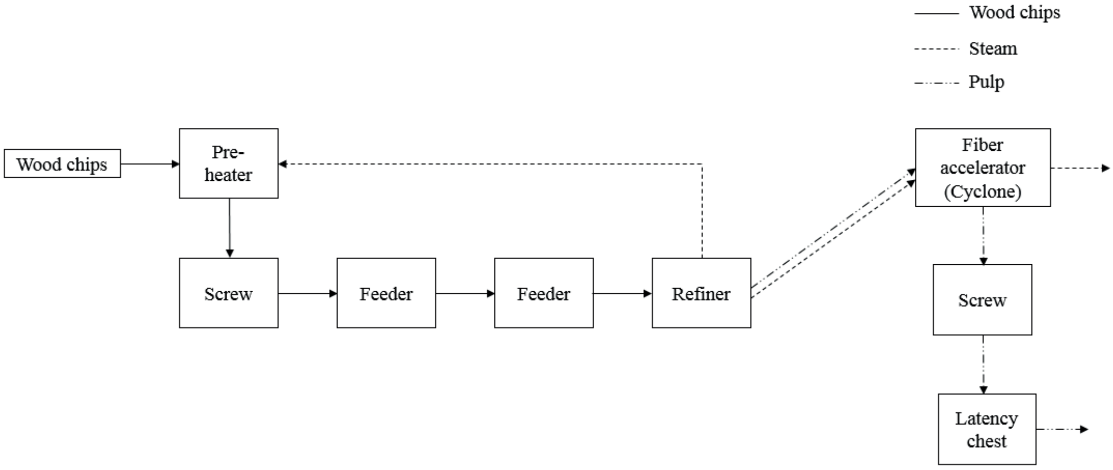

Figure 9. Simplified flow chart of the process from the pre-heater to the latency chest.

Figure 10 visualizes the process boundaries described by showing a simplified 3D sketch of the CTMP process equipment from the preheater to the latency chest.

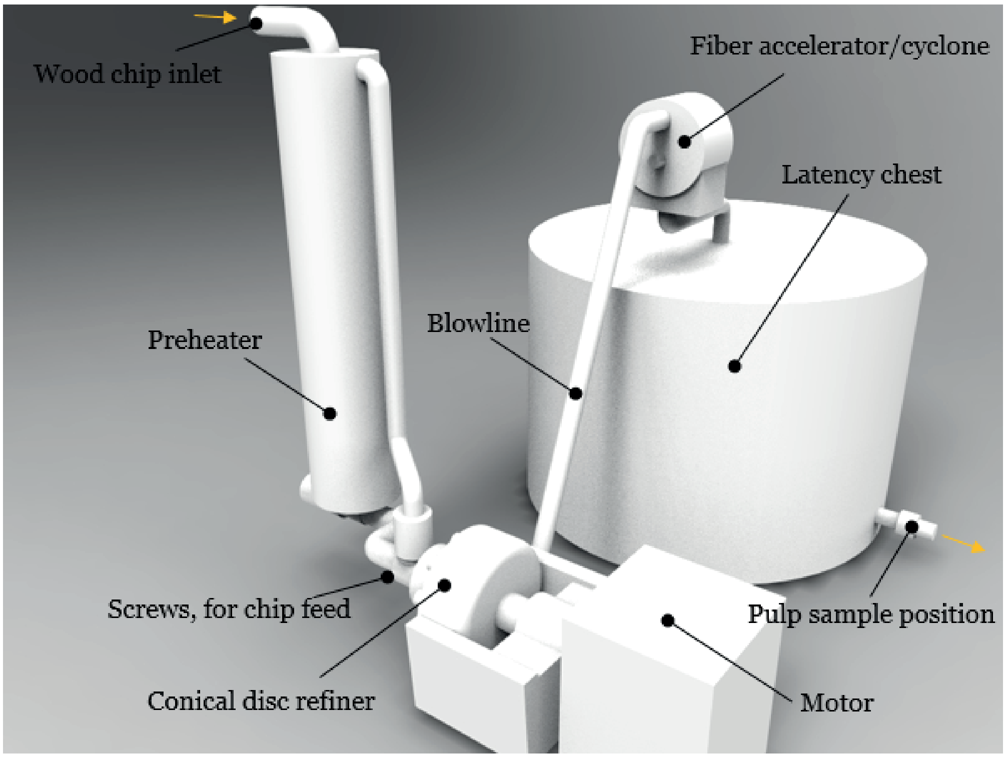

Figure 10. Simplified 3D diagram of parts of the CTMP process, from the preheater to the latency chest.

The CD refiner comprises an electrical motor, shaft, rotor plate and stator plate (Figure 11). The direct-driven refiner treats the wood chips in the narrow gap between the plates.

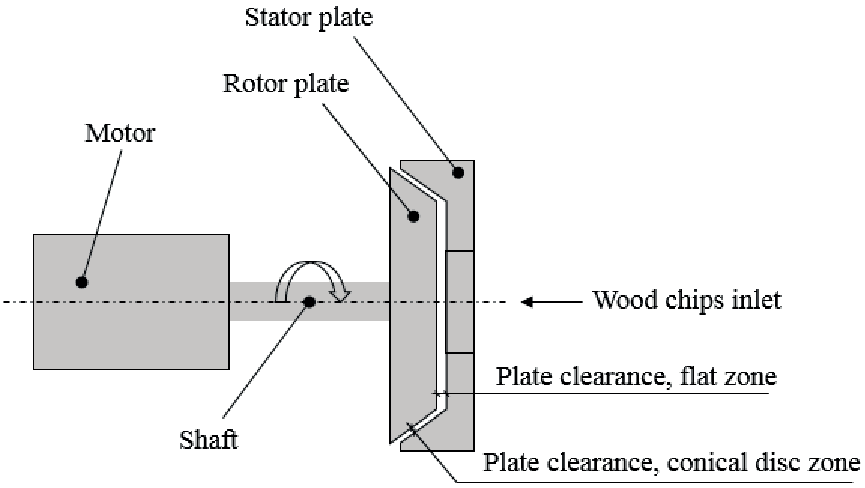

Figure 11. Sketch of a simplified conical disc refiner. The plate clearance is exaggerated for clarity.

Wood chips enter the refiner in the center of the stator plate (Figure 12).

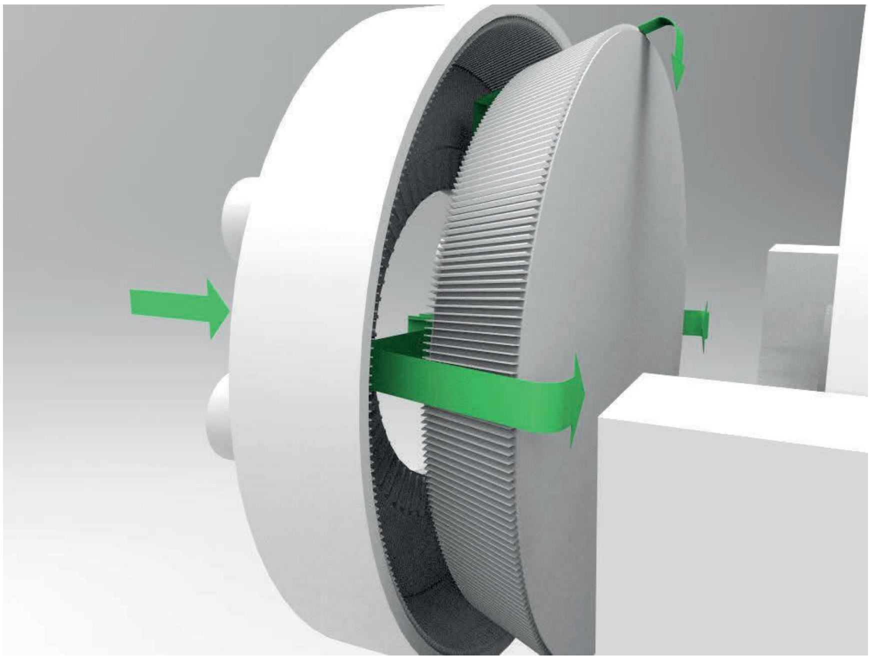

Figure 12. Simplified 3D sketch of a CD refiner in an opened state, with the flow paths of the wood chips and pulp indicated, from refiner entry to passing through the refiner zones.

The chips then pass through the breaker bar zone, followed by the fine bar zone (Figure 13). Sensors continuously measure the temperature and gap distance in these refining zones. Dilution water is fed to both zones, and the flow is measured for each zone. Another important refining variable is the specific consumption of electricity.

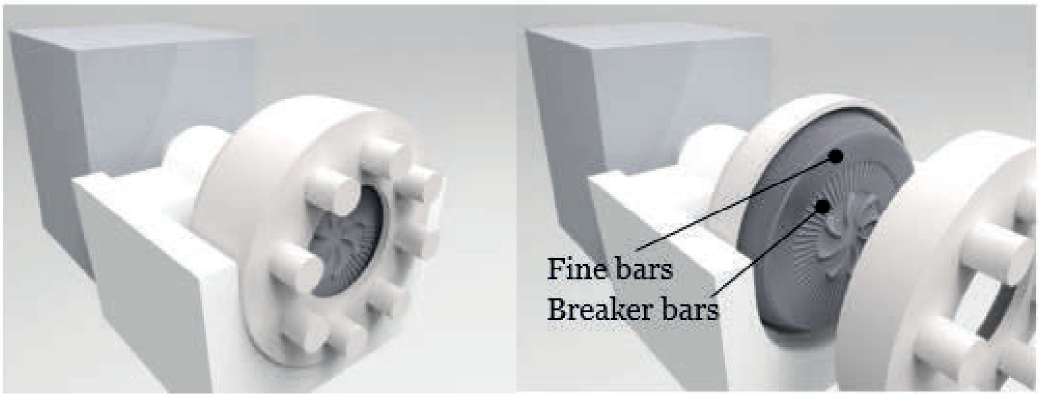

Figure 13. Simplified 3D sketch of the CD refiner, in a closed (left) and opened state (right), showing the positions of the fine bars and breaker bars.

The latency chest has an approximate volume of 200 m^3 and is equipped with a mechanical agitating device. For one specific measurement sequence, the hydraulic residence time was calculated at about 20 minutes. The position at which pulp samples are extracted is located at the flow exit of the latency chest (Figure 10). Samples of pulp from the CTMP flow are removed from the process and subsequently measured for freeness and fiber properties in the online pulp analyzer. This measures freeness according to the Canadian Standard Freeness (TAPPI, 2017) and is also equipped with a camera and a light source to take images of a diluted CTMP stream in order to generate statistics of fiber properties. In summary, the following properties are examples of the data extracted from the device, some of which can be presented as distributions:

1) Freeness
2) Fiber length
3) Fiber width
4) Fiber curl
5) Fines
6) Coarseness
7) Kinks
8) Shives

The frequency at which pulp samples were extracted was much lower than the measurement frequency in the refiner, and this is one of the challenges facing the field of generating models of the process and pulp properties. Refiner measurements are characterized as being relatively frequent and having a constant rate of sampling compared to the pulp measurements, which are more infrequent and have an ever-changing rate of sampling (Figure 14).

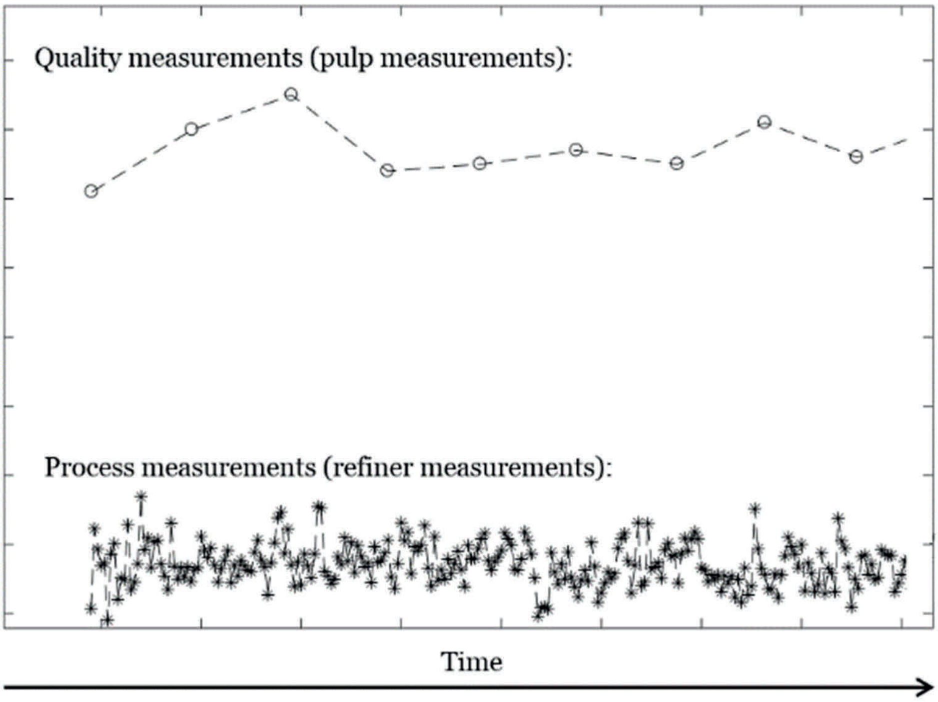

Figure 14. Measurement characteristics of the refiner and pulp measurements, displaying differences in sampling interval.

Another issue that must be addressed with respect to the specific system boundary is the time delay from when a change is made in the refiner until the sample of pulp is extracted and measured in the online pulp sampler: the change in pulp properties due to changes made to the refiner is delayed substantially.

3.6 Modelling techniques of the mechanical pulping process

The specific energy (SE) of the refiner is one of the variables that is stored continuously in the process data system. SE can be defined as follows using the motor load *(*ML [kW]) and feed rate (FR [kg/s]) (Qian, 1997):

$$SE = ML/FR \tag{2}$$

During refining in mechanical pulping processes there can be a time delay from when a change made to the refining conditions can be measured in the pulp's properties. The reasons behind this delay is that the samples of pulp are extracted after the latency chest and that both the extraction process and measurement can be somewhat time-consuming. This issue can be addressed by modelling; related approaches have also been made by Zhou et al. (2016) and Tervaskanto *et al.* (2009). The latter modelled consistency at the refiner outlet (based on the energy and mass balances) and freeness, and they compared the results with an online measurement device. Their steady-state freeness model was a linear function of the specific electricity consumption, defined as the motor load divided by the production rate, and the refining intensity, defined as the specific electricity consumption per total number of bar impacts. The model included parameters that were estimated from data. Some of the modelling results revealed that different refiners require different parameters, and variability in both the process and material causes inaccuracy.

Zhou *et al.* (2016) applied ARMA (Auto Regressive Moving Average) modelling techniques to capture the dynamics based on the argument that it is difficult to develop dynamic models based on the first principles of the process. They concluded that, in the high consistency refining process, freeness reflects the operational and economic performance of the process, and it is typically troublesome to measure and control online (Zhou *et al.,* 2016).

Broderick et al. (1997) used another statistical modelling technique to study the relationship between refiner variables, the quality of the pulp, and the energy efficiency in a chemi-mechanical pulp mill. This model was based on multiple regression analysis and generated a polynomial model of the refiner energy and the quality of a handsheet. For example, the models were used to represent how refiner variables, such as plate gap and consistency, impacted freeness and specific energy, and how optimum combinations of the variables may be found. Different operating points at equal levels of freeness were observed in surface diagrams, indicating that the specific energy could be reduced and that certain combinations could be more energy-efficient, but they also pointed out that the impact on the quality of a handsheet must also be considered (Broderick *et al.,* 1997).

Karlstrom et al. (2015) performed studies on a thermomechanical pulp process that included a conical disc refiner equipped with multiple temperature sensors located at the flat zone and conical disc zone. The paper is based on the combination of process variables and variables originating from laboratory measurements, with the aim of studying dynamic phenomena. The measurements included the refiner temperature profile (measured at the refiner zones), as well as common refiner measurements and pulp samples extracted from the blow line during a set of test periods. The modelling part places focus on estimating the fiber residence time in the refiner zones and its relationship to the properties of the pulp. Applying a linear regression approach (using first-order polynomial fit) and using specific energy as an independent variable allowed an estimate of the mean fiber length to be found; the model had a low degree of experimental data reproduction, generating an R^2 equal to 0.3. The non-linearities were mitigated by incorporating piece-wise linear functions, with the assumption that the residence time was related to the pulp properties. It was found that the draw-back of using piece-wise linear functions is that multiple models were needed in the process operating window. Results showed that the model (referred to as extended entropy model) was good for estimating consistency in parts of the conical disc zone. Residence time and consistency were important to estimate mean fiber length, shives and tensile index (Karlstrom *et al.,* 2015).

3.7 General description of the board machine and stock preparation process

The base structure of paper comprises a fiber network of cellulose fibers that are kept together through chemical and physical bonding. By adding starch or other additives to the refined furnish the paper properties are affected. In the stock preparation process, the furnish is refined mechanically, portions of different furnishes are mixed (Figure 15), and the consistency of the furnish is controlled to be as stable as possible. After refining, it passes through the machine chest and flows to the board machine (Gavelin, 1997).

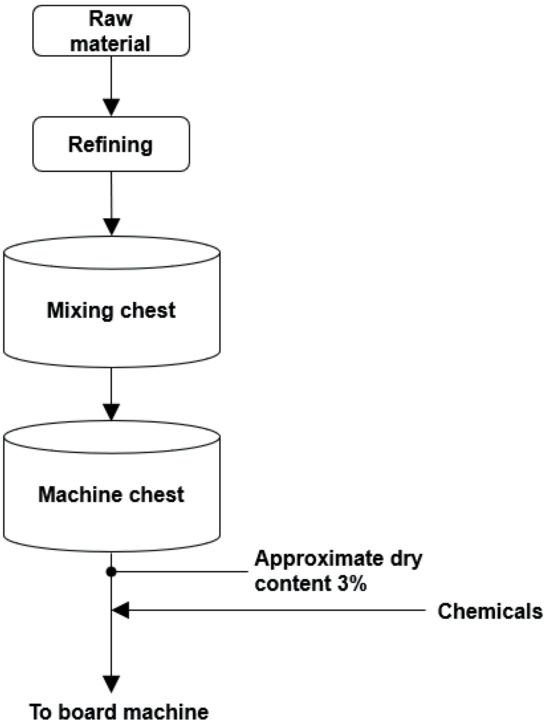

Figure 15. Simplified flow diagram of the stock preparation process.

When leaving the machine chest, the furnish has a dry content close to 3% (Figure 15). It is routed through a short re-circulation of the drainage water (often referred to as white water, the part being removed from the wire section via vacuum and gravity), and it is diluted and evenly distributed to the wire section via the head box. Typically, the dry content of the furnish is about 20% after the wire section (before entering the press section, see Figure 16), and this excess water (due to the increase in dry content up to 20%) is re-used in the short circulation.

After dewatering of the wire section, additional mechanical dewatering takes place by applying mechanical loading at the roller nips and the extended press nip in the press section (Figure 16).

After the press section, the dry content of the paper web is 35-55%, and after the dryer section, where the web is in contact with cylinders heated with steam, it is 90-95%, which are equal moisture conditions to that in the printing and converting environment (Gavelin, 1997).

Basis weight is one of the most important quality parameters in paper manufacturing (Ohenoja et al., 2010).

By use of online scanners this parameter can be continuously monitored.

Scanner measurements are used for two basis weight control systems. Basis weight variations in CD are controlled through changing the shape of the slice jet (on the headbox) with actuators that adjust the distribution of fibers in CD. Variations in MD are controlled by adjusting the undiluted pulp flow that enters the headbox, which results in an altered fiber concentration in the headbox and subsequent number of fibers distributed on the wire (Wang et al., 1993).

Paper strength is dependent on both the contact surface area between the fibers and the ability to create hydrogen bonds. The fibers must be softened so the fiber surfaces can be pulled together via surface tension. During tensile loading the hydrogen bonds are broken until the fibers are pulled out of the fracture surface, and usually the fiber bonds are not so strong that a fiber rupture occurs, meaning that fiber strength is less important than the bond strength. Sufficient formation also mitigates the load distribution over the hydrogen bonds, which supports increased paper strength (Gavelin, 1997).

3.8 Description of the specific board machine and stock preparation process used in this study

The specific board machine studied in this thesis produces 5-ply boards for consumer packaging using CTMP, kraft pulp, short fiber pulp from bale and broke as raw material. In the stock preparation process, refining and blending of pulp takes place followed by addition of chemical components. These parameters change depending on which product is being produced and the current product recipe. To specifically treat the furnishes for each ply, which are 5 in total, according to the recipe, several refining lines are in place. This enables unique refining settings (in terms of specific electricity consumption) for the pulps, depending on their layer position (print, middle or reverse ply). The major design elements of this machine are the press section, dryer section, calender and coater (Figure 16). A quality control system (QCS) is implemented to control the board quality, and it is partly based on measurements executed by two scanners placed between the calender and the coater as well as and between the coater and the reel (Figure 16). By traversing over the board, the web scanner captures several properties such as basis weight and moisture.

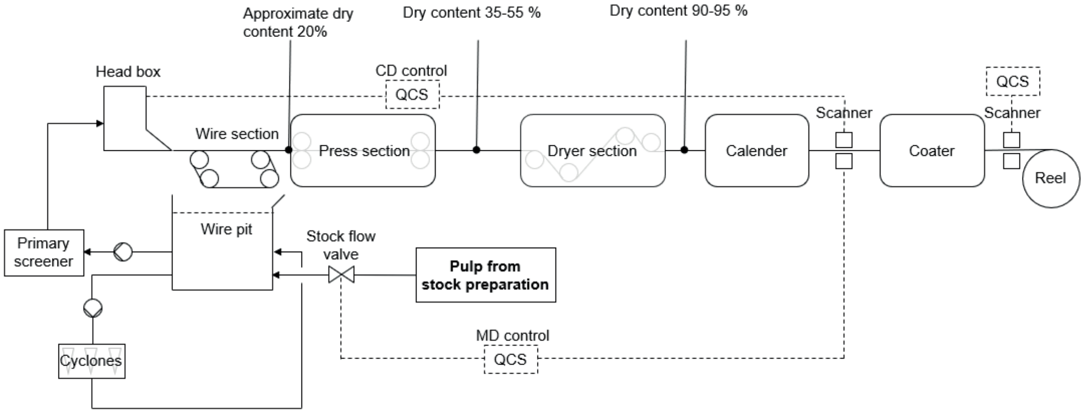

Figure 16. Simplified process flow diagram of the board machine.

3.9 General description of the evaporation and the chemical recovery process

In the chemical pulping process the fibers are separated from the wood matrix by elevated temperature and pulping chemicals, which enable delignification of the wood (Brännvall, 2007). This process, known as cooking, is performed in the digester (Figure 17). The sulphate cooking process (also called kraft cooking) facilitates the separation of fibers by using white liquor, a cooking chemical consisting of sodium hydroxide (NaOH) and sodium sulfide (Na_2S).

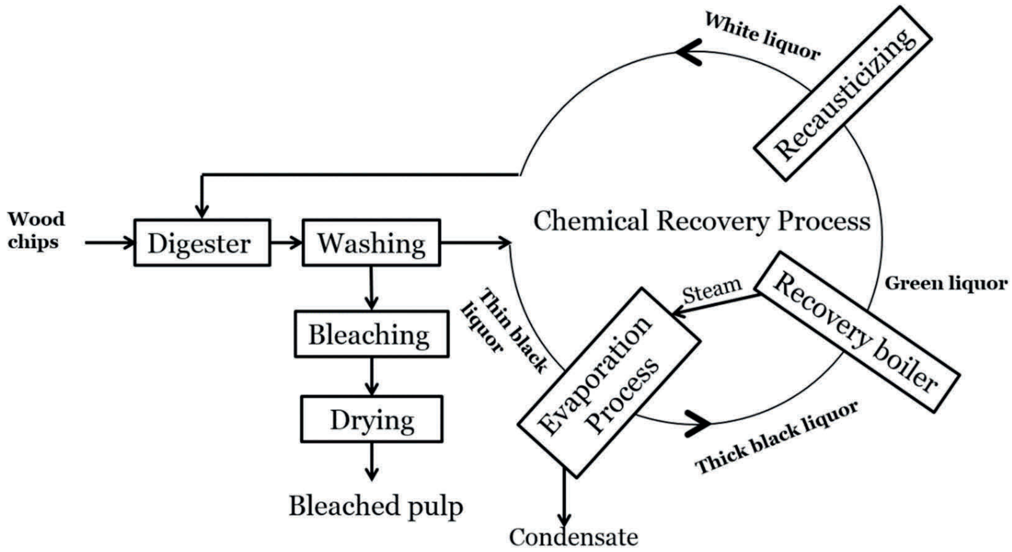

Figure 17. Simplified sketch of the evaporation system in the chemical recovery process, adapted from (Sveriges Skogsindustriförbund, 1978).

In the subsequent process, the thin black liquor, which is composed of the used cooking chemicals and dissolved wood substances, is extracted. It is then evaporated in the evaporation process and later streamed to the recovery boiler.

It is in this boiler that the organic material in the black liquor is recovered as heat. The inorganic materials are recovered and regenerated in the recovery boiler and re-causticizing plant. This process changes the inorganic materials so that they can be reused in the cooking process (Parvianen *et al.,* 2008).

3.10 Description of the specific evaporation system used in this study

The specific evaporation system in this case study was a Multiple Effect Evaporation (MEE) system, designed with several falling film effects (Figure 19). The heat source is the steam that enters the first two evaporators. The inlet steam (primary steam) condenses inside the evaporators, and the heat is transferred to the lower-temperature liquor; this produces secondary steam that, in turn, is fed to the next step in the sequence, thereby resulting in a gradual lowering of the steam's temperature profile along the evaporators (Figure 18).

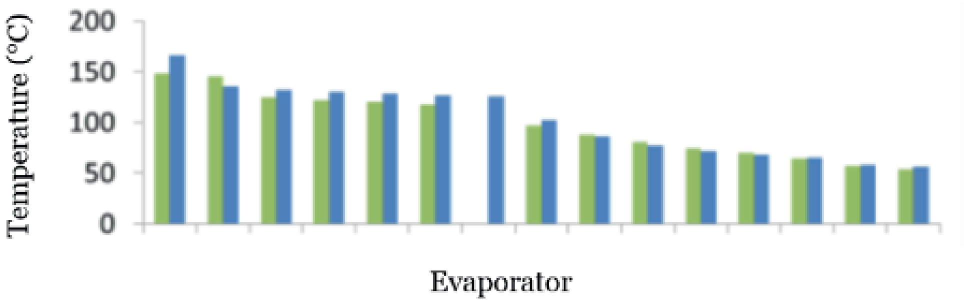

Figure 18. Temperature profile of a specific MEE. Green bars represent black liquor average temperatures, and blue bars represent black liquor temperatures for performance test data.

The basic functionality of the MEE is to remove water from the inlet liquors prior to pumping the concentrated outlet liquor to the recovery boiler. In the configuration shown in Figure 19 (where the dotted lines at F1 to F3 indicate simplification), CTMP liquor is fed to the last effect and the black liquor enters the system at a higher temperature effect. If the configuration is changed, the CTMP liquor can also be fed into the penultimate effect.

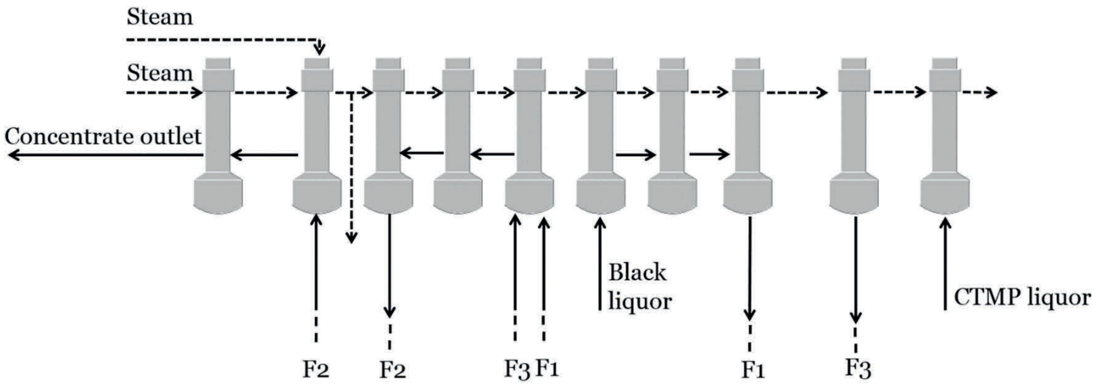

Figure 19. Simplified diagram of the steam and liquor flows in a specific evaporation system.

Each evaporator effect generates warm condensate during heat exchange. These condensates are referred to as grades, depending on their level of purity. This specific system has A, B, C and CTMP condensates, with A being the cleanest grade. Several of the condensates leave the MEE and are led into the aerated lagoon to be cleaned. This is a biological treatment process aimed at reducing the organic content of the inlet streams. The reduction process is dependent on heat being provided, in part, by the condensates, and its performance is dependent on the resulting temperature. Seasonal variations mean that the heat requirement for the biological treatment process varies over time. During the warm season, however, it is likely that excess heat is available in the condensates, and this could be used to improve the energy efficiency of the MEE.

4 Process data system at the specific mill

Pulp and paper mills typically have several control systems that regulate the unit processes. The distributed control system (DCS) is an example of a computerized system that manages autonomous controls at the mill. The control systems can have different data handlings and short-term data storage. It might be difficult to get an overview of these systems without having an overall system that collects important variables from the systems.

MOPS is defined as a manufacturing information warehouse system (MIW) (Mopssys, 2020), which collects data from several production systems, provides analytical tools (like time-based trending analysis) and stores long-term data.

The purpose of the MIW is to provide decision support to improve productivity, reduce production losses and cost, comply with standards and improve quality. As an example, the MIW can collect data from the DCS (Figure 20), the quality control system (QCS), programmable logic controllers (PLC), laboratory data systems, manufacturing execution systems, enterprise resource planning (ERP) systems and other information sources (Mopssys, 2020).

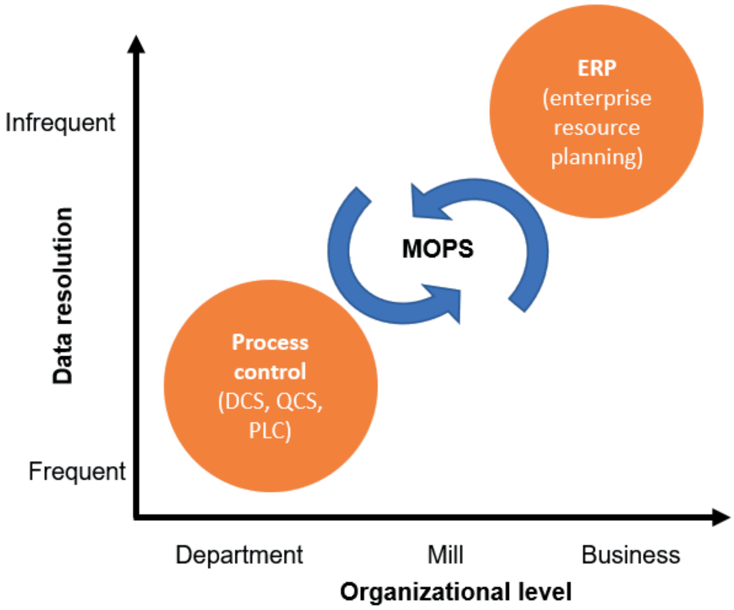

Figure 20. MOPS system. Simplified, modified and based on (Mopssys, 2020).

On top of generating data for decision support, MOPS is an important tool for analysts and researchers, enabling access to process and material data that can be used for extended studies that can create value through optimizing and retrofitting processes.

In this thesis, regarding methods for collecting and processing data, most data used for analysis and modelling purposes were collected from MOPS via an add-in in Excel. The relevant process data variables were also identified and analyzed in WinMOPS, which has a custom-made graphical user interface based on MOPS and adds a graphical overview of the different unit process of the mill. WinMOPS is a primary tool for production and process engineers at the mill to analyze process conditions and product properties.

For each case study in this thesis the unit processes were scrutinized within the system boundaries and this included site visits, discussions with experienced operators, process engineers, development engineers and researchers. The work also involved analyzing process flow diagrams with the main aspects of identifying positions of measurement sensors, identifying of manual sample points (mainly for extraction of pulp) and reading of technical documentation from machine suppliers. The initial part of the work that included this technical analysis was, in some cases, substantially prolonged. Regarding pulp measurements, the outputs from several sensors were analyzed, and this work included collaboration with sensor suppliers. The sensors that were part of the CTMP studies were both installed at the mill (on-line) and in the laboratory (off-line).

5 Process modelling

This chapter describes concepts and methods concerning process modelling techniques in general and the methods applied in this thesis.

Models exist in various disciplines, and a common feature they share is that they are an imitation of the real world. Their usage can be to improve knowledge of the behavior of the system under study; sometimes they can be used for prediction, optimization or control. In process engineering, models take the form of mathematical equations that attempt to capture the characteristics of a system for a specific usage of the actual model; therefore, an important aspect within modelling is the actual purpose of the model (Hangos & Cameron, 2001).

Hangos and Cameron (2001) outline four major steps in model creation:

Step (i) From reality to mathematics. This is about translating the real problem (Figure 21) into mathematical terms, and includes the intended usage and accuracy of the model. Also, mechanisms in the system are studied and determine the system input and output, which are critical issues;

Step (ii) Mathematical solution. When the equations representing the real world are set, the key issues are then the solution technique, displaying the results and the sensitivity (to variations) of the solution's output;

Step (iii) Interpreting the model's output. One of the concepts here is to validate the level of accuracy at which the model imitates the real world. The disturbances, parameters and inputs that need to be known accurately must be uncovered in order to check the quality of the model's prediction;

Step (iv) Using the results in the real world. The last step concerns implementing the model and related issues, such as its maintenance (e.g., keeping it updated), receivers of the model's output and documentation.

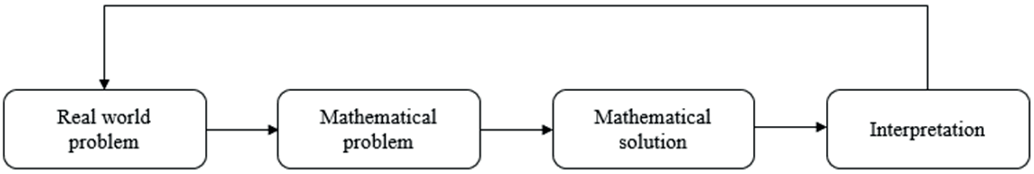

Figure 21. Modelling process based on (Hangos & Cameron, 2001).

Depending on the specific system and the purpose of the model, there are different characteristics that can be coordinated into specific model classifications. A model generated from system mechanisms can be referred to as mechanistic (or phenomenological): the mechanism can be the transfer of mass, heat and momentum. It is not uncommon to use a mechanistic model for design and optimization purposes. This can be labelled as being a “white box” because the mechanisms are given in the description of the model. If the model is derived from observation and experiment, it is empirical and can be referred to as a “black box”, and it includes parameter fitting. These models can be applied when the underlying phenomena (or mechanisms) are not given or adequately understood. Between the white box and the black box model classifications lies the “grey box” model, which represents a middle way that combines empirical and mechanistic components (Hangos & Cameron, 2001).

Additional types are stochastic and deterministic models that can be used when the system consists of natural random variations (where there is no available cause-and-effect relationship) and a clear cause-and-effect relationship, respectively (Hangos & Cameron, 2001). Analogue models are based on physical or physico-chemical analogues between the real process and the model, and they can be exemplified by pilot plants and laboratory-scale equipment that are based on the latter. Analogue models can also be based on electrical or mechanical principles (using springs and damper pots), which is in direct contrast to mathematical models that are outlined by mathematical objects. To summarize the development of process modelling, there are a minimum of two methods. The first method is applied when knowledge of process engineering can describe physico-chemical processes: it is referred to as a white box model and is a “first principles” model. The second one can be used when engineering knowledge of the system is limited, and the model information can be based on input and output measurement data. To extract this information sufficiently well, there is a need to stimulate or excite the system while identifying the model: the resulting model is a black box since the underlying mechanism is not transparent. In process engineering practice, it is common that grey box models are applied based on a combination of knowledge of the system and measured data to generate the model, which involve definitions of mechanisms (Hangos & Cameron, 2001).

Increasing demands placed on high-performance control systems require refined dynamical modelling approaches based on system identification techniques (Santos, 2012). Linear parameter varying (LPV) models play an important role when complex dynamical systems suitable for practical implementation need to be controlled. Santos (2012) outlines regression representations (e.g., ARX), state-space representation and linear fractional representation, and they state that, for application purposes, several real systems can be described plausibly by LPV models.

In summary, the modelling section of this thesis is based on a white box model to describe the heat characteristics of the evaporation plant by using heat and mass balances. The modelling part of the CTMP process and the board strength predictions were based on a black box approach, which was based on statistical data from the process and laboratory measurements.

More specifically, paper 1 applied a time series analysis; paper 2 applied multiple linear regression and cross validation; paper 3 applied cross-correlation and a dynamic WinGEMS model; paper 4 applied neural networks and paper 5 applied Pinch methodology.

5.1 Time series analysis

A time series can be described as an ordered sequence of measurements and, in many cases, as a sequence of discrete time events (Jakobsson, 2013). The modelling of time series data accounts for the internal structure (which can be studied with an autocovariance function) in the measurements and, if certain characteristics of the data can be sufficiently met (e.g., if the measurement can be modelled as being stationary), the model generated is a step towards fulfilling the aims of increasing knowledge of the process and being useful for prediction purposes.

An example of a signal measured in a pulp mill can be the consistency of a pulp, as illustrated in Figure 22. The sampling interval displayed in this measurement sequence is 1 minute. By analyzing the signal, it is possible to extract information regarding potential mechanisms (consistency in this case) or phenomena that are induced in the process data.

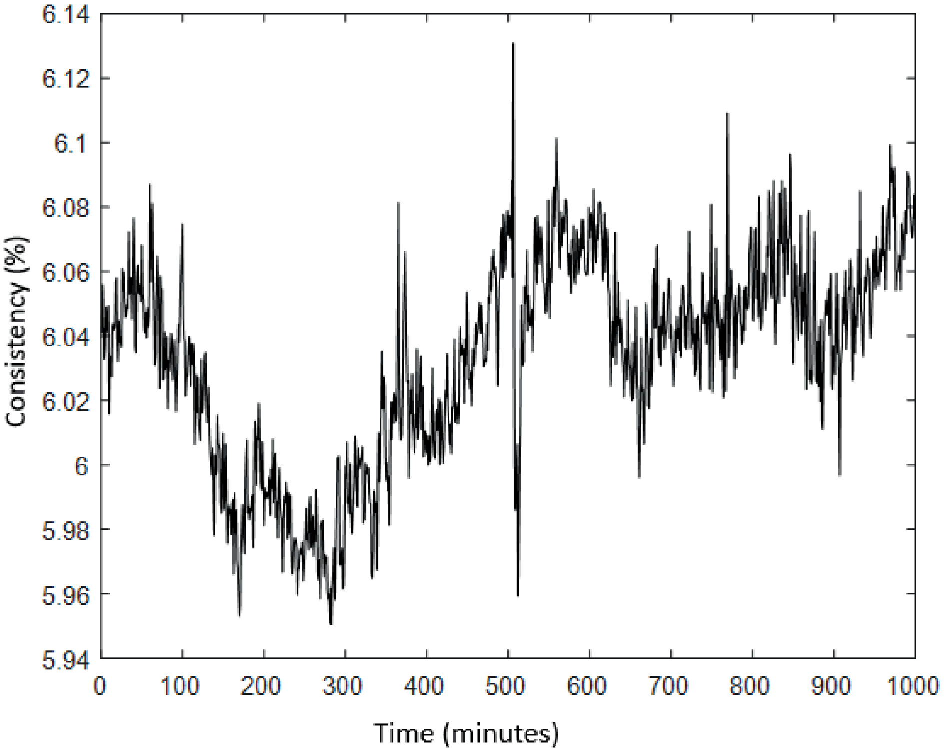

Figure 22. Time series of consistency in a pulp, displayed with a sampling interval of 1 minute.

A key feature in time series modeling is that the signal's characteristics should not change significantly over time, that is, being stationary is relevant for the analysis (Jakobsson, 2013). If a trend is present in the measurements, it could be a characteristic that could have a potential impact on the stationarity of the process.

The modelling procedure of time series can include linear transformations of the measurement so that they may be regarded as stationary signals. This step makes it possible to model the signal and treat the measurement (y_t) as an output from a linear system (h_t) that is fed with a random input (e_t): the potentially demanding part here is to find a good model for the system (h_t) (Jakobsson, 2013). The concept of the linear system is illustrated in Figure 23.

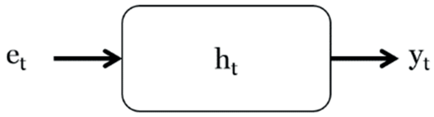

Figure 23. The concept of a linear system (h_t), showing input and output. Adapted from (Jakobsson, 2013)

In paper 1, the process data from the mill were pre-processed using detrend algorithms in order to remove linear trends or the mean value from the time-series. After detrending, the analysis involved searching for systematic variations by calculating the autocovariance for the signal at different lags (the autocovariance function). In this case, lags represent a time step (k) at which the autocovariance is determined. The mathematical expression is defined as (Jakobsson, 2013):

$$Rxx[k] = \frac{1}{N-k} \sum_{t=k+1}^{N} (y_t - \hat{m}_y)(y_{t-k} - \hat{m}_y) \qquad (3)$$

Paper 1, which partly concerns autocovariance analysis and estimates of the pulp's properties, includes estimated confidence intervals to help determine which part of the result is significant. This has been calculated by generating a white Gaussian signal with a variance equal to that of the detrended time series. When autocovariances are being observed, it should be remembered that even if a small number of data points are located outside of the estimated confidence interval, the specific time series may have the characteristics of a white Gaussian signal.

Should the resulting autocovariance be significant for the variables of interest, then the next step is to engage the modelling procedure and identify the system. The ARMA (Auto Regressive Moving Average) model is described by polynomials, with the first representing the AR part and the second the MA part. Jakobsson (2013) defines a process y_t as an ARMA process if it fulfils the following three equations, where the variables p and q are polynomial orders:

$$A(z)y_t = C(z)e_t \tag{4}$$

$$A(z) = 1 + a_1z^{-1} + \cdots + a_pz^{-p} \tag{5}$$

$$C(z) = 1 + c_1z^{-1} + \cdots + c_qz^{-q} \tag{6}$$

To exemplify some of these regarding applications in the pulp and paper industry, board bending strength predictions have been studied using semi-physical auto-regressive moving average (ARMA) models (Gutman & Nilsson, 1998), and freeness index predictions were analyzed by use of dynamic ARMA models (Zhou et al., 2016).

5.2 Multivariate analysis and statistical modelling

In contrast to bivariate analysis, which is defined by analyzing two variables at the same time, multivariate analysis includes three or more variables. Multiple linear regression is a method to analyze the variation in a response variable with the support of several explanatory variables. It applies the least-squares method, which essentially fits a regression line to a number of observations pairs, with the goal of minimizing the residuals, and defines a linear relationship between the response variable and the explanatory variables. A metric for evaluating the explanatory power of the model is the coefficient of determination, which corresponds to how much variation in the response variable can be explained by the explanatory variables. It can be challenging to construct a model with selecting the best variables. On one hand, all pertinent variables should be included, but on the other hand the goal is also to gain a model that is as simple as possible with as few variables as possible (Körner & Wahlgren, 2015).

Statistical modelling and its application to the pulp and paper industry has been studied for decades. These models have been applied in different unit processes with different purposes. To exemplify some of these and to give a brief overview, kappa number predictions in a kraft pulp continuous digester were studied by Correia et al. (2018), and multiple regression models of refiner performance and handsheet properties were used by Broderick et al. (1997).

When a statistical model is developed it is important to consider which variables are relevant for the specific purpose of the model. This process of identifying the relevant variables is called feature selection. Feature selection techniques are based on algorithms that identify important variables for a pre-determined response variable.

These algorithms can be divided into three categories: (1) filter type, based on feature variance and feature relevance; (2) wrapper type, which is initialized with a subset of features and then adds or removes features using a specified criterion and (3) embedded type, which means that, apart from determining the feature importance, it also simultaneously trains the model (Technical documentation, MATLAB and Statistics and Machine Learning Toolbox Release 2019b, MathWorks, Inc., Natick, MA, United States).

Let us assume a large data table containing 100 variables and 1000 observations. Each column of the table corresponds to measurements of one specific variable, and out of the 100 variables 99 are potential explanatory variables and 1 variable is the response variable. The goal with this data-processing technique is to identify the sub-set of the original data table that includes the most important variables with regard to explaining the response variable. This way, the non-important variables can be avoided when creating the model, and on top of that the model can contain fewer variables and ease model interpretations. Some methods also handle overfitting, which is a scenario that reduces the ability of the model to generalize new data.

Cross-correlation is a mathematical method used to calculate similarities between two vectors at different lags. It was applied in paper 3 to study how different sets of process variables (e.g., measurements made in stock preparation and dry-end properties) correlate to each other and when (with respect to the number of lags) the highest correlation occurred.

5.3 Neural network modelling

Neural networks were historically developed based on the idea of resembling the functioning of the brain. Neural networks are part of the field of machine learning algorithms and aimed at data-based problem solving (Ciaburro & Venkateswaran, 2017). In chemical engineering, reported articles and conference papers (Figure 24) that involved neural networks increased rapidly after 2016 (Scopus database, 2020).

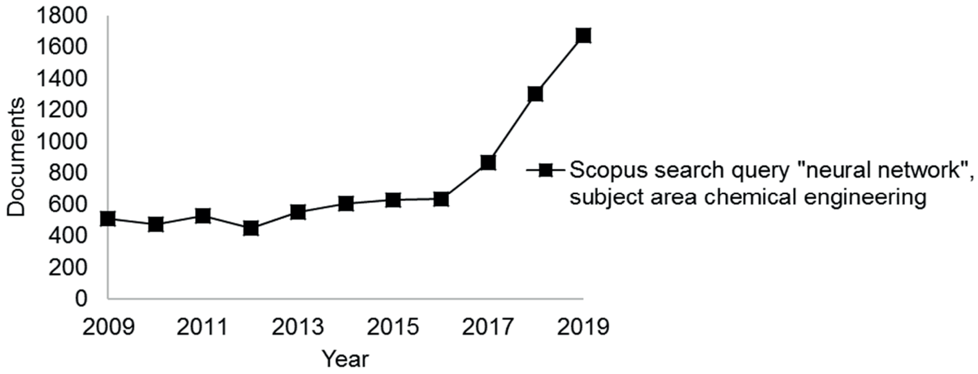

Figure 24. Scopus search for articles and conference papers (documents) mentioning "neural network" in chemical engineering.

Neural networks can be split into two types of network models: Static networks, where the output is a function based on the current input, and dynamic networks that account for past and future inputs and outputs (having a "memory") (Hush & Horne, 1993).

In this thesis one of the case studies was based on the application of a static network to predict board strength properties. Special attention was directed to the neuron structure and its influence on the predictive performance of the model. An important algorithm is the multilayer perceptron (MLP), which was developed by Rosenblatt (1958). The MLP is defined by a transfer function u=G(x), where x represents the input data (input layer) and u the output (output layer). To exemplify, a neural network is an assembly of input and output layers, and the interfaces between these layers are defined as hidden layers (Figure 25). Each neuron (sketched as a circular node in Figure 25) in the input layer corresponds to one input. Weights are assigned based on the connection of the input neurons and the neurons in the first hidden layer.

The weight parameter determines how each of the neurons affects the following connected neuron (Ciaburro & Venkateswaran, 2017). All inputs with the weights are summed with a product function, and a bias parameter is added (Ciaburro & Venkateswaran, 2017; Hush & Horne, 1993). This sum is used as input for the activation function, and the output from this function is used as input for the next layer.

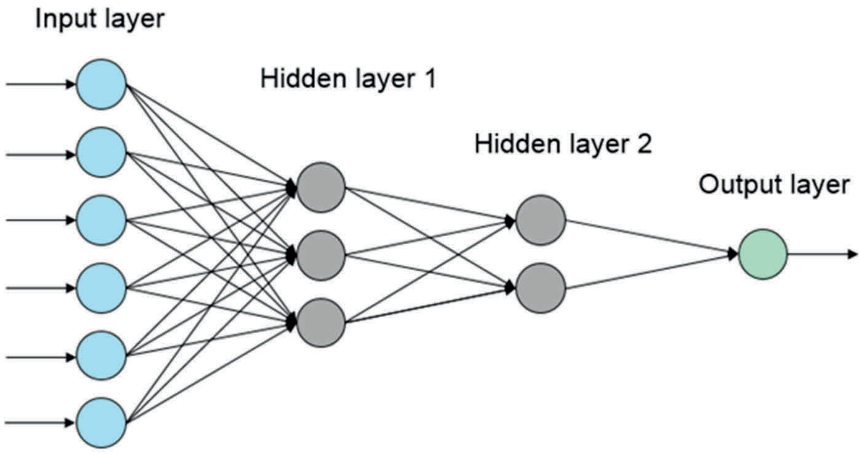

Figure 25. Layer structure of a neural network.

A more complex network can be created if the hidden layers increase in number. If so, high levels of abstraction can be developed. These kinds of complex networks, which have many hidden layers, can be outlined as Deep learning, and these are used in regression problems, image recognition and classification, computer vision and hand writing identification (Ciaburro & Venkateswaran, 2017).

5.4 Pinch methodology applied to the specific evaporation system

A Pinch analysis of the specific MEE requires that the energy–mass balance (excluding heat loss) for an individual evaporator be defined, which can be as follows:

$$S * H_S + F * h_F = K * h_K + L * h_L + V * H_V \qquad (7)$$

The mass balances for each evaporator during a steady state for the shell side are as follows:

$$S = K \quad (8)$$

For the tube side, the corresponding balance is as follows:

$$F = L + V \quad (9)$$

The methodology for analyzing the evaporation system was determined by the heat load of the condensing steam side ($Q_{ev,hot,i}$) and the boiling liquor side ($Q_{ev,cold,i}$) of each evaporator effect.

$$Q_{ev,hot,i} = S_i H_{S,i} - K_i h_{K,i} \quad (10)$$

$$Q_{ev,cold,i} = V_i H_{V,i} + L_i h_{L,i} - F_i h_{F,i} \quad (11)$$

These mathematical relationships were used as the basis for the Pinch analysis script, and they were combined with input from process data and enthalpy scripts for the steam and liquids.

6 Summary of Papers

This chapter includes summaries for the papers in this thesis. Each summary provides a brief overview and key results.

6.1 Summary of Paper 1

The system investigated in this study, based on a full-scale CTMP process, was limited to a high consistency conical disc refiner and the subsequent latency chest with a pulp sample extraction point located near the outlet. These samples were forwarded to an online pulp analyzer that measured freeness and analyzed optical fibers. The primary objective was to study systematic variations via an autocovariance analysis on refiner process data and estimates of pulp properties in order to evaluate the applicability of a dynamic model that would support prediction of some variables in the pulp's quality, and thus yield a faster response and decrease variability. Several measurement trials were conducted where the settings of the pulp analyzer were changed to significantly decrease the sampling interval of the pulp (<10 minutes) compared to normal production settings.

For the trials with decreased sampling intervals, the response (i.e., the pulp measurements) was interpolated to reach an equidistant output signal. The sampling interval in these estimates was equal to the average time between the online measurements. The potential bias or error for the interpolation part (of the system response via the pulp properties) was not investigated, and is suggested as a topic for future work. For the analysis of pulp properties during normal production conditions, the sampling interval was 30 minutes; these estimates were extracted from a unit step sequence generated by the process data system. During one trial, pulp samples were also extracted manually every 10 minutes. The refiner measurements were, in relation to the pulp measurements, oversampled and had a constant sampling interval. To study the impact of a significant change to the clearance of the conical disc on freeness and the specific electricity consumption, one trial was performed where the gap was increased by approximately 0.1 mm, and the pulp response was measured at a

decreased sampling interval.
The results from the trials (with decreased sampling intervals of the online measurements) indicated that the estimated freeness (Figure 26), fiber length and share of fines exposed almost no significant autocovariances.

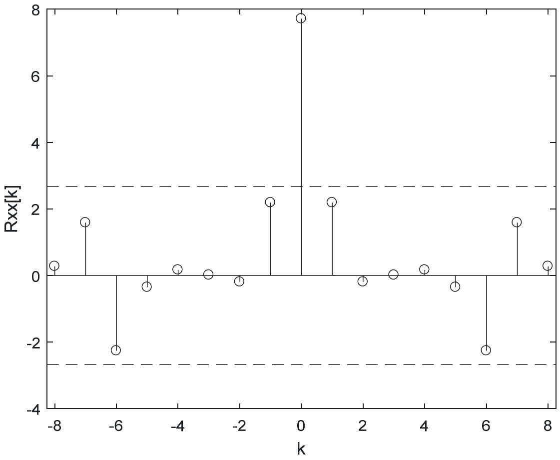

Figure 26. Autocovariance for estimated freeness (k = 8 minutes).

An important aspect of the results is that most of the freeness measurements varied within the uncertainty of the measurement system. During one of the trials with a decreased sampling interval, the refiner power varied +/- 1%; hence, the expectation of changes in freeness was low.

Increasing the refiner gap clearance (Figure 27) resulted in an estimated response time (from a change in the refiner and the related impact on the pulp's properties) of ~19 minutes, which was compared to the hydraulic residence time in the latency chest and calculated to 22 minutes (for a specific sequence).

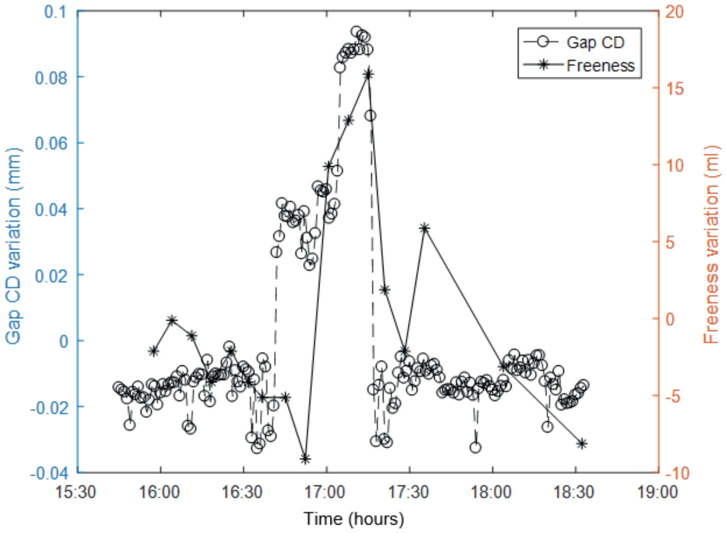

Figure 27. Clearance of the conical disc and measurements of freeness made during a significant change in the gap.

Analysis of the refiner data indicated significant autocovariance values for the specific electricity consumption (up to 150 minutes) and temperature (up to 200 minutes) in the refining zone. Significant autocovariance values were observed when calculating from longer measurement sequences (~1 day), but for shorter sequences (~20 minutes), no significant autocovariances were revealed for these variables.

Many estimates of freeness varied within the uncertainty of the measurement system; multiple refiner and pulp variables had characteristics similar to a white Gaussian signal, supporting the low level of ability to make predictions. For the specific process data in this study extracted for shorter sequences, the level of variability for the refiner power, combined with the indication that most pulp property estimates have a low or non-significant autocovariance, support the fact that variations in the pulp's quality are so small during near to stationary conditions that reducing them is very challenging with the present measurement system.

Considering the results, it was clear that the specific design and conditions of the CTMP process impacted the results; thus, general conclusions should not be drawn from the results, which are closely connected to site-specific conditions.

6.2 Summary of Paper 2

CTMP was extracted from the process for an extended period from a position after the latency chest, defined as primary refined pulp, and from the pulp stream exiting the mill to the board machine, defined as accept pulp (Figure 28). The pulp samples were measured in a pulp analyzer to determine fiber properties. The main objective was to predict the z-directional tensile strength and Scott bond for laboratory handsheets made of the pulps. For the handsheets made from the primary refined pulp, measurements were collected from both the refining process and from morphologic measurements of the pulp.

Process data, pulp data and the handsheet strength property were synchronized according to conditions for the primary refined pulp samples, whereas the accept pulp samples were based on pulp data and the strength property. One important hypothesis in the evaluation of the applied multiple linear regression model was that the crill content, measured off-line with ultraviolet and infrared lights, would improve the statistical models. Results showed that the crill variable (assumed to be related to crill content) was positively correlated to the z-directional tensile strength of the accept pulp, which explained 55% of the variance. Based on a combination of the crill, freeness, fibril perimeter and mean kink angle variables, the estimated model of the z-strength of accept pulp resulted in an R^2 of 0.79. After applying a cross-validation procedure to evaluate predictive performance, the R^2 reduced to 0.57. If only the fiber morphology variables and crill were included in the cross-validated model, R^2 increased to 0.67. The cross-validated models to predict the z-direction tensile strength, which were based on primary refined pulp, showed large variations in R^2 depending on the predicting variables that were included in the model. For the latter models, measurements from the pulp analyzer gave a better validation model compared to using only refining process data.

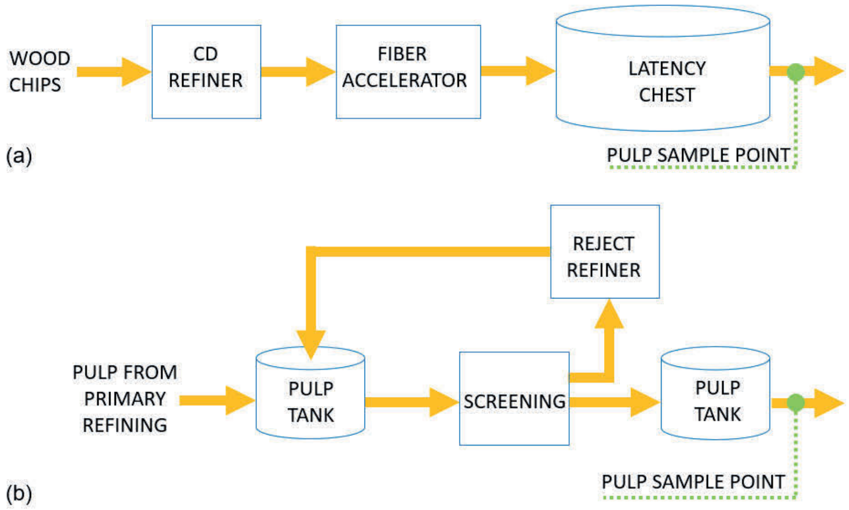

Figure 28. (a) Sample positions in the CTMP process of primary refined pulp and (b) accept pulp.

6.3 Summary of Paper 3

This study focused on characterizing material properties during a grade change, employing extensive laboratory material testing in addition to the normal process data, and it evaluated the impact from lowered chest volume in the stock preparation process. An important aspect of this study was to increase knowledge of the process and material behavior relevant to reducing losses during grade changes.

A machine trial was performed, processing a full-size grade change jumbo reel, and the results showed that Scott bond (Figure 29), along with several other physical properties, were in a transient state during the period that corresponded to a production of 29 tons of board, and it reached a steady state simultaneously as basis weight attained stability.

Analysis of the mixing chest in the stock preparation process indicated that the consistency for lower chest levels was related to a larger confidence interval for most of the samples. A process simulation model of parts of the stock preparation was proposed, which incorporated transient characteristics, and the results showed that the maximum value of the simulated consistency response increased with lowered chest levels, given un-changed controller settings. As indicated in the statistical analysis and simulation results, prerequisites for reaching shorter lags between stock preparation and board machine involves focusing on reduced chest volumes aligned with better controls and standardized operation.

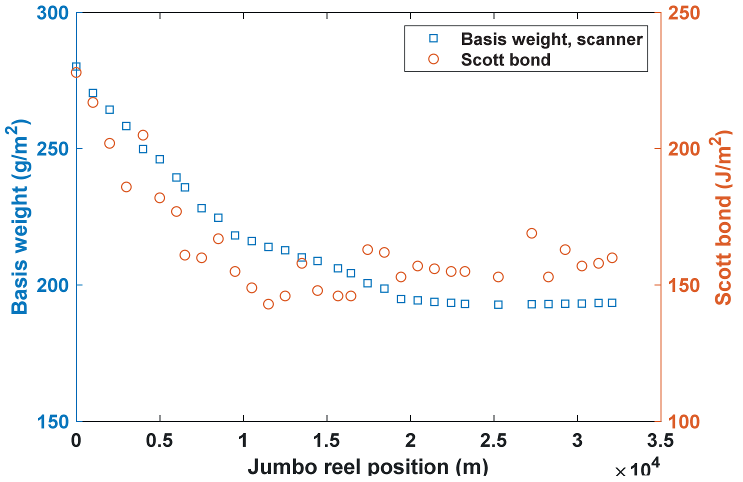

Figure 29. Basis weight measured with scanner and Scott bond per jumbo reel position.

6.4 Summary of Paper 4

The production of boards is a volume-intensive process that is characterized by frequently sampled process data and unfrequently sampled quality properties of the final product. If these product properties could be accurately predicted based on the process data, this would improve production efficiency in terms of quality and energy. This study aimed at increasing knowledge of z-direction tensile strength and Scott bond predictions by evaluating different feature selection algorithms to identify the best subset of data for modelling with neural networks. A central part of the study was the evaluation of the model performance and influence from the neuron structure, where the performance metric was defined as the mean squared error. Results revealed that the *LASSO* algorithm outperformed the models that were based on variables identified with the *relieff* and *fsrnca* algorithms. The neural network model that had the best predictive performance for z-direction tensile strength was based on data that related to refining energy as well as wet-end and stock preparation. Regarding prediction accuracy for Scott bond and z-direction tensile strength, the latter material property resulted in better models. These models indicated an optimal neuron structure when they had close to two-thirds of the number of input neurons in the first hidden layer. For a given consistent neural network structure, several training sequences with different initial randomizations resulted in an MSE variation corresponding to +/- 8%.

6.5 Summary of Paper 5

A full-scale multiple effect evaporation (MEE) system was studied. The aim was to apply Pinch methodology to construct Grand Composite Curves (GCCs) in order to observe the potential energy recovery that could improve the energy efficiency of the MEE. Observations from process data showed warm condensates leaving the MEE to heat the biological treatment process (aerated lagoon). A theoretical temperature window was set to study the scenarios of specific sequences, including a reduction in the heat load to the biological treatment plant. Several case studies of re-directing the heat in the condensates to heat up the MEE were performed. Results showed that the excess energy was greater during the warm season and lower, or even non-existent, during the cold season (Figure 30).

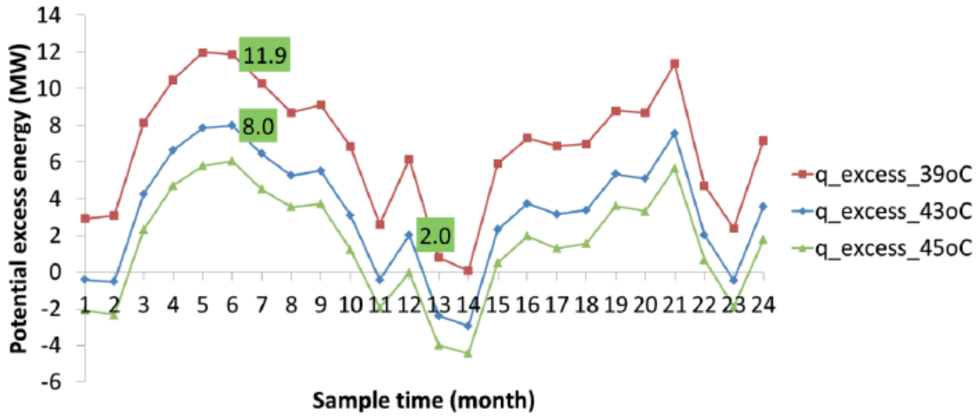

Figure 30. Potential excess energy.

Development of Pinch methodology was implemented in computer scripts by importing process data to visualize graphically how the MEE could be optimized with respect to reducing the consumption of steam for different case studies. From a thermodynamic perspective, it was indicated that, although the case based on using both flash evaporation and sensible heat was the best way of using excess energy to reduce the usage of steam, it was also likely to yield the highest capital cost.

The GCC generated (Figure 31) revealed that higher levels of dry content in the black liquor caused higher temperature differences between the first effects. The last effects (in the evaporator chain) had lower differences in temperature due to the black liquor having a lower level of dry content, resembling the properties of water.

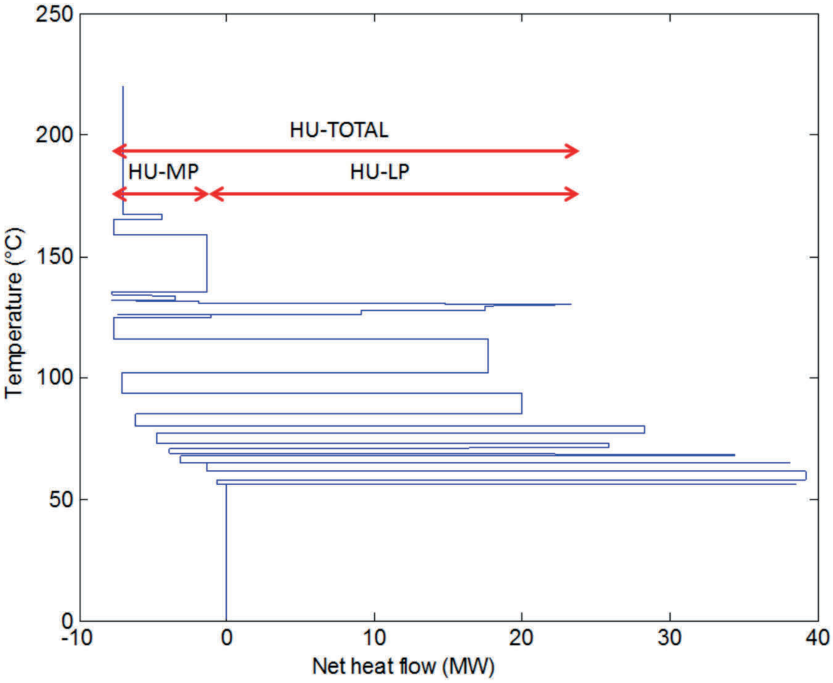

Figure 31. GCC for the MEE. HU-TOTAL = minimum total hot utility; HU-MP=minimum hot utility for medium-pressure steam; HU-LP=minimum hot utility for low-pressure steam.

Case studies showed that, for one of the MEE configurations, pre-heating the CTMP liquor (Figure 32) resulted in a smaller reduction in the consumption of steam (estimated at 1.6 %).

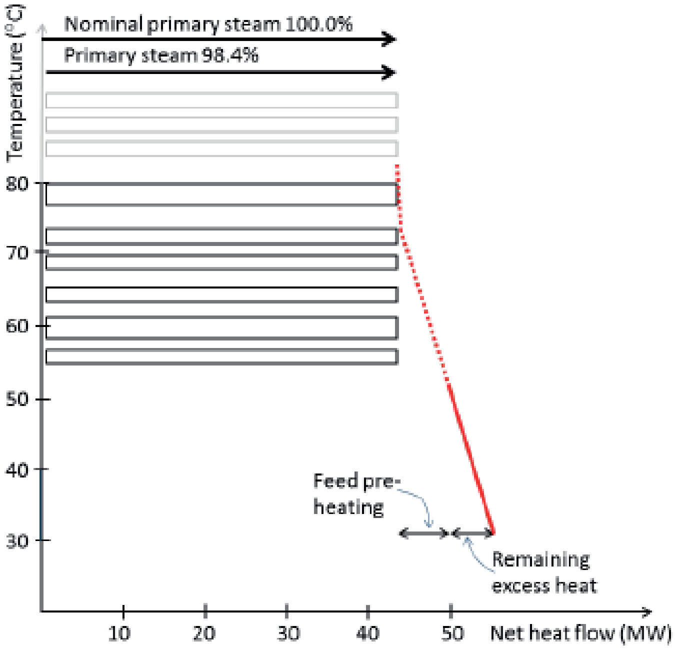

Figure 32. Simplified GCC for one of the case studies.

This study was based on limited operating conditions; the potential impacts of the heat load in the evaporator and the levels of dry content were not studied and are suggested as subjects for future work. This limitation, along with the specific design of the MEE, illustrates that additional work is necessary before definite conclusions can be drawn.

7 Additional results

7.1 Single point morphology measurements and freeness models based on supervised machine learning

This study addressed a new installation of a single point morphology analyzer to capture frequent measurements of the pulp in a full scale CTMP process, at a location of the outlet of the latency chest, directly connected to the CTMP pipe. ‘Single point’ explains that the analyzer is designed to collect pulp from one position only in the process. It used optical measurements to generate statistics of the fiber properties. By enabling measurements with increased output frequency, the idea was to monitor the short-term variations and thereby improve the control of the process, and making it more efficient. With an approximate data output frequency lower than a few minutes, the analyzer was substantially faster compared to the multi point pulp analyzer, which during a specific period generated freeness data on average at about every 34 minutes (Figure 33).

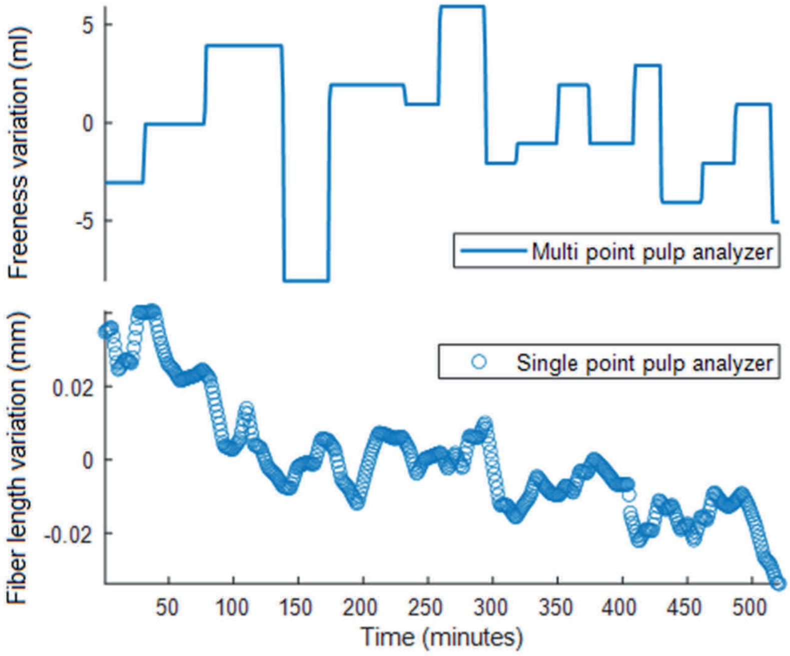

Figure 33. Example of a process sequence, displaying freeness variation measured with the multi point analyzer (upper diagram), and fiber length variation measured with the single point analyzer (lower diagram).

The aim with this study was to apply supervised machine learning to investigate a freeness model based on data from the analyzers combined with refining data. If such a model would be accurate and stable, it would generate a freeness prediction about 17 times more often, compared to the existing freeness measurements. It is relevant to acknowledge that these analyzers differ in several aspects, where two of the most significant are that the multi point pulp analyzer also measures freeness (in addition the morphology measurements captured with a digital camera) and collects pulp from several positions in the CTMP process.

In this study, the data collected from the single point analyzer were average fiber length, shives, fiber fraction 0,2-0,4 mm, fiber fraction 0,4-0,6 mm, fiber fraction 0,6-1,0 mm, fiber fraction 1,0-1,5 mm, fiber fraction 1,5-2,0 mm, fiber fraction 2,0-2,5 mm, fiber fraction 2,5-3,0 mm, fiber fraction 3,0-4,0 mm and fiber fraction >4,0 mm. At the time of performing this study the analyzer was still in the test and validation stage, and the initial results of this study need to be considered in that context. The refiner was a conical disc refiner of type RGP-82CD. For this study, following refining variables were used: specific electricity consumption, plate gap in conical disc, plate gap in flat zone, temperature in conical disc and temperature in flat zone.

Process data was collected for about 23 days of operating conditions. To take account for the hydraulic retention time in the latency chest, all refining variables were shifted with the theoretical retention time. By applying MATLAB and the statistics and machine learning toolbox, 985 consecutive freeness measurements were identified and combined with the single point analyzer and refiner data.

The final data set was then used to predict freeness by applying multiple linear regression (MLR), regression tree (RTree) and support vector machine (SVM). All models applied five-fold cross validation procedure to estimate the predictive performance. Regression tree was constructed using the input and output variables through a binary split at each branch, where the split values were based on the input variables. The regression tree was optimized during the modelling phase to identify the minimum leaf size. To evaluate the performance of a linear support vector machine following parameters were set:

Default linear kernel, standardization of the input data and sequential minimal optimization as solver routine.

Based on the specific measurements and process data, the results indicated that the best model was the regression tree and included fiber length, shives, specific electricity consumption, refiner gaps and refiner temperatures (Figure 34). The residuals of this model (the difference between the predicted and observed freeness value) were not fully symmetrically distributed, shown through too high predictions at the lowest freeness values, and too low predictions at the highest freeness values. This indicates that the model needs to be more flexible or requires either more data or an additional input variable. However, the model captures the overall trends in the data. If using equal input variables as the regression tree, the performance of the multiple linear regression model and the support vector machine were somewhat inferior. However, the predictive power of all models studied were rather low, whereas the best model (with aspect of explained variability) reached an R-squared of 0,56 (Table 1). It was indicated that the refining variables improved the models and that the fiber fraction variables did not improve model performance.

Table 1. Modelling results for the prediction of freeness, using refining and fiber morphology data.

Model	**SEC**	**GapCD**	**GapPlan**	**TempCD**	**TempPlan**	**FLength**	**Shives**	**R-squared**	**MSE**
MLR1						X		0,20	70,22
MLR2							X	0,14	74,50
MLR3						X	X	0,26	64,48
MLR4				X	X	X	X	0,27	64,00
MLR5	X	X	X	X	X	X	X	0,52	42,38
RTree	X	X	X	X	X	X	X	0,56	38,19
SVM	X	X	X	X	X	X	X	0,51	42,51

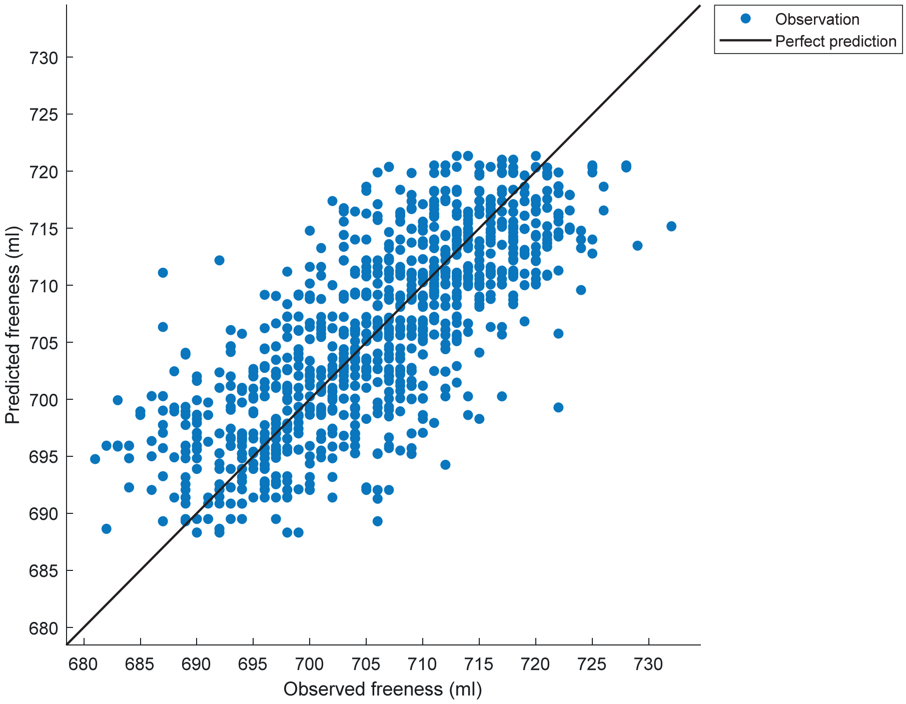

Figure 34. Freeness model, based on the regression tree (RTree).

8 Discussion

With reference to the outlined research questions given in the introduction, the following interpretations and insights were made based on the analyses in this thesis:

1. Since trial measurements during nearby steady-state conditions demonstrated there were no systemic variations in the pulp quality, it was concluded that application of a dynamic model was limited. However, these observations also indicated favorable operations through the actual absence of systematic variations. A challenge regarding the application of a dynamical model was the selection of representative process sequences and the related evaluation of steady- or non-steady-state conditions.
2. Addition of crill to the pulp measurements was motivated since it was one of the top predictors identified for predicting z-direction tensile strength. Measurement of crill is an interesting feature in monitoring refining variations. To make robust models based on this measurement, it appears relevant to constantly control and maintain properties of the water that constitute the crill measurement.
3. It was possible to capture transient board properties during a grade change. This was shown through comparing laboratory measurements of basis weight and online scanner measurements of basis weight. This case study was limited to one machine trial. In contrast, the development of an adequate multivariate model for board predictions, based on process data, during transients would require a large number of trials.
4. Influenced by their structures, neural networks indicated an ability to predict board strength. An optimal neuron structure for the specific z-direction strength data was observed, and it had close to two-thirds of the number of input neurons in the first hidden layer.
5. Observations from process data showed that warm condensates leaving the evaporation system heated the biological treatment process (aerated lagoon). The hypothesis in the study is that the temperature of the stream entering the biological treatment can be reduced periodically to re-direct the potential energy excess

to the evaporation system. Results indicated a reduction of steam consumption. This approach would require retrofitting processes in the case of pre-heating the CTMP liquor.

8.1 Modelling based on process and quality data

When the aim of the work is to develop a model based on full-scale mill process data, a good starting point is to learn about the process in detail and how it is controlled. Of equal importance is to scrutinize the properties that are being measured within the system boundaries, at what position the functionality and uncertainty of the measurement sensor is and, last but not least, how the resulting information is used. After data acquisition is complete, there is a need to view the data not only to find potential outliers but also evaluate their feasibility. In some cases, the data need to be interpolated and synchronized. This part is potentially time-consuming: if the study is multivariate and the measurements are extracted from multiple process sequences, this should be considered when planning the research work. Compared to the initial phase, the subsequent modelling part may be somewhat less time-consuming. A critical aspect in process modelling, which is difficult in some cases, is the differences in dimensionality with respect to the process and quality measurements that are made. It is not uncommon that the process has a large number of measurements with a high sample rate and a number of quality measurements that are much lower and sometimes measured at a lower sample rate. When scrutinizing the process data, the variables need to be divided into categories, typically output variables, manipulated input variables and passive input variables. In order to understand the potential disturbances of the variables, and to divide them correctly into categories, it is relevant to involve experts with knowledge on the specific processes and behaviors of the material. During parts of the data analysis in this study, it was noted that the MOPS system sometimes generated interpolated values. These data were treated “as is” in the analysis and modelling, and there is a risk that these interpolations, if present, may have caused increased uncertainty. The processes and machines that were analyzed in this work were specifically designed for unique site conditions, meaning that while the presented models are representative for these specific conditions, they may not be suitable for generalization purposes.

Paper 1 included a couple of trial-measurements at the CTMP mill with increased frequency of the pulp measurements, and these trials were limited to a few hours of pulp sampling. To enlarge the study of short-term variations in the CTMP process, the additional results of this thesis aim at predicting freeness at high frequency by adding measurements from a single point morphology analyzer, that collected fiber data for an extended period. Compared to the above-mentioned trial-measurements, this analyzer had even higher output frequency (of pulp morphology), approximately 3-4 times higher. The primary goal of such prediction is a fast response to changes in the refiner to reduce the electricity consumption through avoiding over-refining. Besides collecting fiber data for predictive modelling, the idea with the analyzer was to monitor shives and fiber dimensions for optimization purposes.

8.2 Energy aspects within the pulp and paper industry

Energy aspects and efficiency studies have been on the table for some time now in the P&P industry. Simulation models and Pinch methodologies have not seldom been utilized as tools to perform energy-related studies, and this toolbox appears to be successful. R&D programs aimed at reducing resources and the usage of energy have resulted in, for example, new technologies being developed. Some studies from the selected literature are based on theoretical mill models: it appears, in some cases, that there is a gap between full-scale and real-life process conditions where making changes and improvements to the various processes are concerned.

9 Conclusions

9.1 General conclusions

This thesis demonstrates several process-modelling case studies based on data from an integrated board mill, mainly applying supervised learning methods to study relationships between input and output data. A general conclusion that can be drawn is that the analysis and modelling of process and quality data are multidisciplinary tasks, where the applicability of computation techniques depends on the specific characteristics, putting demands towards access to multiple modelling techniques. Multivariate models for quality indicated that they can be used to improve production performance through predictions of strength properties. By using cross-validation techniques, the predictive performance of these models could be evaluated also in the case of having limited data.

9.2 Conclusions per paper

In paper 1, the aim was to study the applicability of a dynamic model for pulp quality predictions and to increase knowledge of the time-varying characteristics in the CTMP process. Most of the estimated pulp properties and refining process data had characteristics similar to a white Gaussian signal, indicating favorable operation of the process through the absence of systematic variations. Trials revealed that many of the pulp observations were within the measurement uncertainty, and variations in the specific electricity consumption were so small that significant variations in the pulp quality could not be expected. In combining these results, it seems that the variations observed in the pulp quality during the nearby stationary operation were so small that they could not be reduced with the current measurement system.

In paper 2, the applicability of multiple linear regression models, based on process and pulp data, to predict strength properties of laboratory handsheets made of CTMP was demonstrated. Measurements of crill were positively weakly correlated with the tensile strength of the handsheets made of accept pulp. In terms of predictive performance for the accept pulp, the best model was based on fiber morphology and crill.

The main purpose of paper 3 was to characterize process and board properties during a grade change machine trial and to study the impact from lowered chest volume in stock preparation with respect to faster grade changes. Machine trial data showed the board quality was transient, and it reached a steady state simultaneously as basis weight attained stability. Supported by indications in the statistics and simulation outcomes, prerequisites for faster grade changes involved focusing on reduced chest volumes aligned with better controls and standardized operation.

In paper 4, the dimensionality issue related to process data and board quality measurements was studied. The performance of feature selection algorithms and neural network structures were studied with aspects of board strength predictions. The best performing neural network model for predicting z-direction tensile strength was based on process data that related to refining energy, CTMP consistency, basis weight of middle plies and chemical components.

In paper 5, process data from a multiple-effect evaporator were analyzed with focus placed on recovering the energy of the condensates. Case analysis indicated that pre-heating the CTMP liquor caused flash evaporation in the low-temperature side of the evaporator chain and a small reduction in the consumption of steam. A greater reduction was indicated for the case in which both sensible heat and flash evaporation were used, which was the optimal way of using the excess energy.

10 Future perspectives

The manufacture of pulp and paper involves many variables that are measured, and large amounts of process data are therefore generated. If a change is made to the process, it is of great importance to know what impact a particular change will have on the response. The response might be delayed, which is not favorable for optimizing the process or the material. Aiming research at modelling critical variables could bring value not only through improving knowledge of the actual process behavior but also by evaluating the applicability of predictive models. Should a predictive model fit the process sufficiently, it could be a potential way of improving the efficiency of the mill.

Suggestions for future work embrace the evaluation of process and quality data, combined with laboratory measurements, to further study the feasibility and long-term robustness of predictive models of specific properties of quality in the mechanical pulping process and the board machine.

In the CTMP process, for example, this could involve developing more advanced definitions of energy efficiency, including specific energy (or other refining variables) and the resulting properties of laboratory sheets, such as density and strength properties. This would also require the extraction of pulp samples during an extended operating window to capture the characteristics of the CTMP process.

The initial dataset of input variables in the predictive model applied to the pulping process would include measurements of both the process and the fibers so that the influence of the added process and fiber data on modelling accuracy could be studied. The objective would be to increase knowledge of how the energy efficiency could be improved and variations reduced.

In the case of predictive modelling with respect to the variables in the board machine, it would be of interest to scrutinize important predictors from the chemical and mechanical pulping processes as well as the board machine; adopting a minimizing approach would increase the likelihood of developing a grey box model. This model would include response variables connected to material losses and have the same objectives as the model for the pulping process, i.e., improving the energy efficiency and reducing variations.

Regarding time series analysis based on CTMP process data, it would also be of interest to study wavelets from the aspects of modelling both stationary and somewhat non-stationary processes.

If a mill is subject to implementing a model for prediction purposes, it is important to consider the material and process variations by evaluating a procedure, manual or preferably automatic, to tune the model at certain intervals. Thereby, more investigations are required to determine acceptable durations for these intervals that establish long-term, robust models.

A lesson learned from this thesis is to work proactively with implementing new sensors in the production process. It is a time-consuming process to install new sensors that are fully integrated and calibrated, and this work likely requires personnel from the supplier, the mill and the R&D organization. It will be interesting to continue developing sensors that measure fiber properties accurately and provide extended statistics of the pulp with a short lag from sample to presented data. These kinds of measurements would support increased understanding of the relationships between the process conditions, the pulp properties and the resulting paper properties, which in turn can form a basis for increased production efficiencies.

The development of process models that are data-driven is a task that requires multidisciplinary competences. It is feasible to establish a work environment that includes experts from different fields including researchers, statisticians, process engineers, operators and development engineers.

Based on the additional results, concerning high frequency fiber measurements in the CTMP process, more work is needed to reach a more flexible model and it is suggested to evaluate additional fiber morphology parameters as part of the input data, as well as extended validation including laboratory measurements. Due to practical reasons the single point sensor was installed at the outlet of the latency chest, meaning the retention time delays the response for process control purposes. If this type of sensor could be installed to collect pulp samples earlier in the process, e.g. at the inlet of the latency chest, or from the top level inside the chest, it would provide a faster response to refining changes and new fiber data that potentially can improve the process control. An evaluation of the feasibility of such installation would require more work.

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Process modelling in pulp and paper manufacture

The manufacture of pulp and paper is an energy intensive process configured of several unit processes that shape a network of flows of wood chips, chemical pulp, mechanical pulp, board and other important components. Improved energy efficiency supports sustainability of the process and the products. With the purpose of monitoring and controlling, information from multiple process and quality variables is continuously collected in the process data system. The data may contain information about underlying patterns and variability, and using statistical and multivariate data analysis can create valuable insights into how reduced variations and predictions of certain properties can be accomplished.

This thesis investigates the application of mathematical models for processes and products. These models can be used to increase the knowledge of the process characteristics and for quality predictions, to support process optimization and improved product quality.

Based on process data from a board machine including the stock preparation process, an evaporation system and a CTMP plant, process models have been developed with the aims of quality predictions, improved energy efficiency and reduced process variability.

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