LICENTIATE THESIS

Process Control and Production Strategies in the Sawmill Industry

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LULEÅ UNIVERSITY OF TECHNOLOGY

Thesis for the Degree of Licentiate of Engineering

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Abstract

The sawmill process itself is not complicated. What makes it complex is the diversity of the raw material, the logs that are processed in the sawmill, and the divergent production with many different end products. In the sawmill various number of measurement and scanning equipments are installed. These are used for controlling the various processes and for measuring how well they are carried through.

The main objective of this thesis is to build knowledge of how we can make the sawing process, one of the main steps within the sawmill process, more efficient with respect to both volume yield and value recovery by new equipment and new production strategies. The intention has been that the conclusions in this thesis can contribute to a knowledge base that can be of assistance in decisions regarding control process parameters and production strategies for a sawmill.

There is a possible economic saving by increased volume yield for the sawmills if the saw kerf width can be reduced, but there is a fear that the presence and magnitude of saw mismatch will be affected by this. Saw mismatch occurs on the sawn boards due to displacement in axial direction of the saw blades in double arbor saw machines as a consequence of wear, heat or mechanical disturbance. It is shown in this thesis that it was possible to measure saw mismatch automatically during sawmill operation by laser triangulation and that the measurements were comparable to manual measurements. It is also suggested how the presence and magnitude of saw mismatch can be evaluated when measurements are carried out in a sawmill.

Another study addressed in the thesis is the consideration of applying an alternative log rotation for each log than the in Scandinavia industrial praxis of horns down (log crook faced upwards). This possibility for a greater profit return comes in question since the development of an industrial computed tomography scanner makes the internal knot structure of the log available.

Log breakdown simulations of about 600 Scots pine (*Pinus sylvestris [L.]*) logs and 800 Norway spruce (*Picea abies [L.] Karst.*) logs mainly from different geographic locations in Sweden showed that there is a potential value increase when rotating each log for greatest profit return. The potential value increase was dependent of the rotational error of the sawing machine and the price differences between quality grades. For the 600 Scots pine logs and the 800 Norway spruce logs in the study an increased average value increase of 13% was obtained if applying the rotation that maximizes the value of each log instead of the horns

down position. An introduced rotational error of the sawing machine reduced the value potential to 6%. There was a weak correlation between the log rotation that maximizes the value of each log and the outer shape of the logs. This means that the outer shape can not be used as an indicator of how the log should be rotated for greatest profit return.

One subject of discussion in the thesis is also the importance of representative input data in order to make as general conclusions as possible. The Swedish stem bank has been an important factor in many studies made in the field of wood technology. It is a well-documented data set and computed tomography scanning of logs has made it possible to represent internal wood features in log breakdown software. Since computed tomography scanning of logs is a time-consuming process the number of scanned logs are relatively small. Now that an industrial computed tomography scanner operating at production speed is entering the market this opens up new possibilities. Hopefully simulation studies that are performed on larger industrial data sets coming from logs processed in the sawmills at a daily basis is not too far away.

Preface

The work of this thesis has been carried out at Wood Technology, Division of Wood Science and Technology, Luleå University of Technology, Skellefteå under the supervision of Professor Anders Grönlund and Professor Johan Oja. This research was financially supported by the Swedish Governmental Agency for Innovation Systems (Vinnova), WoodWisdom-Net and WoodCenterNorth(TCN) for which I am truly grateful.

I wish to express my gratitude to Professor Anders Grönlund for his guidance and support throughout this work. His supervision and expertise within the field has been an inspiration during this time and has made my work both enjoyable and stimulating. I am grateful to Professor Johan Oja for his scientific and professional guidance. His advice has been of great importance in my work.

The collaboration with external partners has been essential for this work. My thanks goes to Norra Timber and SP Technical Research Institute of Sweden, SP Wood Technology.

Thanks and appreciations also goes to all my colleagues at Luleå University of Technology in Skellefteå who have made this work even more worthwhile. It is a privilege to be part of all the interesting and sometimes odd discussions concerning both work and everyday life.

Skellefteå, April 2013

Anders Berglund

Anders Berglund

List of publications

The thesis is based on the following publications:

Paper I
A. Berglund, S. Dahlquist, and A. Grönlund. Detection of saw mismatch in double arbor saw machines using laser triangulation. Submitted to journal, 2013

Paper II
A. Berglund and A. Grönlund. An industrial test of measuring saw mismatch by laser triangulation. Accepted for *21st International Wood Machining Seminar, Tsukuba, Japan*, 2013

Paper III
A. Berglund, O. Broman, A. Grönlund, and M. Fredriksson. Improved log rotation using information from a computed tomography scanner. *Computers and Electronics in Agriculture*, 90(0):152 – 158, 2013

Contents

Part II

Part I

Chapter 1

Introduction

This composite thesis comprises a summary with included articles and conference articles authored during the years 2011 - 2013.

The work carried out during this time in the areas of sawmill process control and sawmill production strategies related to processing of sawlogs are described in the summary of this licentiate thesis. The articles are handled traditionally, one-by-one in the summary.

This first chapter provides an introduction to the thesis first by presenting some background of the field of research in Section 1.1. This is followed by Section 1.2 describing the justification of the work and Section 1.3 stating the objectives. Subsequently Section 1.4 describes the thesis outline and finally Section 1.5 presents the contributions of the thesis.

1.1 Background

In any process industry accurate measurements and measurement techniques are important to assure that the result of the process is the expected. In the sawmill industry and more specific during the processing of sawlogs that this thesis is focusing on there is also a need of measurements in order to gather trustworthy information. This mainly for assuring the fulfilment of quality demands on the sawn products and for improving the sawing efficiency. As for sawing efficiency, volume yield and value recovery have become increasingly important for sawmills in the European countries. Traditionally European sawmills have mostly been focusing on productivity and volume yield. This way of thinking is successively changing due to the fact that it is difficult to increase harvested volumes and so the advantage of increasing the production volume and value recovery with the same log purchases has grown stronger. It is well known that the raw material cost is the largest expense for a sawmill, followed by labour, capital and operation costs. On top of this you have what is referred to as the "sawmill paradox" which points out the fact that close to half of the sawn board volume will be turned in to sawdust or chips and up to half of the produced boards are low priced since no customer really demands them (Grönlund, 1992). These are the problems that European sawmills are struggling with, and as stated by Grönlund (1992) they are probably impossible to eliminate completely even though its effects can be somewhat lessened by new technology, an increased integration, production simulations and individual processing of each log.

The term wood quality is discussed in more detail in Section 1.1.1 while Section 1.1.2 contains a brief description of sawmill technology and the sawmill process.

1.1.1 Wood quality

Quality is a subjective term and so its definition varies. Two famous general definitions of quality are "fitness for use" by Juran (1951) and the more customer-focused "quality should be aimed at the needs of the customer, present and future" by Deming (1986). A technical definition of wood quality defined by Mitchell (1957) was how well wood "meets the technical requirements for a particular product or end use" but Mitchell realized that such a definition disregards monetary values. Mitchell concluded that it is difficult to develop a single, all-inclusive definition of wood quality.

In the definition of wood quality it is important to separate the quality of the logs from the quality of the sawn timber. Typically, logs are quality graded in order to set a price in the negotiation between the forest owner and the sawmill, but they may be quality graded and sorted at the sawmill as well. As for sawn timber it is quality graded in order to set a price for the market customer. The grading is either carried out from a visual appearance perspective (appearance grading) or from a construction perspective (strength grading), or both of them.

For the appearance grading, the quality in the Nordic countries is based on the Nordic timber grading rules (Anon, 1994). Briefly described, the grading rules separate the sawn boards into different quality classes based on the outer features of the boards, e.g., knots, wane, rot and cracks. The quality grading rules for sawn timber used in Europe are the European standards EN1611-1

(Anon, 2000) which are more adapted for the European conditions and tree growth. The subjectivity of wood quality and wood grading was highlighted by Grönlund (1994) and by Grundberg and Grönlund (1997) who proved that different persons manually graded the same boards by the same grading rules differently.

Quality defects must be detected as early as possible in the conversion chain in order to minimize losses in profit. If the final board deviates too much from its target size, it can at best be planed to a lower dimension and sold at a lower price. As an example, if a quality defect like pitch pockets becomes visible after planing at worst the whole board will be chipped. The quality of the sawn products has been and will continue to be an important issue for the sawmills.

1.1.2 Sawmill technology

The sawmill industry was very important for the industrial development that took place in Sweden and the rest of Europe in the 19th and beginning of the 20th century. This section presents a brief review of the sawmill process together with some important terms and definitions and is to a large extent supported by the material found in Grönlund (1992).

The sawing process in itself is not complicated it is the diversity within the raw material, the logs, that makes it complex. The production in a sawmill can be divided into four main steps.

1. Handling and preparation of logs
2. Sawing of logs
3. Drying of timber
4. Handling of dried boards

Handling and preparation of the timber

The timber is transported to the sawmill by truck or rail road. Once at the sawmill the timber is unloaded and its top diameter is measured for sorting the logs into different sawing classes. A sawing class is a group of logs with their smallest top diameter within a stated interval. These sawing class limits are typically in intervals of 10–20 mm and are based on the customers need for board dimensions. Before entering the sawmill, the butt end of the log is reduced and the log is debarked.

Sawing of timber

There is a number of different sawing techniques for log breakdown. In this section the most common sawing technique applied in the Nordic countries, cant sawing combined with curve sawing, is described. A sawing pattern is typically a set of between two to four centre boards and between two to six side boards that together result in an optimal volume yield for the logs in the corresponding sawing class (Figure 1.1).

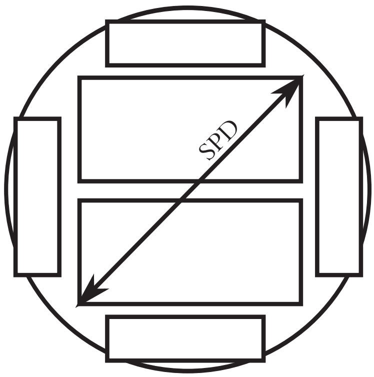


Figure 1.1: A sawing pattern with two centre boards and four side boards and the sawing pattern diagonal, SPD, projected to the top diameter of a log.

It is the diagonal measure of the sawing pattern that determines if a sawing pattern can be applied to a sawing class. Sawing patterns with the same diagonal measure can be applied to the same sawing class. The gross volume yield prior to grading and trimming is mainly dependent of log geometry and sawing method while the final net volume yield is governed by quality defects such as knots, wane, rot and cracks. To assure that the produced centre boards are without wane, the diagonal measure of the sawing pattern should be less than the lower limit of the used sawing class. Here the term sawing allowance is introduced,

$$\begin{aligned}\text{sawing allowance} = {} & \text{deviations in sawing} + \\ & + \text{shrinkage/distortions when drying.}\end{aligned} \tag{1.1}$$

It is defined as the value added to the nominal size of each board dimension because of deviations in the sawing as well as shrinkage and distortions when drying the wood. The nominal size is the desired final size. Hence, the actual board size that is aimed for in the sawing is denoted green size and is defined as

$$\text{green size} = \text{nominal size} + \text{sawing allowance}. \tag{1.2}$$

Prior to sawing, the log is rotated so that the crook is upwards (horns down) and it is centred to the first sawing machine. The log is then cut into a cant and two to four side boards. The cant is rotated 90° and typically cut into one to six centre boards and two to six side boards (Figure 1.2). The side boards are edged where the intent is to maximize the value for the production of side boards by trying to find the width and quality that maximizes the value of each board. After sawing, all boards are sorted with respect to their nominal size before they are dried.

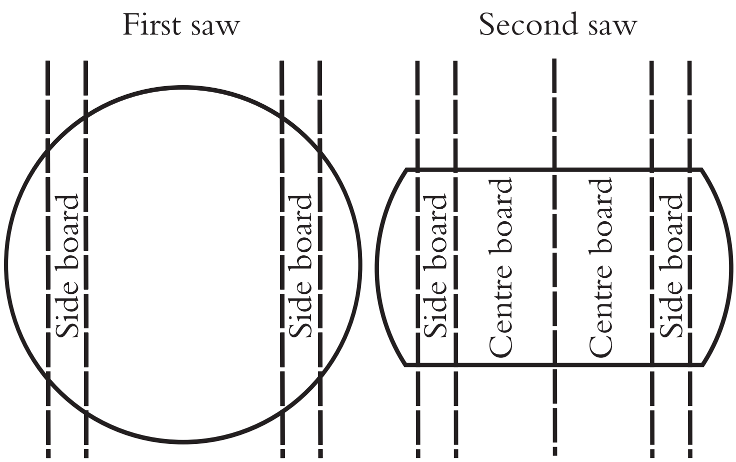


Figure 1.2: Cant sawing. The first sawing machine cuts the log into side boards and a cant. The cant is then rotated 90° and cut by the second sawing machine into side boards and centre boards. Side boards are further processed by edging and trimming, while trimming is the only operation on centre boards.

Drying of timber

The drying of the boards usually takes place in either a batch kiln or a progressive kiln. The main principles are however similar (Morén and Sehlstedt-Persson, 2007),

- Air is used as heat- and moisture transporting media
- The air circles around the boards by use of large fans
- The steam that comes from the boards is ventilated
- Both types of dryers work in the low temperature region (40°C – 80°C)

The difference is mainly that in a batch kiln, the boards are dried by changing the climate for the whole drying batch with time. In a progressive kiln the boards enter the drier in one end and are transported to the other end throughout the drying process. Since the boards contains more moist in the beginning of the drying process than towards the end, the climate will be more humid early in the drying process compared to the end. In Swedish sawmills about as large volume is dried in batch kilns as in progressive kilns.

Handling of dried boards

After drying the boards are trimmed where the intention with the trimming is the same as with the edging of side boards, but now instead to find the length and quality that maximizes the value of each board. All the boards are then sorted according to dimension, length and quality before they are finally packaged and delivered to the customer.

The final volume yield of the sawing is defined as

$$\text{volume yield} = \frac{\text{nominal volume of board(s)}}{\text{green volume of log(s)}} \times 100(\%), \tag{1.3}$$

where the nominal volume is the volume of the boards after drying and trimming.

1.2 Justification of the work

Two different fields of interest has formed the basis of the work presented in this thesis. The first, presented in Section 1.2.1, aims at developing methods and equipment for continuous follow-up of saw mismatch. The second, described in Section 1.2.2, concerns the development of a computed tomography (CT)-scanner for the sawmill industry, which will make it possible to detect the internal features of the log prior to sawing. This leads to questions regarding how to use this new technology efficiently in order to increase the sawmill profit.

1.2.1 Process monitoring in sawmills

In modern sawmills there is a number of measurement and scanning equipments mainly for controlling the different processes but also devices whose primary function is to measure how well the various processes have been carried through. The first category includes 3D-scanners in the saw line and inspection equipment at the edger and in the green sorting, trimming plant and further processing. The latter category includes cant scanner for checking the positioning error in the first saw, measurement systems for measuring green target sizes after the second saw and systems for following up production disruptions.

The need for an accurate process monitoring constantly increases as the material flow increases and the sawing process becomes more complex. How well different measurement equipment works is not fully known and what should be part of a good process monitoring system is not clear neither.

In many sawmills there is a potential to reduce the saw kerf width. Flodin and Grönlund (2011) showed by log breakdown simulation that decreasing the saw kerf width by 1 mm increased the volume yield by 3 percentage units, when applying multiple-ex sawing patterns that are used in a sawmill in northern Sweden.

A counter-question from the sawmills was if it is really possible to reduce the saw kerf width in daily operation. Since this matter is justified, it lead to a group of four sawmills that for a long time would carry out a systematic operational monitoring where they gradually reduced the saw kerf width to a for them sustainable level with respect to yield, reliability and safety.

When doing this the saw mismatch had to be measured manually to ensure that its presence and magnitude was not affected by the reduced saw kerf width. Saw mismatch occurs in double arbor saw machines when the saw blades are displaced with respect to each other due to wear, heat, or mechanical disturbance

(Figure 1.3). The saw blades overlap at the centre of the board width which means that this is where saw mismatch might occur. The saw mismatch (Figure 1.4) along the board depends on the displacement of the saw blades with respect to each other so its amplitude typically varies along the board. Since the two faces of the board are processed by different saw blades, saw mismatch at one of the side faces does not mean that saw mismatch is present on the other side face.

The saw mismatch may result in a larger planer allowance and at worst, it can lead to quality degrading of the sawn timber. In order to consistently carry out these follow-ups it is required to be able to measure saw mismatch automatically, either by further development of existing equipment or by the development of new equipment.

Once saw mismatch can be measured the question that arises is how a response variable for saw mismatch should be defined. For the sawmills the saw mismatch becomes a problem if the presence and magnitude of saw mismatch is too large. However there are no quality rules that clearly defines what is an acceptable level of saw mismatch and what is not in the dialogue between the sawmill and the customer. In light of this, different response variables for saw mismatch have been evaluated.

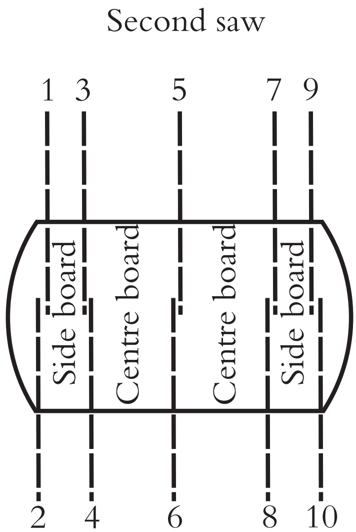


Figure 1.3: Illustration of cant sawing using a double arbor sawing machine where the produced boards have saw mismatch because the saw blades (1-10) are not aligned.

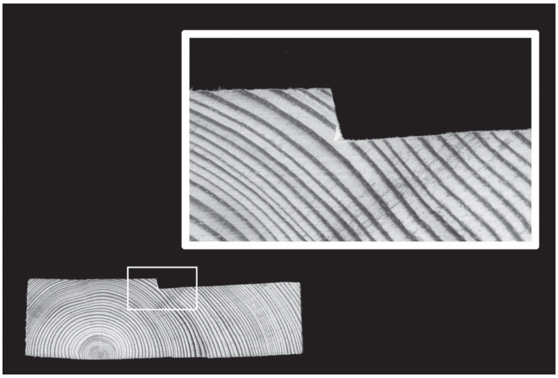


Figure 1.4: Board face with saw mismatch.

1.2.2 CT-scanner for the sawmill industry

For a sawmill about 65 – 75% of the production costs are related to the raw material, the saw logs (Chiorescu and Grönlund, 2003). This fact and the increased competition and adaptation to customers needs that the sawmills are facing increases the need of more accurate production control technologies. X-ray log scanners (Pietikäinen, 1996; Grundberg and Grönlund, 1997) are fast and result in images that show the most distinct internal features such as knots and heartwood, however not their exact size and position. This makes it possible for sawmills to pre-sort logs into high and low-grade batches, but it does not account for the fact that one log can yield boards of different grades. Being able to extract some boards of high grade even from a log with serious internal defects can improve value recovery.

The CT-Pro project aims at taking the CT-technology widely used in medicine into the sawmill (Giudiceandrea et al., 2011). The result is a high resolution scanner that is around eight times faster than before, mainly due to the first application of a new mathematical reconstruction algorithm (Katsevich, 2004).

The system's revolving gantry enables a full digital reconstruction of a scanned log. Based on the scan, the log can be virtually broken down into different cutting patterns until the one that gives the highest value and best suits the customers' needs in terms of appearance, quality and yield is identified. This makes it possible to move from sawing optimization by volume or log grade to board grade in order to maximize value and minimize waste.

The challenge is to identify production strategies that uses the benefits of a CT-scanner in the sawmill and that are realizable under operating conditions.

1.3 Objectives

The intention of this work is to take one step further towards a complete process control by developing new equipment and to investigate how this equipment can be used as efficiently as possible. It is also to investigate new production strategies that makes use of new technology to increase the profit recovery of a sawmill.

More specific, in this thesis the objectives are

- To present a technique for measuring saw mismatch during operating conditions in a sawmill.
- To investigate how the occurrence of saw mismatch in a sawmill should be evaluated.
- To investigate, by log breakdown simulation, if the profit return for a Scandinavian sawmill is greater when for each log applying the rotation that maximizes the value instead of the industrial praxis with the log crook facing upwards (horns down).
- To conclude if the outer shape of the saw logs is related to the most profitable rotational position of each log. This can reduce the number of degrees of freedom in an optimization.

1.4 Outline of the thesis

The thesis consists of two main parts: Part I and Part II.

Part I includes 6 chapters. Chapter 1 introduces the background of this work, discusses the term wood quality, gives a brief description of sawmill technology and its processes and finally presents the justification, objectives and contributions of this work. Chapter 2 describes the work carried out with respect to saw mismatch measurements while Chapter 3 describes the work within sawmill production strategies. Chapter 4 is a discussion with respect to both Chapter 2 and Chapter 3. Finally Chapter 5 summarizes and states the thesis conclusions while Chapter 6 describes future work.

Part II includes the three papers that the thesis is based upon.

1.5 Contributions of the thesis

Contributions are made on two different fields in this thesis: sawmill process control and sawmill production strategies both related to processing of sawlogs. Figure 1.5 illustrates these two fields and where the different articles have made a contribution.

Paper I: Sawmill process control.

- A laser triangulation unit for measuring saw mismatch in the green sorting line of the sawmill was tested and evaluated on a sample of boards in a laboratory.
- The saw mismatch measured by laser triangulation was comparable to manual measurements of saw mismatch.
- The lengthwise position of the estimate of maximal saw mismatch on each side face of the sample occurred close to the board ends and at the centre of the boards.
- The correlation between the lengthwise position of the estimate of maximal saw mismatch on the pith side and the sapwood side was weak for the boards in the sample.
- If two cameras placed 50 cm from the top end on each side face would have been used, 75% of the boards in the sample with an estimate of maximal saw mismatch exceeding 0.5 mm would have been detected using the laser triangulation unit.

Paper II: Sawmill process control.

- A laser triangulation unit for measuring saw mismatch was placed in the green sorting line of a sawmill. The robustness of the measurements of saw mismatch during sawmill operation was satisfactory.
- The most suitable response variable was defined as the share of the latest 500 measured boards exceeding a threshold value of 0.5 mm.
- This response variable was positively correlated with the cant height, feed speed and average log top diameter making it possible to predict 13.5% of the variance in the response variable by a partial least squares (PLS)-model.

Paper III: Sawmill production strategies

- Simulation studies showed that for a Scandinavian sawmill processing Scots pine (*Pinus sylvestris [L.]*) and Norway spruce (*Picea abies [L.] Karst.*) there is a potential value increase if scanning logs in real time with a CT-scanner. For the 600 Scots pine logs and the 800 Norway spruce logs in the study an average value increase of 13% was obtained for both Scots pine and Norway spruce if applying the rotation that maximizes the value of each log. An introduced rotational error of the sawing machine reduced the value potential to 6%.

- The profit return was dependent of the rotational step length and the price differences between the quality grades.

- There was a weak correlation between the outer shape characteristics of the logs and the log rotation for each log that gave the greatest value recovery. This indicates that log outer shape is not by itself the governing factor for how to rotate the log for greatest value recovery in the sawing process.

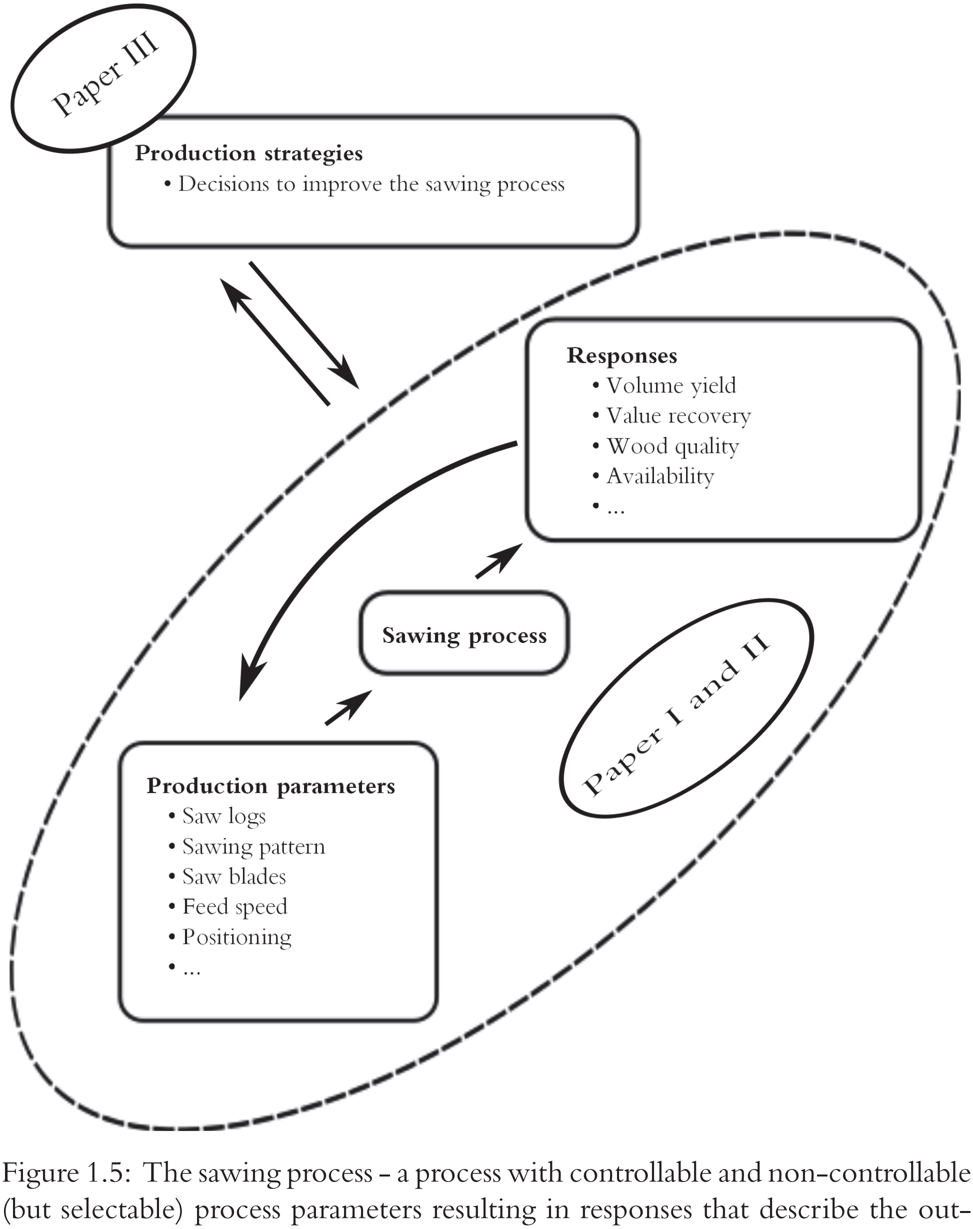


Figure 1.5: The sawing process - a process with controllable and non-controllable (but selectable) process parameters resulting in responses that describe the outcome of the sawing process (Paper I and II). Production strategies - decisions aiming at improving the sawing process (Paper III).

Chapter 2

Sawmill process control

This chapters describes the work carried out within the field of sawmill process control related to processing of sawlogs (Paper I, Paper II). The measurement principle for measuring saw mismatch is described in Section 2.1. Section 2.2 describes the experimental work during the development process, first carried out in a laboratory environment (Paper I) and subsequently in the green sorting line of a sawmill (Paper II). The multivariate technique PLS was used to analyse the data obtained from the sawmill measurements which is briefly described in Section 2.3 while Section 2.4 describes the different response variables for saw mismatch that were evaluated. Last, Section 2.5 presents the results of the experimental work described in Section 2.2.

2.1 Measurement principle

A laser triangulation unit for detecting saw mismatch was developed for placement in the green sorting line of a sawmill. Laser triangulation is a widely used measurement technique for inspection of shape irregularities on sawn wood. It is called laser triangulation since the emitting laser, the camera and the laser line that strikes a surface form a triangle. The principle is the same here, because of the incidence angle α that the laser makes with the surface normal the occurrence of saw mismatch results in a laser line that is displaced (Figure 2.1). This displacement, d, is proportional to the saw mismatch of the board and can be measured by fitting two regression lines to the two groups of separated laser pixels.

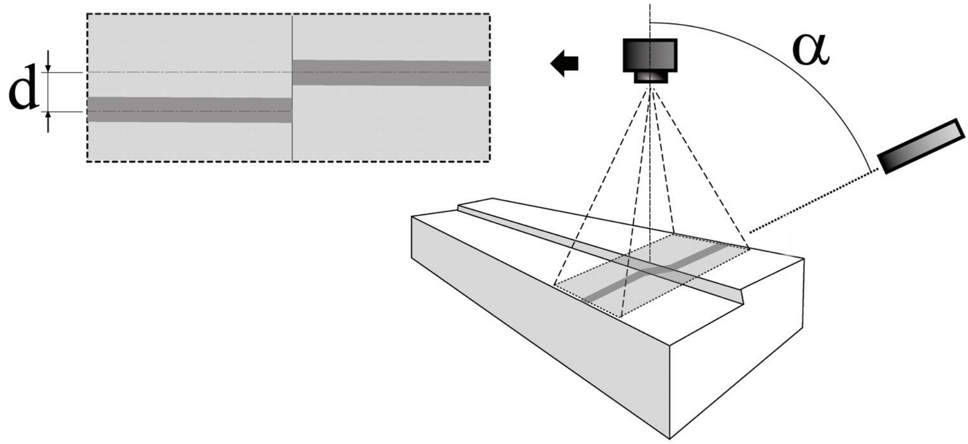


Figure 2.1: Illustration of the measurement set-up, α is the angle between the laser line and the surface normal and d is the displacement of the laser line due to saw mismatch.

2.2 Experimental work

This laser triangulation unit was tested and evaluated at first by selecting 20 boards of final dimension 38 by 125, varying length between 3.4–5.3 m and having different levels of saw mismatch (Paper I). The saw mismatch of each board was measured in a laboratory environment five times on each side face with approximately 1 cm intervals using the laser triangulation unit. The saw mismatch was also measured manually using a depth gage with a specially designed holder for measuring saw mismatch. The manual measurements were carried out at a distance of 50 cm from the top end, on the pith side and by five different individuals. The manual measurements were used to compare and evaluate the performance of the laser triangulation measurement.

Subsequently the laser triangulation unit was installed in the green sorting line (Figure 2.2) of a sawmill and measurements were carried out during 14 days of processing of a wide range of sawing classes (Paper II). The saw mismatch of each board was measured on one side face at a distance of 50 cm from the top end (Figure 2.3). This resulted in approximately 390,000 boards measured for saw mismatch.

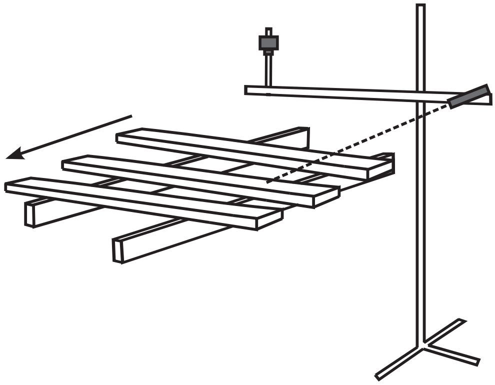


Figure 2.2: The laser triangulation unit was placed in the green sorting line of the sawmill. The direction of transport is perpendicular to the boards' longitudinal extent.

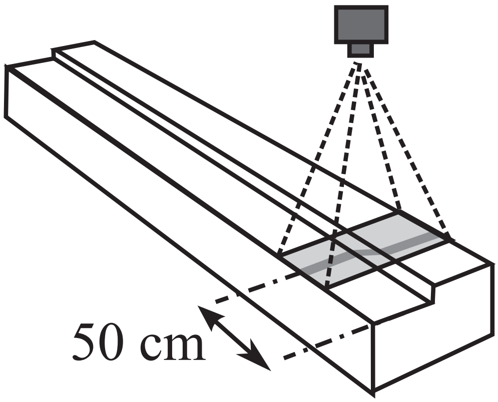


Figure 2.3: The saw mismatch of each board was measured a distance of 50 cm from the top end.

2.3 Partial least squares

To analyse the large number of observations from the sawmill measurements also containing noise and to find the most suitable response variable for saw mismatch, PLS-regression was used. PLS-regression is a regularization of a multiple regression (Ståhle and Wold, 1987), where multiple regression is based on the assumptions that the X-variables (predictors) are all independent and normally distributed. PLS-regression is based on the assumptions that the X-variables are correlated, possibly also noisy and incomplete (Wold et al., 2001), which is likely with industrial data.

The predicting variables used in the PLS were,

- Average log top diameter (mm)
- Cant height (mm)
- Feed speed (m/min)

These where the predictors that were controllable during sawmill operation. These variables are definitely correlated to each other since the feed speed is adapted to the cant height and the cant height, in turn, is dependent of the log diameter. This is one reason for why PLS was preferable in front of multiple regression.

2.4 Response variables

In order to define a suitable response variable of saw mismatch during sawmill operation, three different response variables were evaluated using the PLS-model. The response variables were derived by the following steps. The vector X was defined as containing the saw mismatch data of the measurements,

$$X = (x_1, x_2, \ldots, x_N). \tag{2.1}$$

A sliding window of size S was applied to X and the vector W_j was defined as the saw mismatch values within the sliding window at a given position,

$$\begin{aligned} W_j = (x_{i-S}, x_{i-S-1}, \ldots x_i) \qquad & \forall i \in \{S, S+1, \ldots, N\} \\ & \forall j \in \{1, 2, \ldots, (N-S)\}. \end{aligned} \tag{2.2}$$

The vector W_{j_y} was defined as the values within the sliding window that were larger than y mm,

$$W_{j_y} = (x \in W_j | x > y\,\mathrm{mm}) \qquad \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{2.3}$$

The elements of the first response variable, Y_1, were calculated as

$$Y_1(j) = \frac{\mathrm{length}(W_{j_y})}{S} \qquad \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{2.4}$$

Each element is the share of values within the sliding window that exceeds a threshold value of y mm.

The elements of the second response variable, Y_2 were calculated as

$$Y_2(j) = \overline{W}_{j_y} \qquad \forall j \in \{1, 2, \ldots, (N - S)\}. \tag{2.5}$$

Each element is the average of the values within the sliding window that exceeds a threshold value of y mm.

The elements of the third response variable, Y_3 were calculated as

$$Y_3(j) = P_{95}(W_j). \tag{2.6}$$

Each element is the 95$^{\text{th}}$ percentile of the values within the sliding window.

Different threshold values of y for Y_1 and Y_2 were evaluated using the PLS $y = 0.1$, 0.3, 0.5, 0.7, 0.9, 1.1 and 1.3 mm as well as different window sizes for all three response variables $W_j = 50$, 100, 300 and 500 boards. The PLS-model using the response variable that results in the largest goodness of prediction, $Q2$, is the most suitable response variable since its variance can be predicted to the largest extent.

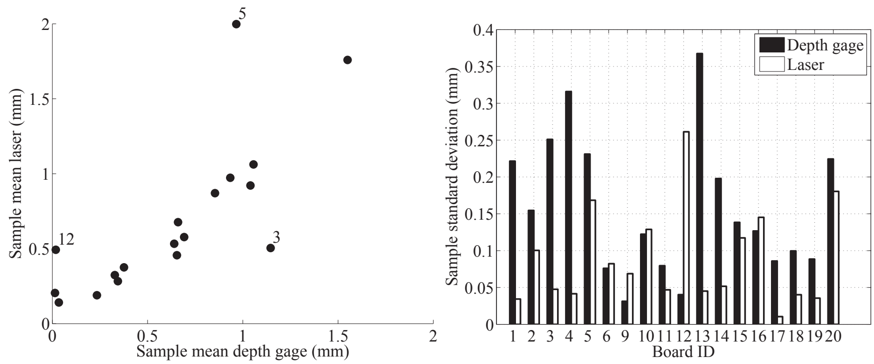
2.5 Saw mismatch measurements

In this section, the results of the measurements of saw mismatch are presented based on the experimental work described in Section 2.2.

2.5.1 Laboratory measurements

The measured saw mismatch of the laser triangulation unit and the manual measurements at the same position are shown in a scatter plot in Figure 2.4a. The figure shows that the laser triangulation measurements are well correlated with the manual measurements. There are some outliers namely boards number 3, 5 and 12. For these boards the laser triangulation method detected a sawing defect other than saw mismatch, which the manual measurement did not. If a displacement of the laser line, d, occurs as a consequence of a sawing defect other than saw mismatch, this sawing defect will still be detected. The image processing algorithm is adapted for measuring saw mismatch occurring close to the centre of the board width. If another sawing defect is present on the board, this defect is not measured as accurately as the saw mismatch since one of the two linear regression lines will be fitted to a smaller number of laser pixels. This is an area of improvement for the implementation of the saw mismatch detection algorithm.

The standard deviation of the same measurements can be observed in Figure 2.4b. The figure shows that in general the standard deviation for the laser triangulation measurements is less than or equal to the standard deviation of the manual measurements. One exception though is board number 12 where, as stated earlier, the laser triangulation measurement detected a sawing defect other than saw mismatch.



(a) (b)

Figure 2.4: Scatter plot of sample means (a) and bar plot of sample standard deviations (b) of five repeated measurements of saw mismatch using depth gage and laser triangulation respectively. The measurements were carried out on the pith side, 50 cm from the top end on each board. Boards 7 and 8 are absent due to missing data.

When analysing these measurements, one point of interest was whether or not the maximal saw mismatch on each side of the board occurs on the same lengthwise position along the board. Figure 2.5 shows a scatter plot of the position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, versus the position of the estimate of maximal saw mismatch on sapwood side, $\hat{S}_s$. The correlation is weak which indicates that a displacement of the cant is not the reason for the occurrence of saw mismatch in the sample. For a definition of $\hat{S}_p$ and $\hat{S}_s$ see Paper I, Section 2.2.

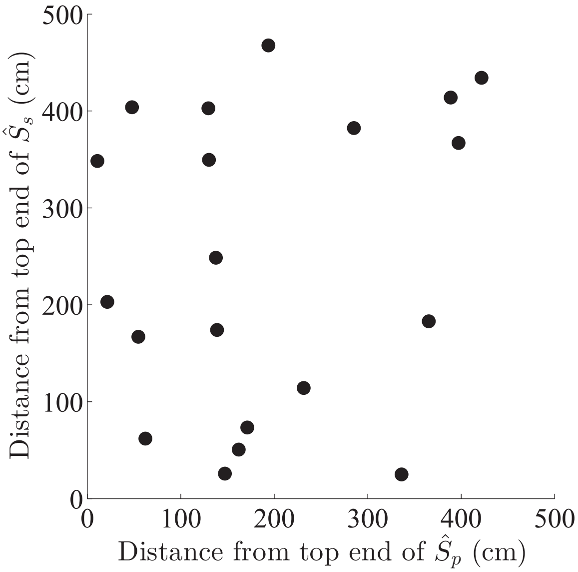


Figure 2.5: Scatter plot of the lengthwise position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, versus the lengthwise position of the estimate of maximal saw mismatch on sapwood side, $\hat{S}_s$.

Another observation was that the estimate of maximal saw mismatch on the board faces was found either close to the centre of the board, with respect to its lengthwise position, or close to the board ends. Figure 2.6 shows the sample distribution of the position of the estimate of maximal saw mismatch on pith side and sapwood side, $\hat{S}_p$ and $\hat{S}_s$ respectively. There is a tendency of three occurring peaks, one close to the two board ends and one peak closer to the centre of the boards.

The sawmill in question had a desire to detect saw mismatch exceeding 0.5 mm on any of the two board sides. Given the fact that saw mismatch is a smooth function that varies along the board length the question was how many laser triangulation units that would be necessary to detect such a deviance?

In the sample, all of the boards had an estimate of maximal saw mismatch, $\hat{S}_b$, that exceeded 0.5 mm. For a definition of $\hat{S}_b$ see Paper I, Section 2.2. Consider the scenario that two laser triangulation units at a distance of 50 cm from the top end would have been used, where each unit is facing one of the two sides respectively and each camera is assumed having two laser lines within

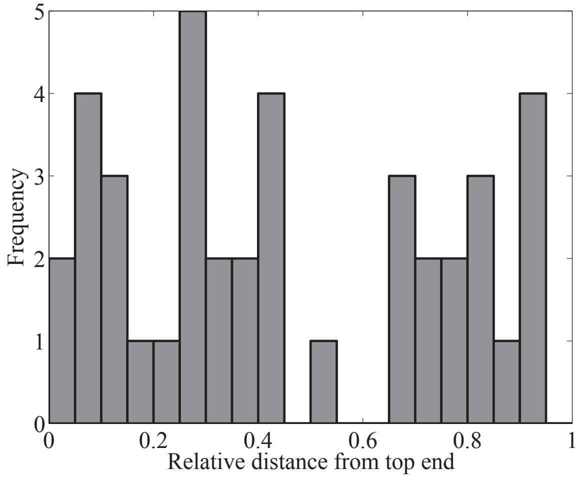


Figure 2.6: The sample distribution of the lengthwise position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, and sapwood side, $\hat{S}_s$.

the field of view (FOV). Given these conditions 75 % of the boards would have been detected as defective for this sample. This is illustrated by Figure 2.7 where the saw mismatch that would have been detected by the two cameras is shown together with $\hat{S}_b$. For five of the twenty boards in the sample the detected maximal saw mismatch was below 0.5 mm.

Since the rate of detection is as large as 75 % for this sample using two laser triangulation units, this indicates that there is no need to use additional laser triangulation units. Even though the saw mismatch was only measured at one lengthwise position on each board, the fact that the number of boards passing the laser triangulation per unit time is large will result in a large number of measurements. This will make it possible to detect a deviation in the sawing process. In fact since the boards pass randomly with pith side or sapwood side faced upwards in the transverse feed of the green sorting line, both the sapwood side and pith side of the boards will randomly be measured using only one camera.

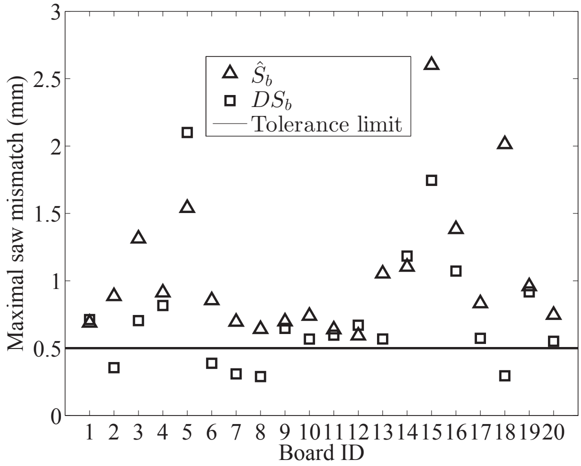
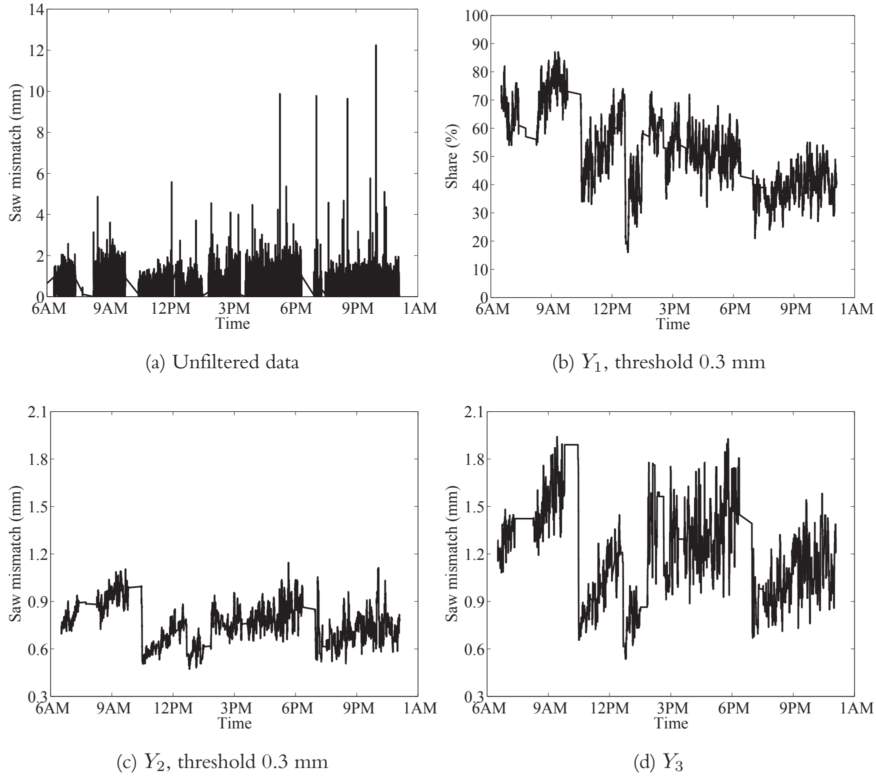


Figure 2.7: Detected maximal saw mismatch of each board, DS_b using two laser triangulation units, one on each side, positioned 50 cm from the top end of the boards. The detected maximal saw mismatch of each board can be compared to the estimate of maximal saw mismatch of each board, $\hat{S}_b$.

2.5.2 Measurements in the sawmill

The saw mismatch measurements from one day of production in the sawmill is shown in Figure 2.8a. Figure 2.8b-2.8d shows the three corresponding response variables, Y1, Y2 and Y3. The used window size was 100 boards and the applied threshold value was 0.3 mm in this case. It is clear by looking in Figure 2.8 that the behaviour of the response variables is somewhat different.

The goodness of prediction, $Q2$, of the PLS-model using one or two principal components is shown in Table 2.1. The best goodness of prediction ($Q2 = 0.135$) was obtained using the response variable Y_1 with a window size of 500 boards and a threshold value of 0.5 mm. This means that 13.5% of the variance in the response variable Y_1 can be predicted by the PLS-model using average log top diameter, cant height and feed speed as predicting variables. The goodness of prediction for Y_1 is not so dependent of window size, the value of $Q2$ for a given threshold value was quite constant for different window sizes. The choice of threshold value is more important and it is clear that a threshold value in the interval 0.3 mm - 0.5 mm is the best choice with respect to the problems with saw mismatch of this particular sawmill. Figure 2.9 shows the centred and scaled PLS regression coefficients using two principal components for the PLS-model



(a) Unfiltered data

(b) Y_1, threshold 0.3 mm

(c) Y_2, threshold 0.3 mm

(d) Y_3

Figure 2.8: Data from measurements of saw mismatch during one day of production and corresponding response variables using a threshold value of 0.3 mm and a window size of 100 boards.

with the best goodness of prediction. All predicting variables are positively correlated with saw mismatch, but average log top diameter and feed speed are more correlated than the cant height.

Table 2.1: Goodness of prediction, $Q2$, for the three response variables Y_1, Y_2 and Y_3 using different threshold values and different window sizes.

(a) Y_1

Threshold (mm)	Window size 50	100	300	500
0.1	0.00716	0.00862	0.0462	0.0502
0.3	0.108	0.118	0.131	0.133
0.5	0.115	0.124	0.132	***0.135***
0.7	0.0921	0.0998	0.107	0.109
0.9	0.0709	0.0782	0.0853	0.088
1.1	0.0555	0.0632	0.0712	0.0746
1.3	0.00935	0.0475	0.0564	0.0611

(b) Y_2

Threshold (mm)	Window size 50	100	300	500
0.1	0.0932	0.0526	0.0813	0.0918
0.3	0.0165	0.00616	0.0324	0.0589
0.5	0.000965	0.00359	0.00508	0.0106
0.7	0.00193	0.00607	0.00941	0.0112
0.9	0.00474	0.0104	0.00851	0.00764
1.1	0.00889	0.0132	0.0140	0.0134
1.3	0.0133	0.014	0.0166	0.0171

(c) Y_3

Window size 50	100	300	500
0.0392	0.0632	0.0926	0.099

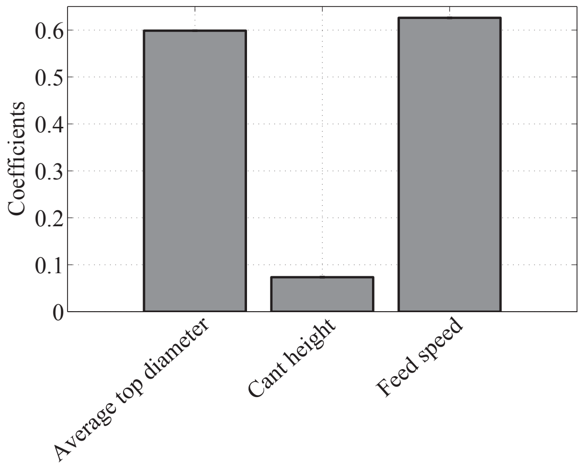


Figure 2.9: The centred and scaled regression coefficients of the PLS using two principal component where the statistical significance of each coefficient is indicated by 95% confidence intervals. The confidence intervals are so narrow that they are not visible.

Chapter 3

Sawmill production strategies

This chapter describes the contributions made in the field of sawmill production strategies for processing of sawlogs (Paper III). The potential value increase when rotating the log differently than the, in Scandinavia, industrial praxis of horns down was investigated by log breakdown simulation of CT-scanned logs. At first, Section 3.1 provides a brief description of the simulation software used for simulating log breakdown. Second, Section 3.2 presents the input data to the simulation software namely the large database of CT-scanned logs in the Swedish stem bank (SSB). Section 3.3 describes the simulations that have been carried out using the software while subsequently Section 3.4 describes the method of investigating whether the log outer shape is related to the log rotational position of greatest profit return. Finally, Section 3.5 presents the main results of Section 3.3 and Section 3.4.

3.1 Log breakdown simulation

Software for simulating the breakdown of a log that has been scanned in a CT-scanner makes it possible to simulate a breakdown of a log an infinite number of times. This enables the study of different log properties, production strategies, price scenarios and machine settings and how the sawing process is effected both with respect to volume yield and value recovery.

This type of software has been used in the field of wood technology for quite some time, consider for example the work by Björklund and Julin (1998); Todoroki and Rönnqvist (1999); Nordmark (2005). The software used in this work is developed by Nordmark (2005) and interacts with the data in the SSB. The simulated boards are graded according to the grading rules applied in Scandinavian sawmills (Anon, 1994), where the boards are separated into three different qualities based only on the outer features of the boards namely knots and wane.

3.2 Swedish stem bank

A database of CT-scanned logs was identified as an important factor in order to gain knowledge of how the sawing process could be improved in Scandinavian sawmills. This lead to the time-consuming work of CT-scanning a large number of logs, mainly from Sweden but also some spruce logs from Finland and France. The SSB (Grönlund et al., 1995) contains data from about 600 Scots pine (*Pinus sylvestris [L.]*) logs and about 800 Norway spruce (*Picea abies [L.] Karst.*) logs from 72 plots in different geographic locations in Sweden.

The logs were selected thoroughly to obtain a diversity within the sample that represents the diversity of the logs in the Scandinavian forests as far as possible. In each plot, six trees were chosen, two in a lower diameter class, two in a middle diameter class and two in a larger diameter class. A medical CT-scanner (Siemens SOMATOM AR.T) was used to scan the logs and the resulting CT images describe the log shape, pith location, heartwood border and knots. The knots are described by nine parameters specifying the knot geometry, position, and direction in the log (Oja, 2000). Putting all this together the outer and inner properties of the logs in the SSB can be used within the simulation software developed by Nordmark (2005).

3.3 Simulations

The Saw2003 software was used to simulate curve sawing of all logs in the SSB in each rotation angle in the interval $[-180°, 180°)$, where the rotation angle of $0°$ corresponds to the horns down position.

The sawing patterns used in the simulations are shown in Table 3.1 where the logs, depending on their top diameter, were sorted into their respective sawing class (SC). The sawing techniques used were cant sawing and curve sawing, which are typical for sawmills in the Scandinavian countries. The sawing allowance, that is, shrinkage as well as deviations in the sawing, was set at 4% of the nominal width for each board dimension and the saw kerf width was set to 4 mm for both the first saw and second saw.

Table 3.1: The logs are sorted into their respective SC with respect to their top diameter. The first saw determines the height of the cant (block), the thickness of the side boards in the first saw and also governs the width of the centre boards. The second saw determines the thickness of the centre boards and additional sideboards. All measures are nominal target values.

SC	Sawing pattern (mm)	Lower limit Top diameter (mm)	Upper limit Top diameter (mm)	Post First saw (mm)	Post Second saw (mm)
1	38 by 75	0	129	19, 75, 19	19, 38, 38, 19
2	38 by 100	130	149	19, 100, 19	19, 38, 38, 19
3	50 by 100	150	169	19, 100, 19	19, 50, 50, 19
4	50 by 125	170	184	19, 125, 19	25, 50, 50, 25
5	63 by 125	185	194	19, 125, 19	19, 63, 63, 19
6	50 by 150	195	209	19, 19, 150, 19, 19	19, 25, 50, 50, 25, 19
7	63 by 150	210	219	19, 19, 150, 19, 19	19, 25, 63, 63, 25, 19
8	50 by 175	220	229	19, 19, 175, 19, 19	19, 25, 50, 50, 25, 19
9	63 by 175	230	249	19, 19, 175, 19, 19	25, 25, 63, 63, 25, 25
10	63 by 200	250	264	19, 19, 200, 19, 19	25, 25, 63, 63, 25, 25
11	75 by 200	265	284	19, 19, 200, 19, 19	19, 25, 75, 75, 25, 19
12	75 by 225	285	304	19, 19, 225, 19, 19	19, 25, 75, 75, 25, 19
13	50 by 200 by 4	305	324	19, 25, 200, 25, 19	19, 25, 50, 50, 50, 50, 25, 19
14	50 by 225 by 4	325	344	25, 32, 225, 32, 25	25, 25, 50, 50, 50, 50, 25, 25
15	63 by 200 by 4	345	384	25, 32, 200, 32, 25	19, 25, 63, 63, 63, 63, 25, 19
16	75 by 200 by 4	385	449	25, 32 200, 32, 25	19, 25, 75, 75, 75, 75, 25, 19

Three different simulations were carried out using the different price differences between the quality grades presented in Table 3.2. The different price settings represents the price range of sawn timber for a Scandinavian sawmill.

An additional simulation was also performed using normal price differences (Table 3.2) but where a normally distributed rotational error for the sawing machine was introduced with mean $0°$ and a typical standard deviation of $5°$.

These simulations made it possible to analyse the effect that different log rotational step lengths as well as a rotational error for the sawing machine would have on the potential value and yield increase when rotating the logs. Also, the consequence of different price differences between the quality grades for the potential value and yield increase could be analysed. What is interesting is the effect of price differences between boards of different qualities, rather than the price differences between centre boards and side boards. This since the price differences between different qualities affect the value optimization during edging and trimming of boards.

Table 3.2: Different prices between quality grades used in the simulations, all prices are in €/m^3. The quality definitions are specified by the criteria for knots and wane in the Nordic Timber Grading Rules (Anon, 1994), boards classified as grade D are chipped.

	PINE & SPRUCE		
	Low	Normal	High
Centre boards grade A	194	208	222
Centre boards grade B	180	180	180
Centre boards grade C	146	112	79
Side boards grade A	247	337	427
Side boards grade B	157	157	157
Side boards grade C	140	123	107

3.4 Log outer shape

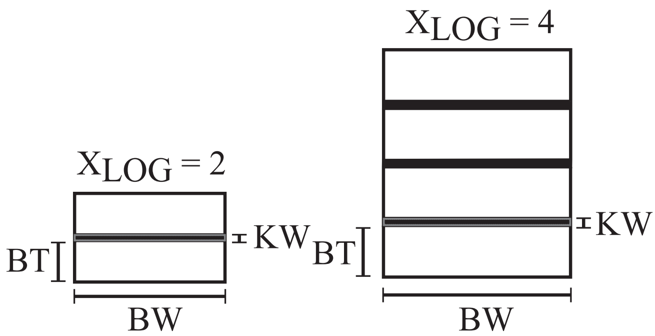
Partial least squares discriminant analysis (PLS-DA) (Ståhle and Wold, 1987) was used to conclude if the rotational position with the greatest profit return was somehow related to the outer shape of the logs in the SSB. Prior to the PLS-DA the obtained value functions (Figure 3.2a - 3.2b) were smoothed by a median filter with a window size of 13°. Subsequently, logs with a unique log rotation for greatest profit return (Figure 3.6a) was selected for the PLS-DA while logs that had more than one or more equally profitable log rotations were excluded (Figure 3.6b). The idea was to select typical logs with a distinct log rotation for greatest profit return to get as strong PLS-DA-model as possible. This resulted in the selection of 28% or 408 of the logs in the SSB.

The selected logs where divided in two classes. Class I was defined as those logs having the log rotation with greatest profit return $\pm 30°$ from the horns down position, that is in the interval $[-30°, 30°]$. Class II was defined as logs having the log rotation with greatest profit return different than the horns down position, in the interval $[-90°, -30°)$ or $(30°, 90°)$. PLS-DA maximizes the separation between the two classes with respect to a set of predictors. This was used to investigate whether the logs having the log rotation with greatest profit return close to the horns down position had different outer shape characteristics than those logs having the log rotation with greatest profit return in a different log rotation.

Two of the variables used in the PLS-DA needs to be explained more in detail starting with the variable SPR that describes the shape of the sawing pattern. If the value of the variable SPR is smaller than one, then the green board width is larger than the total green thickness of the centre boards, including the saw kerf as in Figure 3.1a. If the value is larger than one then the green board width is smaller than the total green thickness of the centre boards, including the saw kerf as in Figure 3.1b. The variable $DIFF$ describes how much space there is between the sawing pattern and the log perimeter in the top end of the log. A smaller $DIFF$ value means a larger risk of having boards with wane if the log is rotated.

The predictors used in the PLS-DA were

- Log volume (V) $[m^3sub]$
- Log length (L) $[m]$
- Top diameter inside bark (D_{TOP}) $[mm]$
- Butt diameter inside bark (D_{BUTT}) $[mm]$
- Bow height (BH) $[mm]$
- Log taper (T) $[m/m$, dimensionless]
- Sawing pattern ratio (SPR) [dimensionless]
- The difference between the sawing pattern diagonal and the top diameter of the log $(DIFF)$ $[mm]$

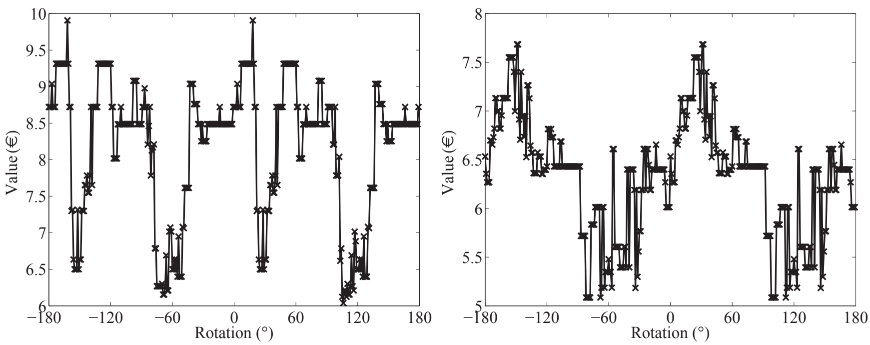


(a) $SPR < 1$ (b) $SPR > 1$

Figure 3.1: Examples of sawing patterns with different sawing pattern ratio, SPR. Here, X_{LOG} is the number of centre boards in the sawing pattern, BT is the green centre board thickness, KW is the kerf width and BW is the green centre board width.

3.5 Log rotation for increased value recovery

The simulations resulted in value as a function of log rotation for each log, as the examples shown in Figure 3.2. Applying the log rotation that maximizes the value for each log results in an average value increase of about 13% both for the pine and the spruce logs in the SSB. The variability is large however, for pine the standard deviation is 16% and for spruce it is 14%. Looking at the volume yield there is an average yield increase of about 5% and a standard deviation of 4% for both species. This is presented in Figure 3.3, which also shows the effect if the log breakdown is not simulated in every rotational position but simulations are made in larger steps. The effect of a normally distributed rotational error with mean 0° and standard deviation of 5° is that the average value increase and average yield increase drops to 6% and 2% respectively for both pine and spruce.



(a) (b)

Figure 3.2: The total value of the sawn products for two logs where log breakdown was simulated in different log rotations. The rotation angle of 0° corresponds to the horns down position.

The average value increase is as expected dependent of the price levels. An increased price difference between the quality grades (Table 3.2) results in an increased average value increase (Figure 3.4). What is a bit surprising is that the same goes for the average yield increase. Here rather the opposite would be expected since an increase in price differences should lead to the trimming of boards to shorter lengths of higher quality, i.e. the average yield increase was

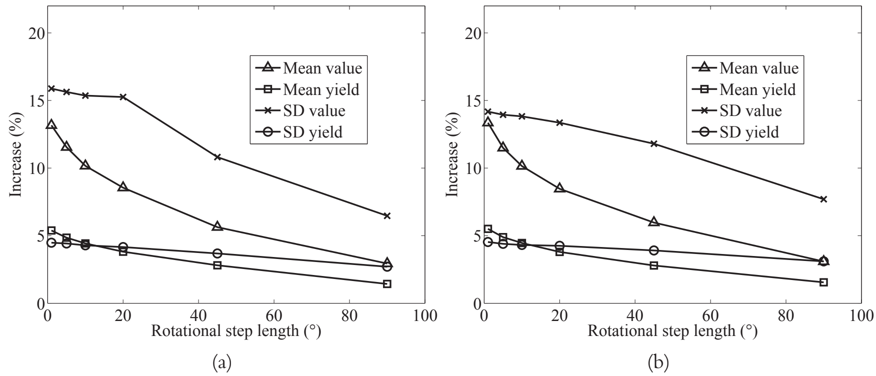


Figure 3.3: The average value increase and the average yield increase compared to the horns down position together with standard deviations for all logs in the SSB. The result for pine is shown in (a) while the result for spruce is shown in (b). The different log rotational step lengths are $1°, 5°, 10°, 20°, 45°$ and $90°$.

expected to decrease with increased price differences rather than increase. The standard deviations of both the value increase and the yield increase becomes larger with increased price differences since the value increase and yield increase will differ even more between logs.

The filtered value functions in Figure 3.5 were used to make the selection of logs with a distinct log rotation for greatest profit return (Figure 3.6a). These 408 selected logs were then divided in two classes. Class I, having the the log rotation with greatest profit return $\pm 30°$ from the horns down position and Class II having the log rotation with greatest profit return in the interval $[-90°, -30°)$ or $(30°, 90°)$.

The regression coefficients for Class I (Figure 3.7a), logs sawn to the greatest profit return $\pm 30°$ from the horns down position, shows that the predictors that significantly separate the two classes are bow height and log taper. The 95% confidence intervals imply that the coefficient for bow height is positive while it is negative for log taper. Logs in Class I significantly have larger bow height and are less tapered than the logs in Class II.

Figure 3.7b shows the complementary regression coefficients for Class II and describes how the predictors of the logs in Class II are described relative to the predictors of the logs in Class I. Consequently, it is significant that logs belonging

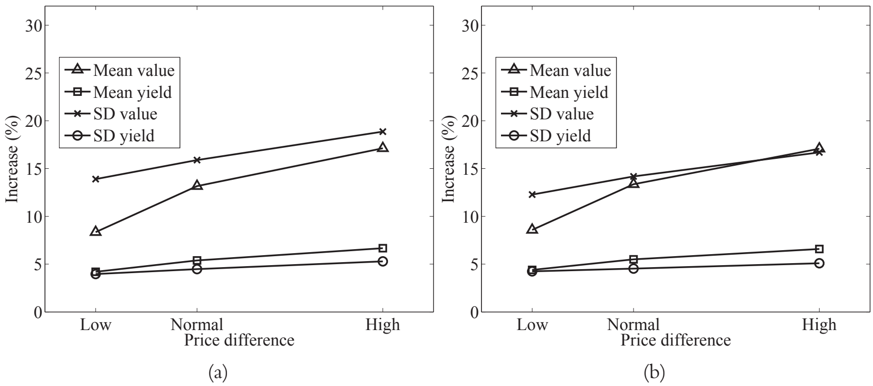


Figure 3.4: The average value increase and the average yield increase compared to the horns down position together with standard deviations for all logs in the SSB. The result for pine is shown in (a) while the result for spruce is shown in (b). The price differences between the quality grades are specified by Table 3.2.

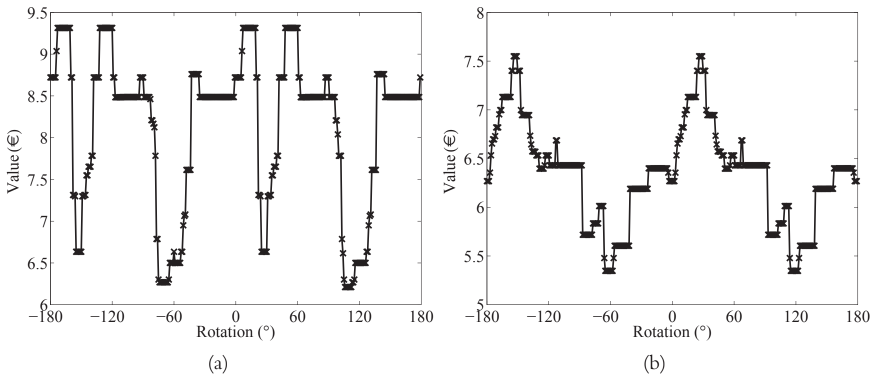


Figure 3.5: The value functions of the same logs as in Figure 3.2, but where the value functions have been submitted to a median filter of window size 13°. The rotation angle of 0° corresponds to the horns down position.

to Class II have a smaller bow height and are more tapered compared to logs in Class I.

The predictability of the model is poor, which means that it is difficult to

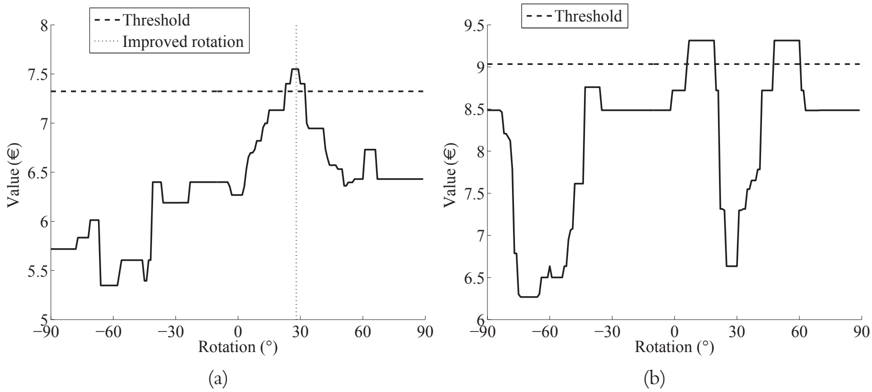
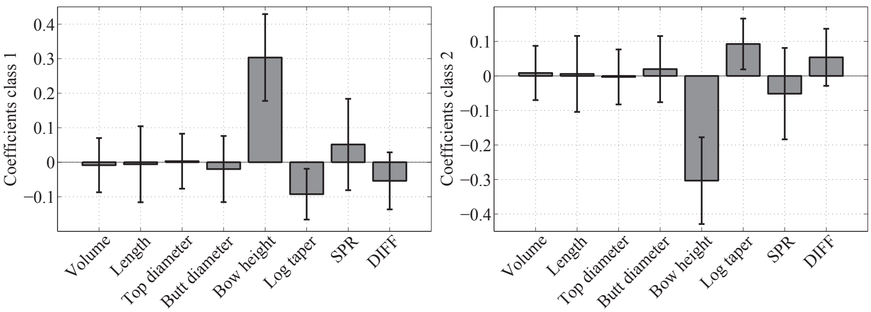


Figure 3.6: The total value of the sawn products as function of log rotation for two different logs. The log in example (a) was selected for the PLS-DA while the log in example (b) was excluded. The rotation angle of 0° corresponds to the horns down position.

identify logs as belonging to either Class I or Class II, based on their outer properties. Table 3.3 shows that when trying to predict the class of the 190 logs belonging to Class I, only 102 of these logs are classified correctly. As for Class II, 161 out of the 218 logs in Class II are classified correctly. This means a correct classification of 53.7% for Class I and 73.9% for Class II, resulting in an overall correct classification of 64.5%. The larger misclassification of logs in Class I is due to the fact that Class I contains straight logs which are classified as belonging to Class II to a larger extent than Class II contains logs with sweep classified as belonging to Class I.

Table 3.3: Prediction of class for the selected logs.

	No.	No. predicted class 1	No. predicted class 2	Correct
Class 1	190	102	88	53.7%
Class 2	218	57	161	73.9%
Total	408	159	249	64.5%



(a) (b)

Figure 3.7: The regression coefficients of the PLS-DA using one principal component where the statistical significance of each coefficient is indicated by 95% confidence intervals. The coefficients for Class I are shown in (a), while the coefficients for Class II are shown in (b).

Chapter 4

Discussion

4.1 Tolerance for saw mismatch

For the sawmills the saw mismatch becomes a problem if the presence and magnitude of saw mismatch magnitude is too large. This means that the monitoring of saw mismatch in the sawmill must be made both with respect to the magnitude of saw mismatch but also with respect to the share of boards having saw mismatch.

In this thesis a method for measuring saw mismatch has been presented (Paper I) and three different ways of assessing saw mismatch during sawmill operation have been investigated (Paper II). The way of measuring saw mismatch, for which most of the variance could be predicted, was by looking at the share of the latest 500 measured boards exceeding a threshold value of 0.5 mm (Table 2.1).

This work is a good start for increasing our understanding of what is causing saw mismatch and which variables that have the largest effect on its presence and magnitude. This work is not by any means finished, first of all an improved installation of the measurement unit must be carried out in a sawmill. Subsequently it must be further investigated how to evaluate saw mismatch by relating the measurements to additional production parameters such as saw blade characteristics for example.

At the moment it is clear that the occurrence of saw mismatch increases with increased log diameter and feed speed and that 13.5% of the variance in saw mismatch is predicted by these variables. It is desirable to investigate the effect that saw blade characteristics have on the saw mismatch as well as to see if the prediction of occurrence and magnitude of saw mismatch can be improved.

4.2 The value potential in an alternative log rotation than horns down

One field of application for an industrial CT-scanner is, as described in Paper III, to find the log rotation that maximizes the value of each processed log. The advantage of the CT-scanner prior to X-ray scanning in discrete directions is the precise detection of the knot structure within the log, which can be used to determine the most profitable log rotation. The results indicated that there is a potential for a greater profit return for a Scandinavian sawmill if rotating each log in the rotation that maximized the value. Log breakdown simulations of about 600 Scots pine logs and about 800 Norway spruce logs resulted in an increased profit return of 13% for both species compared to sawing each log in the horns down position. A rotational error to the sawing machine reduced the potential to 6% for both species

The value optimization of a log has many degrees of freedom, except log positioning and sawing pattern with respect to knots and wane it is also desirable to consider additional internal wood defects such as pitch pockets, splits and rot. It was of interest to investigate whether the outer shape of the log was correlated with the most profitable log rotation. In such case this can be used to reduce the number of degrees of freedom in an optimization and instead use the computational time to consider other wood defects,

The result indicated that log crook and log taper was correlated with the most profitable log rotation. Since the horns down position is the praxis of log rotation in Scandinavian sawmill it is reasonable that logs more profitably sawn in a different log rotation than horns down are straighter logs. Also tapered logs are more tolerant to an alternative log rotation since the risk of wane on the boards is reduced. Unfortunately the log crook and log taper cannot be used to predict how to rotate a log for greatest profit return.

The question is, if it’s not the outer shape of the log that determines how the log should be rotated in order to maximize the value than which parameter is actually controlling this? Is the harsh truth that the problem is too complex, that there exists no single variable or set of variables which we can use to decide the most profitable log rotation? First the significance of the internal knot structure of the log must be further investigated. Perhaps a stronger variable regarding the log rotation is found by considering the internal log structure.

It should be pointed out that the work in Paper III is entirely based on a simulation study of log breakdown of the logs in the SSB. A simulation model is an attempt to model, as accurately as possible, a real system. This means that it is not possible to make any absolute conclusions from a simulation, but rather see the result in a relative sense, as a tool for comparing and evaluating different decisions against each other.

4.3 The need of an industrial CT-scanner

For many studies in this field, including Paper III in this thesis, the SSB has been a prerequisite (Grundberg and Grönlund, 1997; Björklund, 1997; Lundahl and Grönlund, 2010). The work behind collecting data from about 1400 logs from 72 different plots in Sweden, representing the diversity in Swedish forests was very time-consuming but has been well worth the effort. However any conclusions made in papers based on the SSB must always be made with respect to the fact that it is a limited material with the aim of representing the diversity in Scandinavian forests.

With an industrial CT-scanner available on the market, scanning logs at operating speed, the importance of the data that will be produced in a sawmill must be highlighted. The industrial CT-scanner can scan the same amount of logs as the whole SSB in about 2 hours, which gives some perspective. Instead of performing studies on a relatively small number of logs, that indeed are carefully selected, the amount of available data in studies such as the rotational study (Paper III) presented in this thesis could be multiply increased. It is of greatest importance that data from such a scanner can be used in future research at the department to make new findings possible and to be able to make conclusions with respect to a larger data material.

Chapter 5

Conclusions

Reduced saw kerf width leads to economic savings for the sawmills. To accomplish this the saw mismatch has to be automatically monitored. In this thesis it was shown how saw mismatch can be measured and how the presence and magnitude of saw mismatch can be evaluated.

Also, the potential in an alternative log rotation than the horns down position was evaluated by log breakdown simulation. With an industrial CT-scanner entering the market the possibility for finding and improved log rotation of each log with respect to log outer shape and position of knots is realisable.

The most important conclusions of this thesis are that

- Measurements of saw mismatch using laser triangulation are correlated with manual measurements of saw mismatch and the standard deviations of the laser triangulation measurements are in general smaller in comparison with the manual measurements.

- The correlation is weak between the lengthwise position of the estimate of maximal saw mismatch on pith side and sapwood side respectively for a sample of boards.

- Using one laser triangulation unit in the green sorting line of a sawmill measuring saw mismatch during sawmill operation should be enough for detecting a trend in the sawing process.

- The robustness when measuring saw mismatch using laser triangulation during sawmill operation is satisfactory.

- The saw mismatch response variable defined as the share of the latest 500 measured boards exceeding a threshold value of 0.5 mm is positively correlated with the cant height, feed speed and average log top diameter. This makes it possible to predict 13.5% of the variance in the response variable by a PLS-model.

- For a Scandinavian sawmill processing Norway spruce and Scots pine there is a potential for a greater profit return if scanning logs in real time with a CT-scanner. Simulations of log breakdown of 600 Scots pine logs and 800 Norway spruce logs and applying the rotation that maximizes the value of each log resulted in an increased average value of 13% compared to the horns down position. An introduced rotational error to the sawing machine reduced the average value increase to 6%.

- The potential value increase is dependent of the rotational step length and the price differences between the quality grades.

- Logs sawn for the greatest profit return in a rotation different than horns down are straight and tapered in comparison with logs sawn for the greatest value in the horns down position. The separation is not strong enough to be used for prediction.

Chapter 6

Future work

In this chapter thoughts for future work are presented. In Section 6.1 the continuing work of saw mismatch measurements in a sawmill environment is described whereas in Section 6.2 it is described how to investigate, still by log breakdown simulation, the effect that an error in the knot detection algorithm would have on an improved log rotation for greater value recovery. Section 6.3 describes how the study on an improved log rotation can be continued.

6.1 Designed experiment

In the industrial tests of the automatic saw mismatch measurements 13.5% of the variance in saw mismatch was predicted by a PLS-model. In this model no consideration was given to the characteristics of the saw blades and the effect of wear on the occurrence of saw mismatch. For future work, it is of interest to perform a designed experiment where additional influencing variables are varied systematically in order to obtain an improved prediction.

Possible influencing variables that needs to be investigated further are

- Saw kerf width
- Saw blade collar size
- Number of saw teeth on saw blade
- Number of resharpenings of saw blades
- Number of saw teeth replaced on saw blades

- The gap between logs in the saw line

6.2 The effect of an error in the knot detection algorithm

The effect that a rotational error in the sawing machine has on the potential value increase in an improved log rotation was investigated in this thesis. What has not been considered in this work and which is also of importance is how an error in the knot detection algorithm affects the search for an improved log rotation. It is necessary in future work to investigate the effect of knot detection errors with respect to the chosen rotational position for greatest value recovery.

6.3 Log rotation for improved board strength

The appearance grading according to Anon (1994) is one important quality sorting applied in Scandinavian sawmills. Another important way of sorting the sawn boards is for strength grading.

There are two types of grading systems for strength grading practised, namely *visual strength grading* and *machine strength grading*. Visual strength grading is, as the name implies, based on visual inspection of the boards and ensures that the visible defects of the pieces does not exceed the limits specified by the grading rule. In machine strength grading the pieces are passed through a machine which estimates the strength and stiffness of the piece, based on one or several non-destructively measured parameters mainly modulus of elasticity.

Is it possible that the CT-scanner be used for finding an improved log rotation, but with respect to visual strength grading in the same way as for appearance grading. Visual grading in Scandinavia is performed either according to the Nordic Standard (INSTA 142), or alternatively according to the European Standard (SS-EN 14081-1). In future work it would be interesting to investigate the potential in applying an improved log rotation with respect to the value of strength graded boards instead of appearance graded boards.

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Part II

Paper I

Detection of saw mismatch in double arbor saw machines using laser triangulation

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Reformatted version of paper submitted to journal

Detection of saw mismatch in double arbor saw machines using laser triangulation

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Abstract

In the sawing process of a sawmill, not only are the target sizes of great importance. The saw mismatch that may occur in double arbor saw machines is also an essential parameter that affects the planing allowance, as well as the quality of the sawn products. In this study, a newly developed measurement equipment for detecting saw mismatch in the green sorting line of a sawmill has been evaluated in an initial experimental test. The obtained data has been compared to manual measurements of saw mismatch with good results. Also, based on a small sample, 75 – 95% of the boards with a maximal saw mismatch exceeding 0.5 mm are detected. The rate of detection depends on the number of cameras used.

Keywords: Double arbor saw machine, Laser triangulation, Saw mismatch, Surface profile

1 Introduction

Issues of yield and value have become increasingly important for the sawmills in the European countries. This is mainly because it is difficult to increase harvested volumes, and so the advantage of increasing the production volume with the same log purchases has grown stronger.

A traditional way to increase the volume yield is by reducing the saw kerf width (Wasielewski et al., 2012). An ongoing project in Sweden is to develop techniques to increase the volume yield by a reduced saw kerf width, an adapted shrinking allowance and a lower sawing allowance (Grönlund et al., 2009). A difficulty with a reduced saw kerf width is the fear of a worse sawing accuracy and precision, as well as more frequent saw blade failures (Maness and Lin, 1995; Steele et al., 1992). As presented by Vuorilehto (2001), the accuracy of a saw machine refers to the uniformity of sawn sizes around a target size, and precision refers to the degree of variation of size. Furthermore Vuorilehto states that when accuracy and precision are under control the sawing machine will demonstrate consistent reproducibility.

Grönlund et al. (2009) has pointed out the industrial need of a measurement system detecting not only the sawn sizes but also the saw mismatch in double arbor saw machines. Saw mismatch occurs when the saw blades are displaced in axial direction with respect to each other due to wear, heat or mechanical disturbance (Figure 1). The saw blades overlap at the centre of the board width which means that this is where saw mismatch might occur. The saw mismatch (Figure 2) along the board depends on the displacement of the saw blades with respect to each other so its amplitude typically varies along the board. Since the two faces of the board are processed by different saw blades, saw mismatch at one of the side faces does not mean that saw mismatch is present on the other side face.

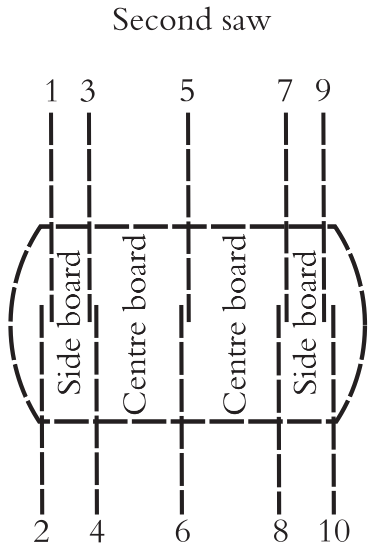


Figure 1: Illustration of cant sawing using a double arbor sawing machine resulting in saw mismatch because the saw blades (1-10) are not aligned.

A lot of work has been done within the field of surface roughness- and surface profile measurements in order to detect biological and mechanical defects of wood. Elmas et al. (2011) evaluated two optical profile measurement methods for

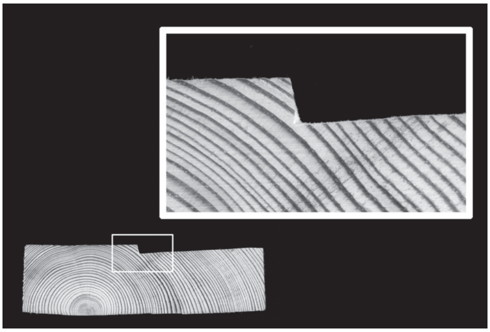


Figure 2: Saw mismatch seen from the board end.

planed wooden surfaces: namely, light-sectioning and two-image photometric stereo. Sandak and Tanaka (2003) used a laser displacement sensor to determine roughness profiles of wooden surfaces and Stojanovic et al. (2001) investigated the use of area-scan cameras for automated inspection of boards. However, no previous work with the aim of measuring saw mismatch specifically has been found.

For the industrial partners in this project, the mismatch between saw blades in double arbor saw machines is an essential parameter for process monitoring. The saw mismatch may result in a larger planer allowance and at worst, it can lead to quality degrading of the sawn timber.

The objective of this study is to suggest a design of a system specialized at detecting saw mismatch on sawn timber using laser triangulation. A specific demand from the industrial partners is that the measurement system would be simple and cost effective and that it should be able to detect saw mismatch exceeding 0.5 mm.

2 Materials and methods

2.1 Experimental work

The proposed measurement system consists of a laser triangulation unit that is intended to be placed in the transverse feed at the green sorting line of a sawmill. In the transverse feed, the speed of the conveyor is relatively low which makes the influence of vibration small and also the computational time for an image processing algorithm is less restricted.

In this study however, measurements were performed entirely in a laboratory environment. A stand was assembled above a conveyor and a laser triangulation unit consisting of a GigE UI-5240CP-M-GL camera and a Lasiris SNF 660 nm laser was mounted on the stand. The camera was connected to a PC and a photocell connected to the PC by an I/O card was used to trigger the camera. Because of the angle α that the laser makes with the surface normal, a saw mismatch results in a laser line that is displaced (Figure 3). The displacement, d, is proportional to the saw mismatch and can be measured by fitting two linear regression lines to the two groups of separated laser pixels. Image acquisition, image processing and image analysis was implemented in C++. The Field Of View (FOV) of the camera was 30 cm in the lengthwise direction of the board and the equipment was calibrated for measuring saw mismatches in the interval 0.5 – 1.5 mm.

A sample of 20 boards of final dimension 38 by 125 mm and varying length between 3.4 – 5.3 m with different levels of saw mismatch were selected. The boards were measured before drying and consequently the deformations in shape were small. In order to test the reliability and repeatability of the measurement system, all boards in the sample were measured five times with 1 cm intervals on each side face. The saw mismatch of the sample was also measured manually by using a depth gage with a specially designed holder for measuring saw mismatch. The measurements were performed independently by five different persons 50 cm from the top end of the board, on the pith side face.

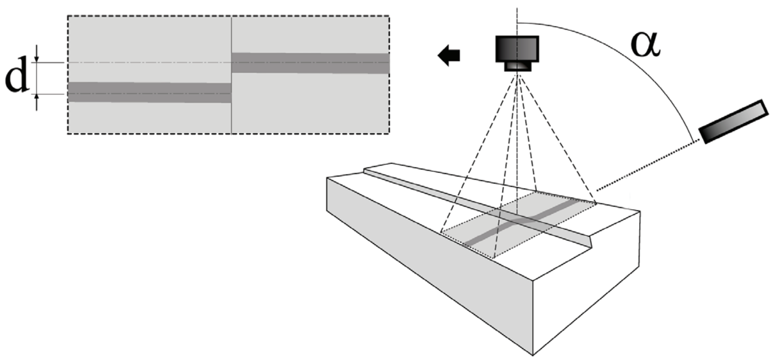


Figure 3: Illustration of the measurement set-up, α is the angle between the laser line and the surface normal and d is the displacement of the laser line due to saw mismatch.

2.2 The maximal saw mismatch of a board

Grönlund et al. (2009) pointed out that the highest correlation between manual judgements of the severity of saw mismatch of a board was found with the maximal saw mismatch, independent of side face. Therefore the maximal saw mismatch of a board was used as reference in this study. This section describes how an estimate of the maximal saw mismatch of a board was defined in this paper.

Consider an example of measurements of saw mismatch of a side face from one of the five measurement runs in Figure 4a. Define the vector X_i as containing the saw mismatch measurements of a side face from one of the five measurement runs

$$X_i = (x_1, x_2, \ldots, x_N), \qquad i = 1, 2, 3, 4, 5 \tag{1}$$

where N is the total number of data points in the measurement.

To reduce the noise of the saw mismatch measurements, a median filter was applied to X_i. As stated by Pratt (2007), the median filter in one-dimensional form consists of a sliding window encompassing an odd number of values. The centre value in the window is replaced by the median of the values in the window. The used window size was 51 values ($\approx$ 50 cm). The reason for applying the median filter was to detect the overall saw mismatch profile of a board, which varies smoothly along the board, and to filter out detected sawing defects other than saw mismatch.

In this paper the median filter is denoted as

$$\text{medfilt}(A, w), \tag{2}$$

where A is the vector to be filtered and w is the window size.

The vector M_i containing the median filtered values of X_i is calculated as

$$M_i = \text{medfilt}(X_i, 51). \tag{3}$$

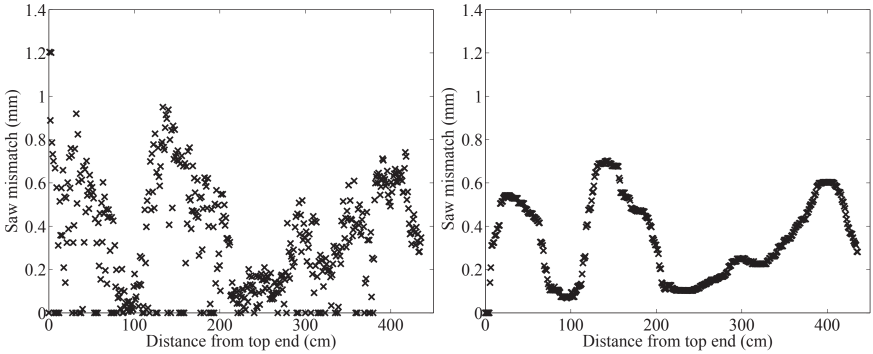
$\hat{S}_p$ and $\hat{S}_s$ are estimates of maximal saw mismatch on pith side face and sapwood side face respectively, obtained by taking the average of the five repeated measurement runs

$$\hat{S}_{p,s} = \frac{1}{5} \sum_{i=1}^{5} \max(M_i). \tag{4}$$

An estimate of the maximal saw mismatch of a board, $\hat{S}_b$, is defined as

$$\hat{S}_b = \max(\hat{S}_p, \hat{S}_s), \tag{5}$$

where $\hat{S}_p$ and $\hat{S}_s$ are the estimates of maximal saw mismatch on pith side face and sapwood side face respectively.



(a) Unfiltered (b) Median filtered

Figure 4: Detected saw mismatch of a side face before and after applying a median filter with a window size of 51 values ($\approx$ 50 cm).

2.3 Number of cameras and positioning

The unfiltered measurements of saw mismatch of all boards in the sample was used to investigate how the number, and position, of cameras fulfil the demand of detecting whether the maximal saw mismatch of a board exceeds 0.5 mm. The estimate of maximal saw mismatch of a board, $\hat{S}_b$, was used as reference.

The sample distribution of the lengthwise position for where the estimates of maximal saw mismatch on the two side faces, $\hat{S}_p$ and $\hat{S}_s$, occur is shown in Figure 5. Since there are positions at which these are more likely detected, the following cases of pairwise positioned cameras were investigated.

1. Two cameras, one on each side face, with the Field Of View (FOV) centred with a 50 cm offset from the top end.

2. Four cameras, two on each side face, with the FOV centred with a 50 and 150 cm offset from the top end respectively.

3. Six cameras, three on each side face, with the FOV centred with a 50, 150, and 200 cm offset from the top end respectively.

4. Eight cameras, four on each side face, with the FOV centred with a 50, 150, 200, and 400 cm offset from the top end respectively.

Each camera is assumed having two laser lines within the FOV, positioned symmetrically with a 2.5 cm offset from the centre of the FOV.

The detected maximal saw mismatch of a board, DS_b, is defined as

$$DS_b = \frac{1}{5}\sum_{i=1}^{5} \max(d_{i1}, d_{i2}, \ldots, d_{iN}), \tag{6}$$

where d_{i1}, d_{i2}, $\ldots d_{iN}$ is the detected saw mismatch of the N number of laser lines and i is the index of the five measurement repetitions.

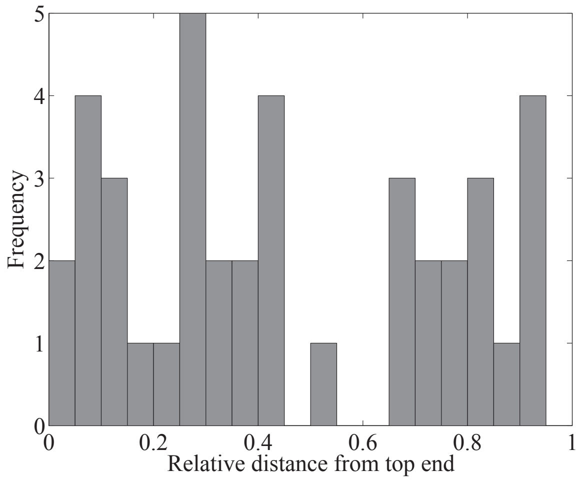


Figure 5: The sample distribution of the lengthwise position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, and sapwood side, $\hat{S}_s$.

3 Results and discussion

3.1 Reliability and repeatability of measurement

The result shown in Figure 6 indicates that the sample mean of the saw mismatch measured by laser triangulation correlates to the sample mean measured manually with the depth gage. There are a some outliers though namely boards 3, 5 and 12. For these boards the laser triangulation method detected a sawing defect other than saw mismatch, which the manual measurement did not.

The sample standard deviation of the laser triangulation measurement is comparable to the sample standard deviation of the depth gage which is shown in Figure 7. In fact the sample standard deviation of the laser triangulation measurement is similar to or smaller than the sample standard deviation of the depth gage, except for board number 12 where it is significantly larger for the laser triangulation measurement. As stated earlier, for board number 12 the laser triangulation measurement detected a sawing defect other than saw mismatch.

If a displacement of the laser line, d, occurs as a consequence of a sawing defect other than saw mismatch, this sawing defect will still be detected. The image processing algorithm is adapted for measuring saw mismatch occurring close to the centre of the board width. If another sawing defect is present on the board, this defect is not measured as accurately as the saw mismatch since one of the linear regression lines will be fitted to a smaller number of laser pixels. This is an area of improvement for the saw mismatch detection algorithm in its current implementation.

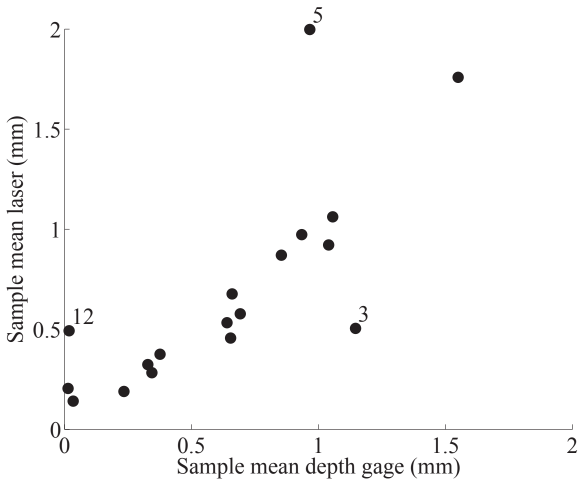


Figure 6: Scatter plot of sample means of five repeated measurements of saw mismatch using depth gage and laser triangulation respectively. The measurements were carried out on the pith side, 50 cm from the top end on each board. Boards 7 and 8 are absent due to missing data.

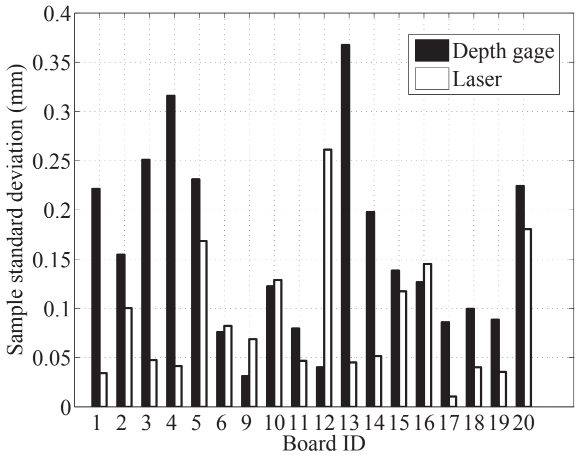


Figure 7: Sample standard deviations of five repeated measurements of saw mismatch using depth gage and laser triangulation respectively. The measurements were carried out on the pith side, 50 cm from the top end. Boards 7 and 8 are absent due to missing data.

3.2 Number of cameras and positioning

The sample distribution of the lengthwise position of the estimate of maximal saw mismatch on pith side face, $\hat{S}_p$, and sapwood side face, $\hat{S}_s$, is shown in Figure 5. The lengthwise position of $\hat{S}_p$ and $\hat{S}_s$ is mainly close to the board ends as well as close to the centre of the boards.

Figure 8 shows a scatter plot of the lengthwise position of $\hat{S}_p$ and $\hat{S}_s$ respectively. The correlation between the position of $\hat{S}_p$ and $\hat{S}_s$ is weak which indicates that a displacement of the cant is not the reason for the occurrence of saw mismatch for the boards in this sample. This also suggests that it is more efficient to distribute two cameras on the same side but at different positions rather than having the two cameras on the same position at opposite sides. If the correlation had been strong between the position of $\hat{S}_p$ and $\hat{S}_s$ then placing two cameras in the same position on opposite sides would increase the chance of detecting the maximal mismatch of the board.

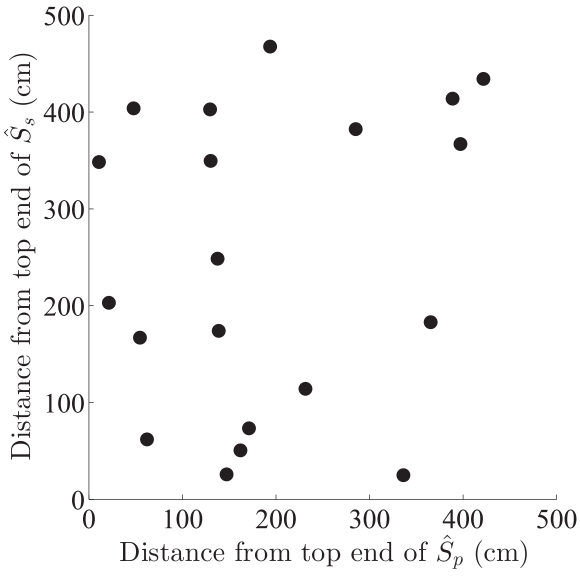


Figure 8: Scatter plot of the lengthwise position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, versus the lengthwise position of the estimate of maximal saw mismatch on sapwood side, $\hat{S}_s$.

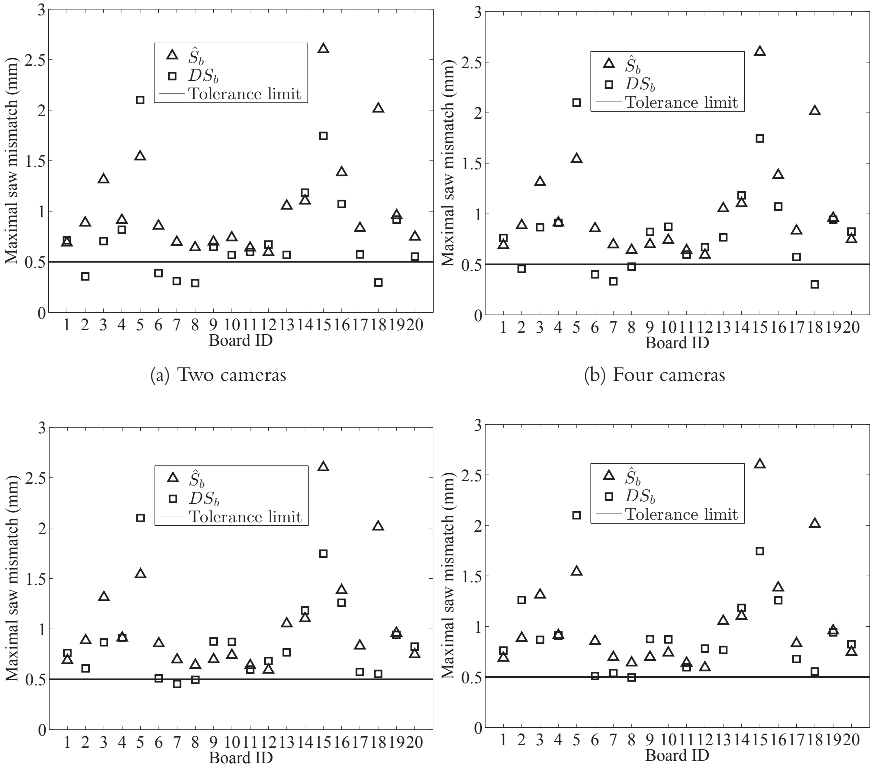
Additionally if the cameras are installed so they are measuring only one side face of each board, measurements of both pith side and sapwood side will be made at group level. This since the boards pass randomly with pith side or sapwood side faced upwards in the transverse feed. There are other practical advantages with installing the cameras with the camera lenses facing downwards, since difficulties with chips and dust covering the lenses can be avoided. However with the small sample size of this study, the effect of randomly measuring each side face was not evaluated.

The detected saw mismatch of each board for the different numbers of cameras and the different camera positions, DS_b, is shown in Figure 9. The result is compared to the estimate of maximal saw mismatch of each board, $\hat{S}_b$, and it can be observed that DS_b approaches $\hat{S}_b$ as the number of cameras increase.

The value of $\hat{S}_b$ exceeded 0.5 mm for all boards in the sample, which can be observed in Figure 9. Table 1 shows the number of these boards that would have been detected using different numbers of cameras. The gain of using more than two cameras in this case is not cost effective, since the rate of detection is as large as 75% using only two cameras. This reasoning is also supported by the sample distribution of all measurements of saw mismatch along the length of the boards shown in Figure 10. Since such a large number of measurements of saw mismatch exceeds 0.5 mm, this indicates that using only two cameras will still be efficient in this case. This with respect to the fact that a large number of boards will be measured in a short period of time during operating conditions in a sawmill.

Table 1: The number of boards where the detected maximal saw mismatch of a board, DS_b, exceeded 0.5 mm for different number of cameras. The estimate of maximal saw mismatch of a board, $\hat{S}_b$, exceeded 0.5 mm for all boards in the sample. This means that the ideal detection rate is 100%.

Number of cameras	Number of detected boards	Rate of detection (%)
2	15	75
4	15	75
6	18	90
8	19	95



(a) Two cameras

(b) Four cameras

(c) Six cameras

(d) Eight cameras

Figure 9: Detected maximal saw mismatch of each board, DS_b, for different numbers of cameras and different camera positions and the estimate of maximal saw mismatch of each board, $\hat{S}_b$.

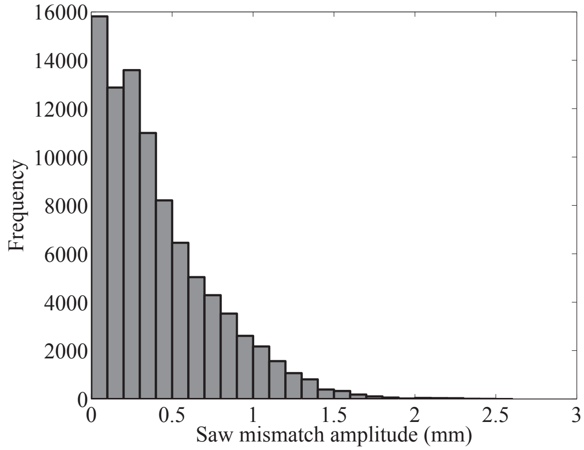


Figure 10: The sample distribution of all measurements of saw mismatch along the length of the boards.

4 Conclusions

In this study, the objective was to suggest a design of a system specialized in detecting saw mismatch on sawn timber using laser triangulation. A specific demand from the industrial partners was that the measurement system would be simple and cost effective and that it should be able to detect saw mismatch exceeding 0.5 mm.

The proposed laser triangulation unit measures saw mismatch comparable to manual measurements. This means that in terms of precision and repeatability, the measurement system has shown promising results. It should be pointed out though, that a sawing defect other than saw mismatch may be detected. This is a problem with the saw mismatch detection algorithm that needs to be improved in future work before a final implementation of a measurement system can be used in a sawmill.

The lengthwise position of the estimate of maximal saw mismatch on pith side, $\hat{S}_p$, and sapwood side, $\hat{S}_s$, for all board side faces in the sample occurs at the centre of the boards or close to the board ends. Also the correlation between the lengthwise position of $\hat{S}_p$ and $\hat{S}_s$ is weak. This indicates that a displacement of the cant is not the reason for the occurrence of saw mismatch for the boards in this sample.

By using two cameras placed 50 cm from the top end on each side face, 75% of the boards in the sample exceeding the demanded limit of 0.5 mm for maximal saw mismatch of a board, $\hat{S}_b$, were detected. Since the rate of detection is as large as 75% using two cameras and the correlation is weak between the lengthwise position of $\hat{S}_p$ and $\hat{S}_s$, future work will be to evaluate the effect of one camera in the transverse feed at the green sorting line during operating conditions.

One camera will still randomly measure saw mismatch on both pith side face and sapwood side face. This should be sufficient for detecting a trend in the sawing process, given the size distribution of saw mismatch in this specific case. In general, the equipment must be adjusted with respect to the sample distribution of measurements of saw mismatch and the desired tolerance limit.

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Paper II

An industrial test of measuring saw mismatch by laser triangulation

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An industrial test of measuring saw mismatch by laser triangulation

Anders Berglund, Anders Grönlund

Abstract

Sawing yield is an important parameter for the sawmill profit. One way to increase the sawing yield is by a reduced saw kerf width, an adapted shrinking allowance, and a lower sawing allowance. The Swedish sawmills on the other hand see a risk of poorer sawing accuracy and sawing precision and at worst, more frequent saw blade failures.

One problem with a reduced saw kerf width is the saw mismatch that may occur in double arbor saw machines. Saw mismatch occurs when the saw blades are displaced in axial direction with respect to each other due to wear, heat or mechanical disturbance. In this study the aim was to test the robustness of a laser triangulation unit used for measuring saw mismatch during sawmill operation. The aim was also to find a suitable response variable for saw mismatch which was done by using the cant height, feed speed and average top diameter of the logs as predicting variables in a partial least squares regression. The goodness of prediction for each response variable was used to compare the response variables with each other.

The results showed that the robustness when measuring saw mismatch by laser triangulation during ongoing sawmill production was satisfactory. The response variable with the best goodness of prediction (Q2 = 0.135) was defined using a sliding window with a size of 500 boards. Each element of the response variable was calculated as the share of boards within the sliding window exceeding a threshold value of 0.5 mm. This response variable was positively correlated with the cant height, feed speed and average top diameter of the log. Future work requires a designed experiment where the predicting variables are varied systematically and where the effect of characteristics and wear of the saw blades is also considered.

Keywords: Double arbor saw machine, Laser triangulation, Saw mismatch, Surface profile

1 Introduction

In order to to maximize the profit return for a sawmill the sawing yield is important since 65% to 75% of the total costs are related to the raw material (Chiorescu and Grönlund, 2003). One way to increase the volume yield is by reducing the saw kerf width (Wasielewski et al., 2012; Steele et al., 1992). Combining this with an adapted shrinking allowance and a lower sawing allowance can increase the sawing yield further (Grönlund et al., 2009; Flodin and Grönlund, 2011). Sawmills in Sweden see a risk that a reduced saw kerf width can lead to a poorer sawing accuracy and sawing precision (Steele and Araman, 1996), and at worst more frequent saw blade failures. This is holding back the development towards thinner saw blades.

If the saw kerf is reduced measurements of size and shape of the sawn timber becomes even more important. Grönlund et al. (2009) pointed out the need of measuring saw mismatch to ensure that its presence and magnitude does not increase. Saw mismatch (Figure 1) occurs in double arbor saw machines when the saw blades are displaced with respect to each other due to wear, heat, or mechanical disturbance.

A laser triangulation unit for measuring saw mismatch has been developed and evaluated in an initial laboratory test. The next step is to evaluate the robustness of the measurement unit during industrial conditions, namely by installing it at the transverse feed in the green sorting line of a sawmill. Measurements of surface profile and surface roughness of wood has been an area of interest to wood researchers earlier (Sandak and Tanaka, 2003; Elmas et al., 2011), but not to measure saw mismatch specifically.

Axelsson et al. (1991) has experimentally determined the side forces when sawing with sharp compared to dull tools, side forces that lead to deviations in green target sizes. The saw mismatch occurring in double arbor saw machines can be a process parameter that gives information of the sawing process in the same way as the deviation of green target sizes.

The objective of this work was to investigate

- Is laser triangulation used for measuring saw mismatch robust during sawmill operation?
- How should the occurrence of saw mismatch be assessed during ongoing production?

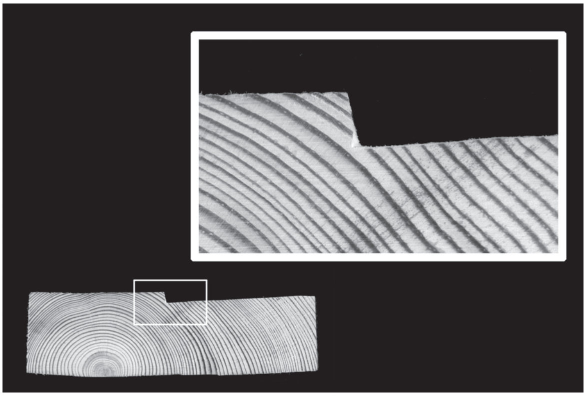


Figure 1: Saw mismatch seen from the board end.

2 Materials and methods

2.1 Setup

The set-up used was a stand that was assembled above the boards in the transverse feed (Figure 2) in the green sorting line of a sawmill. A laser triangulation unit consisting of a GigE UI-5240CP-M-GL camera and a Lasiris SNF 660 nm laser laser was mounted on the stand. The camera is connected to a PC and a photocell connected to the PC by an I/O card is used to trigger the camera.

The laser was positioned in the green sorting line so that it measured saw mismatch 50 cm from the board end board in the lengthwise direction (Figure 3). Because of the angle α that the laser makes with the surface normal, a saw mismatch results in a laser line that is displaced. The displacement, d, is proportional to the saw mismatch and can be measured in the captured images.

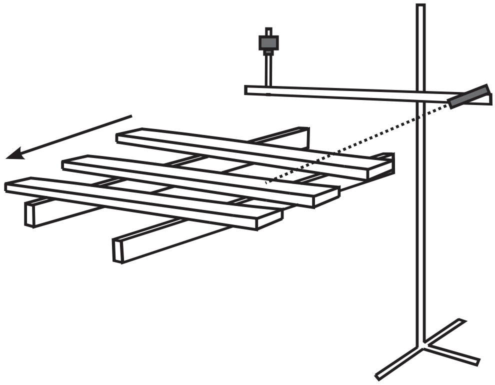


Figure 2: The laser triangulation unit as it is installed at the transverse feed in the green sorting line of a sawmill.

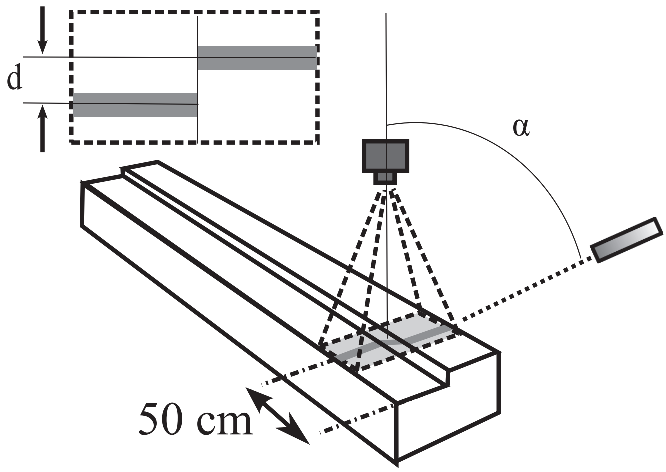


Figure 3: The laser line is positioned a distance of 50 cm from the board end in the lengthwise direction.

2.2 Measurements

Measurements of saw mismatch was performed during 14 days at a sawmill in northern Sweden. Approximately 390,000 boards passed the measurement unit during this time, resulting in the same number of measurements of saw mismatch.

During the time period of the measurements, the different sawing classes that were processed and the sawing patterns applied can be seen in Table 3, Appendix A. The feed speed used is presented in Table 2, Appendix A.

2.3 Data analysis

To analyse this large number of observations, also containing noise, and to define a suitable response variable for saw mismatch PLS regression was used. PLS regression is a regularization of a multiple regression (Ståhle and Wold, 1987), where multiple regression is based on the assumptions that the X-variables (predictors) are all independent and normally distributed. PLS regression is based on the assumptions that the X-variables are correlated, possibly also noisy and incomplete (Wold et al., 2001), which is likely with industrial data.

Choice of predictors

The X - variables used in the PLS were,

- Average log top diameter (mm)
- Cant height (mm)
- Feed speed (m/min)

Choice of response variable

In order to define a suitable response variable of saw mismatch during sawmill operation, three different response variables were evaluated using the PLS-model. The response variables were derived by the following steps. The vector X was defined as containing the saw mismatch data of the measurements,

$$X = (x_1, x_2, \ldots, x_N). \tag{1}$$

A sliding window of size S was applied to X and the vector W_j was defined as the saw mismatch values within the sliding window at a given position,

$$\begin{aligned} W_j = (x_{i-S}, x_{i-S-1}, \ldots x_i) \qquad & \forall i \in \{S, S+1, \ldots, N\} \\ & \forall j \in \{1, 2, \ldots, (N-S)\}. \end{aligned} \tag{2}$$

The vector W_{j_y} was defined as the values within the sliding window that were larger than y mm,

$$W_{j_y} = (x \in W_j | x > y\,\mathrm{mm}) \qquad \forall j \in \{1, 2, \ldots, (N - S)\}. \tag{3}$$

The elements of the first response variable, Y_1, were calculated as

$$Y_1(j) = \frac{\mathrm{length}(W_{j_y})}{S} \qquad \forall j \in \{1, 2, \ldots, (N - S)\}. \tag{4}$$

Each element is the share of values within the sliding window that exceeds a threshold value of y mm.

The elements of the second response variable, Y_2 were calculated as

$$Y_2(j) = \overline{W}_{j_y} \qquad \forall j \in \{1, 2, \ldots, (N - S)\}. \tag{5}$$

Each element is the average of the values within the sliding window that exceeds a threshold value of y mm.

The elements of the third response variable, Y_3 were calculated as

$$Y_3(j) = P_{95}(W_j). \tag{6}$$

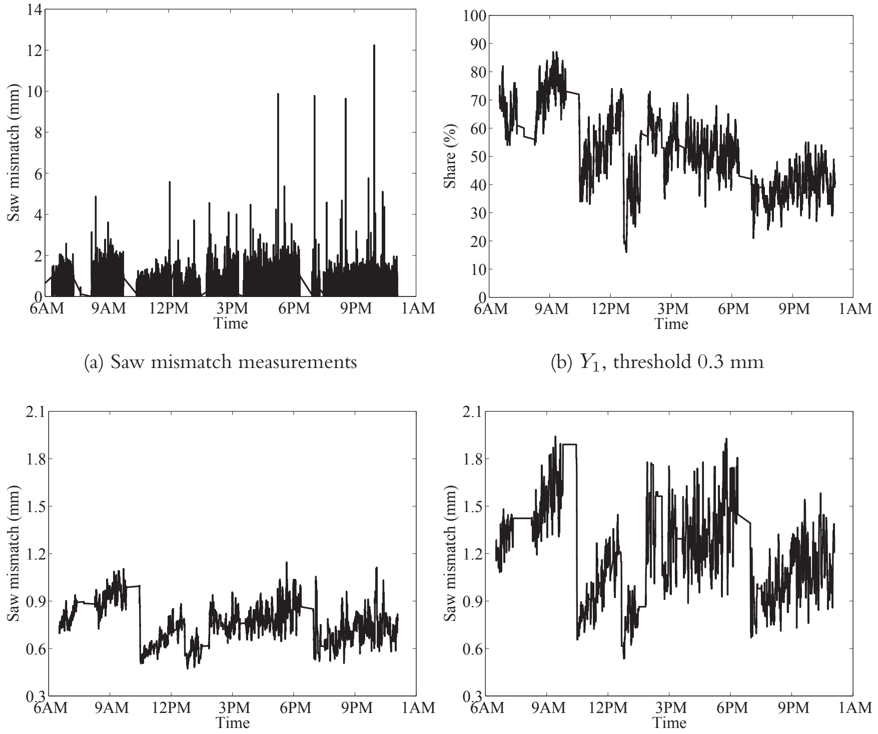
Each element is the 95$^{\mathrm{th}}$ percentile of the values within the sliding window.

Different threshold values of y for Y_1 and Y_2 were evaluated using the PLS $y = 0.1$, 0.3, 0.5, 0.7, 0.9, 1.1 and 1.3 mm as well as different window sizes for all three response variables $W_j = 50$, 100, 300 and 500 boards. The PLS-model using the response variable that results in the largest goodness of prediction, $Q2$, is the most suitable response variable since its variance can be predicted to the largest extent.

3 Results and discussion

3.1 Response variables

The data from the saw mismatch measurements from one day of production together with the three corresponding response variables, Y_1, Y_2, Y_3, are shown in Figure 4. The used window size was 100 boards and the applied threshold value was 0.3 mm in this case. It is clear by looking at Figure 4 that the behaviour of the response variables is different.



(a) Saw mismatch measurements

(b) Y_1, threshold 0.3 mm

(c) Y_2, threshold 0.3 mm

(d) Y_3

Figure 4: Data from saw mismatch measurements during one day of production and corresponding response variables using a threshold value of 0.3 mm and a window size of 100 boards.

3.2 PLS

The goodness of prediction, $Q2$, of the PLS model using one or two principal components is shown in Table 1. The best goodness of prediction ($Q2 = 0.135$) was obtained using the response variable Y_1 with a window size of 500 boards and a threshold value of 0.5 mm. This means that 13.5% of the variance in the response variable Y_1 can be predicted by the PLS-model using average log top diameter, cant height and feed speed as predicting variables. The goodness of prediction for Y_1 is not so dependent of window size, the value of $Q2$ for a given threshold value was quite constant when the window size was varied. The choice of threshold value is more important and it is clear that a threshold value in the interval 0.3 mm - 0.5 mm is suitable with respect to the level of saw mismatch of this particular sawmill. Figure 5 shows the centred and scaled PLS regression coefficients using two principal components for the PLS model with the best goodness of prediction. All predicting variables are positively correlated with saw mismatch, but average log top diameter and feed speed are more correlated than the cant height.

A goodness of prediction of $Q2 = 0.135$ using log diameter, cant height and feed speed as predicting variables is a good start. To improve our understanding of what is causing the saw mismatch further tests needs to be carried out. What would be interesting is to take saw blade characteristics into account. The effect of variables such as saw kerf width, saw blade collar size, number of saw teeth on saw blade, number of resharpenings of saw blades etc. would be interesting to study. This should be done using a designed experiment where the predicting variables are controlled and varied systematically. Further adjustments of the installation of the laser triangulation unit in the sawmill can also reduce the noise of the measurement.

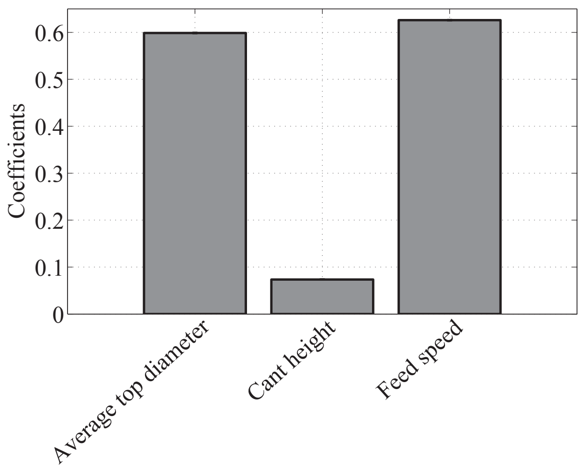


Figure 5: The centred and scaled regression coefficients of the PLS using two principal component where the statistical significance of each coefficient is indicated by 95% confidence intervals. The confidence intervals are so narrow that they are not visible.

Table 1: Goodness of prediction, $Q2$, for the three response variables Y_1, Y_2 and Y_3 using different threshold values and different window sizes.

(a) Y_1

Threshold (mm)	Window size 50	100	300	500
0.1	0.00716	0.00862	0.0462	0.0502
0.3	0.108	0.118	0.131	0.133
0.5	0.115	0.124	0.132	**0.135**
0.7	0.0921	0.0998	0.107	0.109
0.9	0.0709	0.0782	0.0853	0.088
1.1	0.0555	0.0632	0.0712	0.0746
1.3	0.00935	0.0475	0.0564	0.0611

(b) Y_2

Threshold (mm)	Window size 50	100	300	500
0.1	0.0932	0.0526	0.0813	0.0918
0.3	0.0165	0.00616	0.0324	0.0589
0.5	0.000965	0.00359	0.00508	0.0106
0.7	0.00193	0.00607	0.00941	0.0112
0.9	0.00474	0.0104	0.00851	0.00764
1.1	0.00889	0.0132	0.0140	0.0134
1.3	0.0133	0.014	0.0166	0.0171

(c) Y_3

Window size 50	100	300	500
0.0392	0.0632	0.0926	0.099

4 Conclusions

This work showed that the robustness when measuring saw mismatch during sawmill operation using laser triangulation was satisfactory. The response variable for measuring saw mismatch that resulted in the largest goodness of prediction (Q2 = 0.135) of a PLS-model was when using a sliding window where each element was calculated as the share of the latest 500 measured boards exceeding a threshold value of 0.5 mm. The predicting variables of the model were all positively correlated with saw mismatch meaning that increased log diameter, cant height and feed speed lead to increased presence and magnitude of saw mismatch.

The choice of window size was not so critical, the goodness of fit was almost the same if a smaller window size was used for a given threshold value. A smaller window size would be preferable in such case since the lag in the saw mismatch measurement would be reduced. The choice of threshold value was more important and should be in the interval 0.3 – 0.5 mm with respect to the presence and magnitude of saw mismatch in this particular case.

This work is a good start for increasing our understanding of what is causing saw mismatch and which variables that have the largest effect on its presence and magnitude. To continue this study it is necessary to take the effect of saw blade characteristics into account as well and to design an experiment where the predicting variables are varied systematically.

A Sawing classes and sawing patterns

Table 2: The used feed speed for different cant heights.

Cant height (mm)	Feed speed (m/min)
100	130
125	125
150	110
175	90
200	80
225	70

Table 3: Processed sawing classes and applied sawing patterns during the period of the measurements. The lower and upper limit specifies the lower and upper limit of the top diameter of the log in each sawing class.

SC	Sawing pattern(mm)	Lower limit (mm)	Upper limit (mm)	Start time	Stop time
P11	32 by 125	144	152	2012-08-24 14:36	2012-08-27 14:02
P18	63 by 125	197	219	2012-08-27 14:02	2012-08-28 06:09
P22	75 by 150	228	237	2012-08-28 06:09	2012-08-28 18:37
P20	75 by 125	220	227	2012-08-28 18:37	2012-08-29 09:23
P21	63 by 125	190	210	2012-08-29 09:23	2012-08-29 15:04
P14	50 by 100	174	186	2012-08-29 15:04	2012-08-29 21:36
P15	50 by 100	162	171	2012-08-29 21:36	2012-08-30 07:50
P24	38 by 150	238	254	2012-08-30 07:50	2012-08-30 12:35
P26	38 by 150	255	271	2012-08-30 12:35	2012-08-30 18:01
S30	100 by 200	287	320	2012-08-30 18:01	2012-08-31 07:49
S28	63 by 200	260	286	2012-08-31 10:59	2012-09-03 11:16
S14	50 by 100	167	180	2012-09-03 11:16	2012-09-03 22:12
S12	38 by 125	159	166	2012-09-03 22:12	2012-09-04 08:56
S26	63 by 175	241	259	2012-09-04 18:26	2012-09-05 12:53
S04	32 by 100	124	137	2012-09-04 08:56	2012-09-04 18:26
S24	47 by 150	218	240	2012-09-05 12:53	2012-09-05 21:52
P04	32 by 100	120	131	2012-09-05 21:52	2012-09-06 07:28
P08	32 by 100	141	144	2012-09-06 07:28	2012-09-06 16:12
P06	38 by 100	132	140	2012-09-06 16:12	2012-09-07 07:00
S06	38 by 100	138	148	2012-09-07 07:00	2012-09-10 21:04
S16	50 by 125	181	190	2012-09-10 21:04	2012-09-11 14:21
S18	63 by 125	191	206	2012-09-11 14:21	2012-09-12 11:50
S20	63 by 150	207	210	2012-09-12 11:50	2012-09-12 18:13
S22	63 by 150	211	217	2012-09-12 18:13	2012-09-13 16:16
P26	38 by 150	255	271	2012-09-20 21:59	2012-09-21 10:59
P10	38 by 100	145	151	2012-09-21 10:59	2012-09-24 15:48
P21	63 by 125	190	210	2012-09-24 15:48	2012-09-24 23:25
P24	38 by 150	238	254	2012-09-24 23:25	2012-09-25 13:34
P15	50 by 100	162	171	2012-09-25 13:34	2012-09-25 21:02
P18	63 by 125	197	219	2012-09-25 21:02	2012-09-26 22:50
P14	50 by 100	174	186	2012-09-26 22:50	2012-09-27 00:01

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S. Wold, M. Sjöström, and L. Eriksson. Partial least squares regression: a basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems*, 58(2): 109–130, 2001. PLS Methods.

Paper III

Improved log rotation with an industrial computed tomography scanner

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Improved log rotation with an industrial computed tomography scanner

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Abstract

The development of an industrial CT-scanner for the sawmilling industry raises the question of how to find a production strategy that uses a CT-scanner in the sawmill production line to its full potential. This study was focused on a Scandinavian sawmill processing Scots pine (*Pinus sylvestris [L.]*) and Norway spruce (*Picea abies [L.] Karst.*). The potential value increase when allowing an alternative log rotation other than the horns down position was investigated using a log breakdown simulation. The resulting data was analysed with respect to the size of the log rotational step, an introduced rotational error of the sawing machine and different price differences between the quality grades. It was also of interest to define the outer log properties that characterise the logs sawn for the greatest profit return close to the horns down position compared to logs sawn for a greater profit return in a different log rotation. Such characteristics can be used to reduce the number of degrees of freedom in an optimization and consider instead other parameters, such as positioning and sawing pattern. Other defects such as pitch pockets, splits and rot are also of interest.

The results show that there is a potential value increase when applying the log rotation that maximizes the value for each log instead of processing all logs in the horns down position. However, the potential value increase depends on the rotational error of the used sawing machine and the price differences between the quality grades. The log properties that differ between logs sawn for the greatest profit return close to the horns down position compared to a different log rotation are the bow height and the log taper. Unfortunately, predictability of log rotation for greatest profit return based on the outer properties of logs is poor. It is not possible to differentiate logs which would be sawn for the greatest profit return close to the horns down position from those where a different log rotation results in the greatest profit return, based only on their outer properties.

Keywords: CT-scanner, Improved log rotation, Multivariate analysis, Profit, Sawmill, Simulation

1 Introduction

The task of improving the use of the raw material in a sawing process is challenging. An efficient breakdown depends on a knowledge of the properties of each log, and each log must be processed individually (Vuorilehto and Tulokas, 2007). Today, X-ray scanning is used in sawmills to determine the inner properties of logs, typically with scanning in 1–4 directions (Pietikäinen, 1996; Grundberg and Grönlund, 1997). However a discrete X-ray scanner only provides longitudinal information of the inner properties of a log. The development of an X-ray CT-scanner for the sawmilling industry (Giudiceandrea et al., 2011) will make three dimensional information about the inner properties of the log available at production speed. This gives new possibilities, but also raises questions of how to use such a machine.

To accomplish an efficient breakdown with respect to volume yield the governing factors are a correct sawing pattern, log rotational positioning, and log parallel positioning in the sawing machines together with a correct usage of curve or straight sawing techniques (Lundahl and Grönlund, 2010). Lundahl and Grönlund (2010) studied the potential, with respect to volume yield, for an alternative log rotation other than the horns down position and found that the yield could be increased by 5.8%. Here, the term *horns down* refers to the log position in which a log with sweep (end-to-end curvature) is positioned so that the log ends are set down on the log carriage while the middle section of the log is off the carriage (Lundahl and Grönlund, 2010).

A CT-scanner installed in a sawmill, scanning logs in real time, introduces the possibility of applying an improved log rotation with respect to the value yield. If the inner properties of the logs are known, this can be used to achieve a higher quality of the sawn products.

The objective of this study was to investigate if there is a potential value increase when allowing an alternative log rotation other than the horns down position. A secondary objective was to decide whether there are any typical characteristics related to the outer properties of those logs that are sawn for the greatest profit return close to the horns down position, unlike logs that yield a greater profit return in an alternative log rotation.

The study was focused on a Scandinavian sawmill processing Scots pine (*Pi-*

nus sylvestris [L.]) and Norway spruce (*Picea abies [L.] Karst.*). The information from a CT-scanner about the log characteristics and the log rotation for greatest profit return could be used to reduce the number of degrees of freedom in an optimization. Instead, other parameters, such as positioning and sawing pattern, could be considered as well as other defects, such as pitch pockets, splits and rot.

2 Materials and methods

2.1 The Swedish stem bank

The SSB (Grönlund et al., 1995) contains data from about 600 Scots pine (*Pinus sylvestris [L.]*) logs and about 800 Norway spruce (*Picea abies [L.] Karst.*) logs from 72 plots in different geographic locations in Sweden. Some of the spruce logs are collected from plots in Finland and France. In each plot, six trees have been chosen, two in a lower diameter class, two in a middle diameter class and two in a larger diameter class. The stems were divided into the diameter classes based on the quadratic mean diameter at breast height (DBH) of the stand, with class limits at half a standard deviation above and below this mean (Björklund and Moberg, 1999).

A medical CT-scanner (Siemens SOMATOM AR.T) was used to scan the logs and the resulting CT images describe the log shape, pith location, heartwood border and knots. The knots are described by nine parameters specifying the knot geometry, position, and direction in the log (Oja, 2000). Putting all this together the outer and inner properties of the logs in the SSB can be used within saw simulation software. The diversity of the logs in the SSB is great and it is a representative data set for logs in the Scandinavian countries, which is why it is suitable for the objectives of this study.

2.2 The Saw2003 simulation software

To study different log properties, production strategies, machine settings and their effects on the breakdown process, simulation software has been widely used within the field of wood technology research (Björklund and Julin, 1998; Todoroki and Rönnqvist, 1999; Nordmark, 2005). The Saw2003 software (Nordmark, 2005) was developed to interact with the data in the SSB and simulates the breakdown process according to the grading rules applied in Scandinavian sawmills (Föreningen Svenska Sågverksmän, 1997). Briefly described, the grading rules separate the sawn boards into three different qualities, based on the outer features of the boards. The sawing procedure is governed by the specified sawing patterns and prices of sawn timber.

The sawing patterns used in this research are shown in Table 1 where the logs, depending on their top diameter, were sorted into their respective SC. The sawing techniques used were cant sawing and curve sawing, which are typical for sawmills in the Scandinavian countries. Figure 1 illustrates cant sawing, where the first sawing machine cuts the log into side boards and a cant. The cant is then rotated by 90 degrees and cut by the second sawing machine into side boards and centre boards. The sawing allowance, that is, shrinkage as well as deviations in the sawing, was set at 4% of the nominal width for each board dimension and the saw kerf width was set to 4 mm for both the first saw and the second saw.

Table 1: The logs are sorted into their respective SC with respect to their top diameter. The first saw determines the height of the cant (block), the thickness of the side boards in the first saw and also governs the width of the centre boards. The second saw determines the thickness of the centre boards and additional sideboards. All measures are nominal target values.

SC	Sawing pattern (mm)	Lower limit Top diameter (mm)	Upper limit Top diameter (mm)	Post First saw (mm)	Post Second saw (mm)
1	38 by 75	0	129	19, 75, 19	19, 38, 38, 19
2	38 by 100	130	149	19, 100, 19	19, 38, 38, 19
3	50 by 100	150	169	19, 100, 19	19, 50, 50, 19
4	50 by 125	170	184	19, 125, 19	25, 50, 50, 25
5	63 by 125	185	194	19, 125, 19	19, 63, 63, 19
6	50 by 150	195	209	19, 19, 150, 19, 19	19, 25, 50, 50, 25, 19
7	63 by 150	210	219	19, 19, 150, 19, 19	19, 25, 63, 63, 25, 19
8	50 by 175	220	229	19, 19, 175, 19, 19	19, 25, 50, 50, 25, 19
9	63 by 175	230	249	19, 19, 175, 19, 19	25, 25, 63, 63, 25, 25
10	63 by 200	250	264	19, 19, 200, 19, 19	25, 25, 63, 63, 25, 25
11	75 by 200	265	284	19, 19, 200, 19, 19	19, 25, 75, 75, 25, 19
12	75 by 225	285	304	19, 19, 225, 19, 19	19, 25, 75, 75, 25, 19
13	50 by 200 by 4	305	324	19, 25, 200, 25, 19	19, 25, 50, 50, 50, 50, 25, 19
14	50 by 225 by 4	325	344	25, 32, 225, 32, 25	25, 25, 50, 50, 50, 50, 25, 25
15	63 by 200 by 4	345	384	25, 32, 200, 32, 25	19, 25, 63, 63, 63, 63, 25, 19
16	75 by 200 by 4	385	449	25, 32 200, 32, 25	19, 25, 75, 75, 75, 75, 25, 19

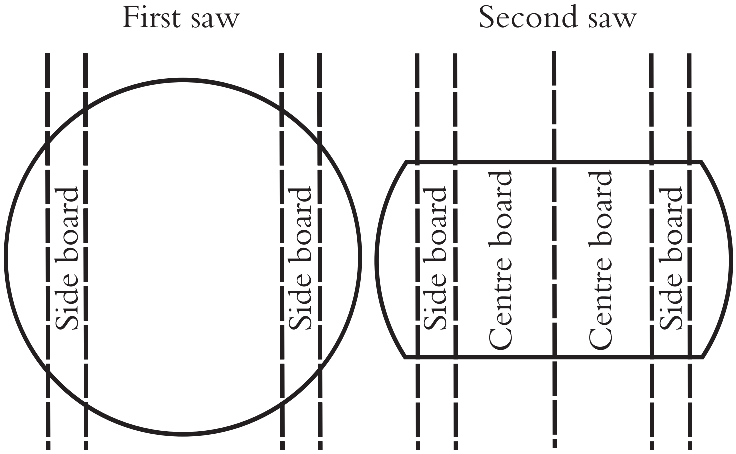

Figure 1: Cant sawing. The first sawing machine cuts the log into side boards and a cant. The cant is then rotated by 90 degrees and cut by the second sawing machine into side boards and centre boards. Side boards are further processed by edging and trimming, while trimming is the only operation on centre boards.

2.3 Simulations

The Saw2003 software was used to simulate curve sawing of all logs in the SSB in each rotation angle in the interval $[-180°, 180°)$, where the rotation angle of $0°$ corresponds to the horns down position. Three different simulations were carried out using the different price differences between the quality grades presented in Table 2. The different price settings represents the price range of sawn timber for a Scandinavian sawmill.

An additional simulation was also performed using normal price differences (Table 2) but with a normally distributed rotational error for the sawing machine introduced with mean $0°$ and a typical standard deviation of $5°$. Note that from now on, if not specified, the normal price differences between the quality grades has been used.

These simulations made it possible to analyse the effect that different log rotational step lengths as well as a rotational error for the sawing machine would have on the potential value and yield increase, when using the log rotation that maximizes the value or yield for each log instead of sawing all logs in the horns down position. Also, the consequence of different price differences between the quality grades for the potential value and yield increase could be analysed. What is interesting is the effect of price differences between boards of different qualities, rather than the price differences between centre boards and side boards. This since the price differences between different qualities affect the value optimization when edging and trimming boards.

Table 2: Different prices between quality grades used in the simulations, all prices are in €/m^3. The quality definitions are specified by the Nordic Timber Grading Rules (Föreningen Svenska Sågverksmän, 1997), boards classified as grade D are chipped.

	PINE & SPRUCE		
	Low	Normal	High
Centre boards grade A	194	208	222
Centre boards grade B	180	180	180
Centre boards grade C	146	112	79
Side boards grade A	247	337	427
Side boards grade B	157	157	157
Side boards grade C	140	123	107

The simulations resulted in value as a function of log rotation for each log, as shown in Figure 2a - 2b. To reduce the noise of the curve, a median filter was applied with a window size of 13°, where periodic boundary conditions were used. As described by Pratt (2007), the median filter in one-dimensional form consists of a sliding window encompassing an odd number of values. The centre value in the window is replaced by the median of the values in the window. Periodic boundary conditions mean that the function is made periodic so that the sliding window never extends beyond the end points. The choice of window size is not an easy task since it governs what is considered as noise and what is not. In this case the chosen window size of 13° corresponds to just over two standard deviations of the rotational error of a sawing machine. The effect is that the range of an increase or decrease in the value function has to be greater than one standard deviation to not be considered as noise.

The resulting filtered curves can be observed in Figure 2c - 2d, where the rotation angle of 0° corresponds to the horns down position. Since the curve is periodic with periodicity 180° (Figure 2), only the interval ±90° from the horns down position was considered in the analysis, i.e., the interval $[-90°, 90°)$.

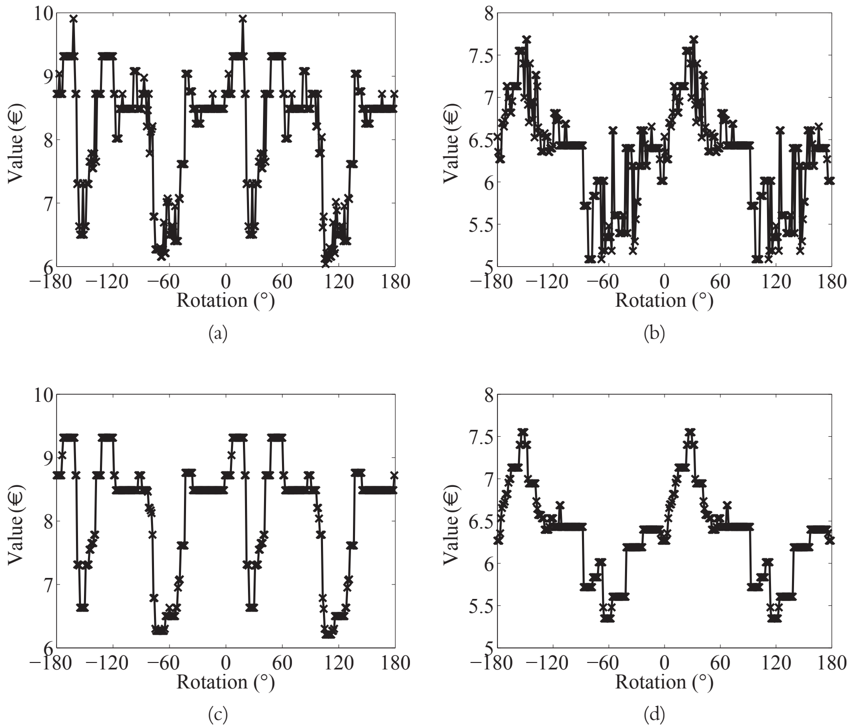

Figure 2: The total value of the sawn products for two logs sawn in different log rotations. The value functions shown in example (a) and (b) are unfiltered, while the value functions submitted to a median filter are shown in example (c) and (d). The rotation angle of 0° corresponds to the horns down position.

2.4 Multivariate model

Multivariate partial least squares discriminant analysis (PLS-DA) (Ståhle and Wold, 1987) with the software Simca (Umetrics, 2009) was used to find the differences between the logs having the greatest profit return in a log rotation close to the horns down position, compared to the logs that have a greater profit return in a different log rotation. PLS-DA can be seen as the PLS solution to the linear discriminant analysis (LDA), in analogy with the ordinary PLS regression being the regularization of a multiple regression (Ståhle and Wold, 1987). The reason for using PLS-DA instead of the traditional linear discriminant analysis is that LDA is based on the assumptions that the X-variables (predictors) are all independent and normally distributed. PLS regression is based on the assumptions that the X-variables are correlated, possibly also noisy and incomplete which are more in line with reality than those of LDA (Wold et al., 2001).

Selection of logs

Out of the 1465 logs in the SSB, 408 logs were selected for the PLS-DA with respect to the characteristics of the filtered value functions shown in Figure 2c and Figure 2d. The reason for selecting logs from the SSB was to identify logs where the value of the sawn products could be increased by an alternative log rotation other than the horns down position. Logs that had a unique log rotation for the greatest profit return were included in the PLS-DA (Figure 3a) while logs that had several equally profitable log rotations were excluded (Figure 3b). The reason for excluding logs with several equally profitable log rotations was to make the PLS-DA-model as strong as possible, and for that, it was necessary to select typical logs with a distinct log rotation for greatest profit return.

The criteria for the selection of logs was that only the maximal plateau should be larger than a threshold value, defined as 97% of the maximum value, which is the case in Figure 3a but not in Figure 3b. Also, at the threshold level, the maximal plateau had to be at least 5° wide, but not wider than 20°. These values correspond to one and four, respectively, standard deviations in the rotational error of a sawing machine. The choices of thresholds were difficult since on one hand, it was desirable to select logs with a distinct log rotation for greatest profit return while on the other hand the selected logs should not be too few. The compromise between these two aspects resulted in the described thresholds and the selection of 28% or 408 of the logs in the SSB.

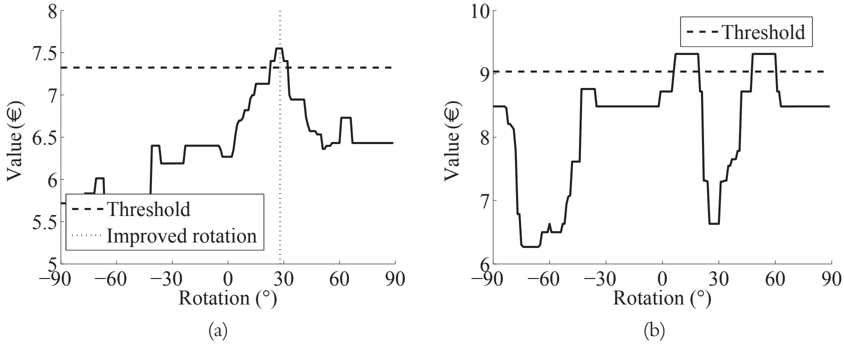

Figure 3: The total value of the sawn products as function of log rotation for two different logs. The log in example (a) was selected for the PLS-DA while the log in example (b) was excluded. The rotation angle of 0° corresponds to the horns down position.

Classes

To inspect whether the logs having the log rotation with greatest profit return close to the horns down position had different outer shape characteristics than those logs having the log rotation with greatest profit return in a different log rotation, the selected logs were divided into two classes. This classification was supported by the distribution of the log rotation for greatest profit return of the selected logs (Figure 4). Class I was defined as those logs having the log rotation with greatest profit return $\pm 30°$ from the horns down position, that is in the interval $[-30°, 30°]$. Class II was defined as logs having the log rotation with greatest profit return different than the horns down position, in the interval $[-90°, -30°)$ or $(30°, 90°)$.

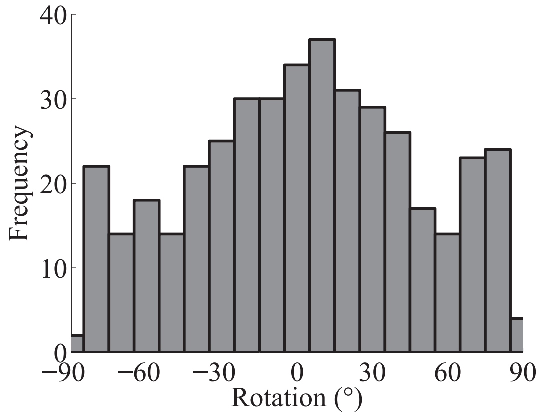

Figure 4: The distribution of log rotation for greatest profit return for the 408 selected logs. The rotation angle of 0° corresponds to the horns down position.

The predictors used in the PLS-DA were

- Volume (V) $[m^3sub]$
- Length (L) $[m]$
- Top diameter, inside bark (D_{TOP}) $[mm]$
- Butt diameter, inside bark (D_{BUTT}) $[mm]$
- Bow height (BH) $[mm]$
- Log taper (T) $[m/m$, dimensionless$]$
- Sawing pattern ratio (SPR) [dimensionless]
- The difference between the sawing pattern diagonal and the top diameter of the log $(DIFF)$ $[mm]$

Since the SSB contains data from logs that have been scanned with a medical CT-scanner it is possible to determine variables related to the outer log shape precisely.

The log taper is calculated as

$$T = \frac{D_{BUT} - D_{TOP}}{L}. \tag{1}$$

The bow height is calculated as the Euclidean distance from the centre of gravity of the log to a reference line. The coordinates controlling the reference line is calculated as the average centre of gravity of a section in the top end and of a section in the bottom end. A detailed description of the algorithm for calculating the bow height is described by Nordmark (2005).

The sawing pattern ratio, SPR, is calculated from the green target sizes by

$$SPR = \frac{X_{LOG} \cdot BT + (X_{LOG} - 1) \cdot KW}{BW}, \tag{2}$$

where X_{LOG} is the number of centre boards in the sawing pattern, BT is the green centre board thickness, KW is the kerf width and BW is the green centre board width. The variable SPR describes the shape of the sawing pattern. If it is smaller than one, then the green board width is larger than the total green thickness of the centre boards, including the saw kerf as in Figure 5a. If it is larger than one, then the green board width is smaller than the total green thickness of the centre boards, including the saw kerf as in Figure 5b.

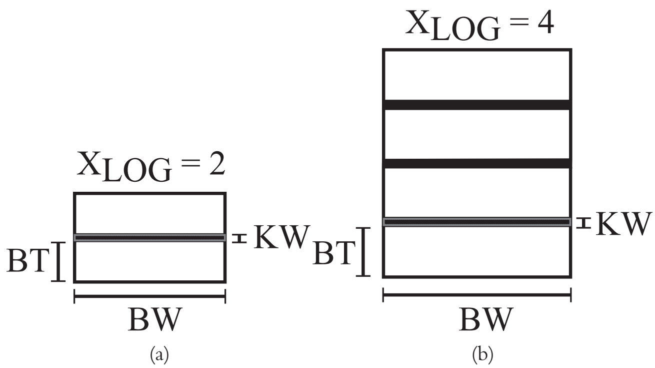

Figure 5: Examples of sawing patterns with different sawing pattern ratio, SPR. Here, X_{LOG} is the number of centre boards in the sawing pattern, BT is the green centre board thickness, KW is the kerf width and BW is the green centre board width. Example (a) shows a sawing pattern where the SPR is smaller than one, while example (b) shows a sawing pattern where the SPR is larger than one.

The difference, $DIFF$, between the sawing pattern diagonal, SPD (see Figure 6), and the top diameter of the log, D_{TOP}, is

$$DIFF = D_{TOP} - SPD. \tag{3}$$

The sawing pattern diagonal, SPD, is calculated from the green target sizes by

$$SPD = \sqrt{(X_{LOG} \cdot BT + (X_{LOG} - 1) \cdot KW)^2 + (BW)^2}. \quad (4)$$

The variable $DIFF$ describes how much space there is between the sawing pattern and the outer border in the top end of the log. A smaller $DIFF$ value means a larger risk of having boards with wane if the log is rotated.

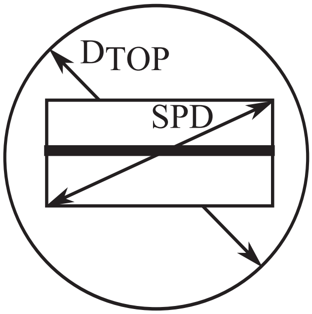

Figure 6: Illustration of the sawing pattern diagonal, SPD, and the top diameter of the log, D_{TOP}.

3 Results and discussion

3.1 Impact of rotational step length, rotational error and price differences

Looking at the unfiltered curves (Figure 2a, Figure 2b) and choosing the log rotation that maximizes the value for all logs in the SSB, there is a value increase compared to the horns down position with a mean of about 13% for both pine and spruce (Figure 7). But, the standard deviation is large: about 16% for pine and 14% for spruce. Using the same approach for yield shows that there is a yield increase with a mean of about 5% and a standard deviation of about 4% for both species. If the log rotational step size increases, the mean of the value increase and the mean of the yield increase are reduced since log rotations for greater profit return are being overlooked.

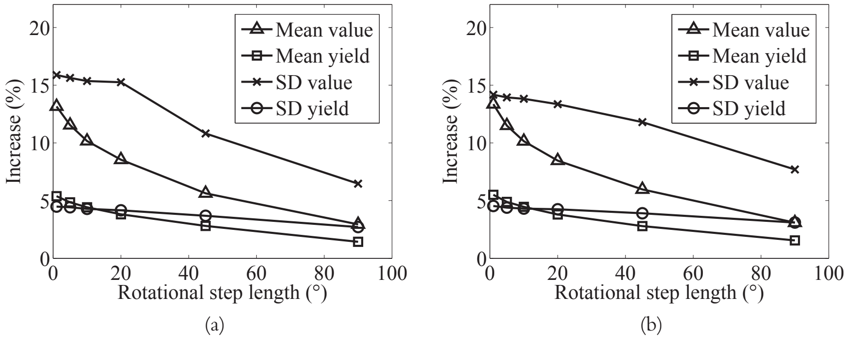

Figure 7: The mean of the value increase and the mean of the yield increase compared to the horns down position together with standard deviations for all logs in the SSB. The result for pine is shown in (a) while the result for spruce is shown in (b). The different log rotational step lengths are 1°, 5°, 10°, 20°, 45° and 90°.

Figure 8 shows the mean of the value increase and the mean of the yield increase when a normally distributed rotational error with mean 0° and standard deviation of 5° was introduced. The rotational error reduces the mean of the value increase to about 6% and the mean of the yield increase to about 2% for both species. As before the mean of the value increase and the mean of the yield increase drops with increased log rotational step length.

The impact of different price differences between the quality grades (Table 2) on the mean of the value increase and the mean of the yield increase can be observed in Figure 9. As expected, larger price differences leads to an increase in the mean of the value increase with similar results for both spruce and pine. This is because an improved quality of the sawn products will be more profitable if the relative prices between different qualities are larger. The same goes for the mean of the yield increase, which is surprising. An increase in price differences was expected to lead to the the trimming of boards to shorter lengths of higher quality, i.e., the mean of the yield increase would decrease rather than increase. The standard deviations for both the value increase and the yield increase becomes larger with increased price differences between the quality grades since the value increase and yield increase will differ even more between logs.

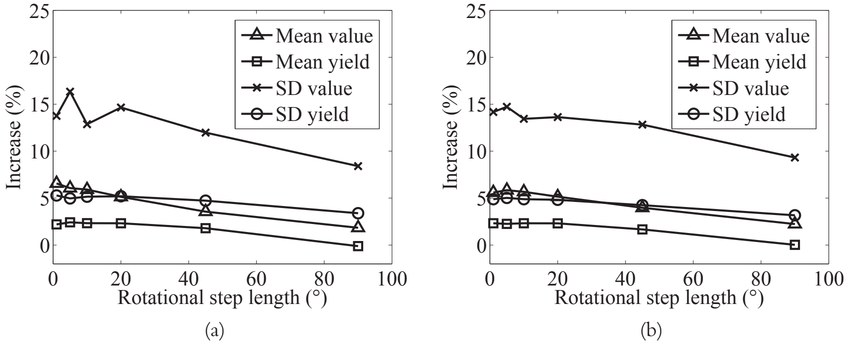

Figure 8: The mean of the value increase and the mean of the yield increase compared to the horns down position together with standard deviations for all logs in the SSB. The result for pine is shown in (a) while (b) shows the result for spruce. The different log rotational step lengths are $1°, 5°, 10°, 20°, 45°$ and $90°$. A rotational error with standard deviation of $5°$ was introduced.

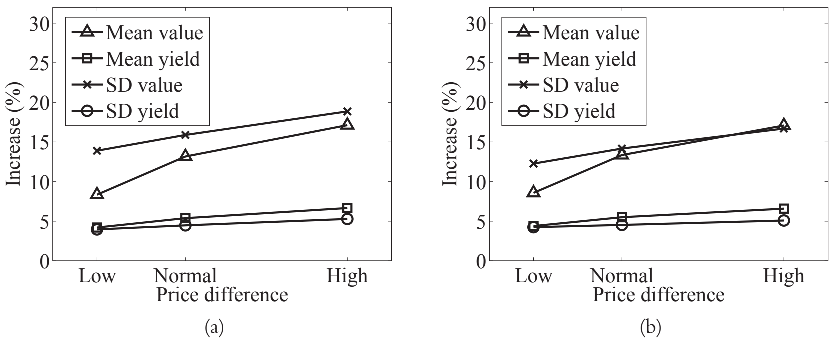

Figure 9: The mean of the value increase and the mean of the yield increase compared to the horns down position together with standard deviations for all logs in the SSB. The result for pine is shown in (a) while the result for spruce is shown in (b). The price differences between the quality grades are specified by Table 2.

3.2 Multivariate model

Figure 10 shows the regression coefficients of the PLS-DA using one principal component where the statistical significance of each coefficient is indicated with 95% confidence intervals. The coefficients are related to centered and scaled coefficients, so the size and sign of the coefficients indicate how each predictor is described relative to the logs in the other class. The confidence intervals have been estimated directly from the data using jack-knifing (Efron and Gong, 1983), which was recommended originally by Wold (1982) and has been revived by Martens and Martens (2000). Jack-knifing is an extension of the predictive validity done by cross validation and also assesses the uncertainty in the individual model parameters (Martens and Martens, 2000).

The regression coefficients for Class I (Figure 10a), logs sawn to the greatest profit return $\pm 30°$ from the horns down position, shows that the predictors that significantly separate the two classes are bow height and log taper. The 95% confidence intervals imply that the coefficient for bow height is positive while it is negative for log taper. Logs in Class I significantly have larger bow height and are less tapered than the logs in Class II.

Figure 10b shows the complementary regression coefficients for Class II and describes how the predictors of the logs in Class II are described relative to the predictors of the logs in Class I. Consequently, it is significant that logs belonging to Class II have a smaller bow height and are more tapered compared to logs in Class I.

These significant predictors are reasonable, since logs sawn for the greatest profit return close to the horns down position should be characterized by actually having sweep. For straighter logs, more common in Class II, the horns down position becomes less distinct and these logs are more often sawn for greater profit return when rotated differently than the horns down position. Also, the logs in Class II are more tapered, which reduces the risk of having wane on the sawn boards when rotating these logs. This reasoning is also applicable for the space between the outer border of the log top end and the sawing pattern, whose coefficient $(DIFF)$ is close to being significant (Figure 10). More space between the sawing pattern and the outer border of the log reduces the risk of having wane on the sawn boards.

The predictability of the model is poor, which means that it is difficult to identify logs as belonging to either Class I or Class II, based on their outer properties. Table 3 shows that when trying to predict the class of the 190 logs belonging

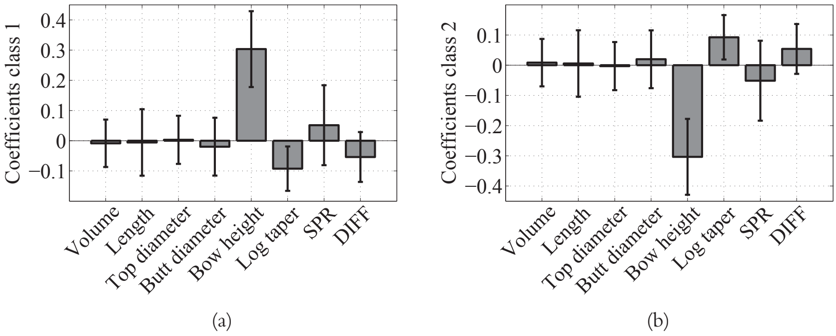

Figure 10: The regression coefficients of the PLS-DA using one principal component where the statistical significance of each coefficient is indicated by 95% confidence intervals. The coefficients for Class I are shown in (a), while the coefficients for Class II are shown in (b).

to Class I, only 102 of these logs are classified as belonging to that class. As for Class II, 161 out of the 218 logs in Class II are classified as belonging to that class. This means a correct classification of 53.7% for Class I and 73.9% for Class II, resulting in an overall correct classification of 64.5%. The larger misclassification of logs in Class I is due to the fact that Class I contains straight logs which are classified as belonging to Class II to a larger extent than Class II contains logs with sweep classified as belonging to Class I.

Table 3: Prediction of class of the selected logs.

	No.	No. predicted class 1	No. predicted class 2	Correct
Class 1	190	102	88	53.7%
Class 2	218	57	161	73.9%
Total	408	159	249	64.5%

4 Summary & conclusions

The promising result of this study is that for a Scandinavian sawmill processing Norway spruce and Scots pine there is a potential value increase if scanning logs in real time with a CT-scanner. If an alternative log rotation other than the horns down position is allowed for each log, there is a potential for a greater profit return. But, the potential value increase differs a lot from log to log and it should also be pointed out that in practice, the potential value increase is reduced by the rotational error of the sawing machine used. It is also dependent of the current prices for sawn timber where larger price differences between the quality grades results in a larger potential value increase. The reason for this is that an improved quality of the sawn products will be more profitable if the relative prices between different qualities are larger.

When determining the characteristics that describe the logs that are most profitably sawn close to the horns down position (Class I), as opposed to the logs that yield a higher value in an alternative log rotation (Class II), the predictors that were significant at the 95% confidence level were the bow height and the log taper. The bow height was larger for the logs in Class I than those in Class II. This was expected, since logs sawn for the greatest profit return close to the horns down position should be characterised by actually having sweep. The log taper was larger for logs in Class II, as was the space between the sawing pattern and the outer border of the log top end which was a predictor that was close to being significant. Both factors reduce the risk of having wane on the sawn boards when rotating these logs different than the horns down position. The logs cannot be accurately identified as belonging to either class based on their outer properties since the predictability of the model is poor.

These results indicate that the log shape is not by itself the governing factor for how to rotate the log so as to get the highest value in the sawing process. Instead, what becomes interesting in future work will be to take the inner properties of the log into consideration and investigate their correlation with the improved log rotation.

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