Efficient Utilization of Sawlogs Using Scanning Techniques and Computer Modelling

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The main question asked of the work described in this thesis was how the sawing of logs into sawn timber can be performed more efficiently with respect to the choice of raw material, volume and value yield in the sawing and in the grading of the sawn timber produced.

The development of industrial computed tomography scanning provides information about the external and internal properties of a sawlog at production speed. This opens up new possibilities of controlling the flow of raw material early in the process and of optimizing the breakdown of each sawlog. Another use of industrial computed tomography scanning is for predicting the strength of sawn timber better than is possible with current visual and machine strength grading equipment.

A more traditional way of increasing sawmill profitability is by increasing the volume of sawn timber. One way of doing this is by reducing the saw blade thickness which results in less sawdust. With the use of thinner saw blades however there is a risk that the saw blades become misaligned which in turn leads to saw mismatch, an unevenness seen on the surface of the sawn timber. In this work, attempts were made to automatically measure and monitor saw mismatch in a sawmill during ongoing production.

It is also possible for a sawmill to increase its profitability by measures not related to the sawing process. One such example is customer adaptation when delivering the sawn timber. Different customers use the sawn timber for different purposes and consequently have different requirements, which is why the sawn timber produced is graded and sorted before it is delivered to the customer. In this work, an alternative method for grading sawn timber more efficiently using a multivariate method was developed and evaluated.

The following results have been obtained:

Log breakdowns of 716 Scots pine logs and 750 Norway spruce logs that had been scanned using computed tomography were simulated and the rotational position of each log was optimized. The results showed an average relative value increase of 16% for appearance graded sawn timber compared to the conventional horns down position. When simu-
lating log breakdowns of 677 Norway spruce logs with respect to visually strength graded sawn timber, an average relative value increase of 11% was obtained. The effect that errors in knot detection algorithms had on a breakdown optimization was also analysed when optimizing breakdown of 57 Norway spruce sawlogs. The results showed that errors in the knot diameter had the most severe impact on the average relative value increase of a log rotation optimization, followed by errors in the dead knot border. The smallest effect was observed in the case of errors in rotational position of the knots.

Computed tomography scanning can also be used in a sawmill for log sorting in relation to different end-uses of the sawn timber. A simulation software for cross-cutting optimization based on computed tomography data was developed and it was shown that there was a reasonable correlation between these results and the results of an industrial system. Since the developed software can be combined with log breakdown simulations based on computed tomography data, it is evident that computed tomography can be used to identify logs that would result in a poor volume yield in the subsequent cross-cut optimization.

Destructive bending strength tests were performed on 113 pieces of Norway spruce sawn timber. Multivariate models for predicting the bending strength of the sawn timber were created using computed tomography data of the sawlogs from which the sawn timber originated. The results showed that computed tomography scanning of logs produced prediction models of bending strength with a higher accuracy than discrete X-ray scanning. The main advantage was the detailed knot information that could be used in the prediction models.

A method to measure saw mismatch automatically in a sawmill based on laser triangulation was developed and the measurements were well correlated with manual measurements of saw mismatch. When laser triangulation was used to measure saw mismatch in a sawmill, a distinguishable trend of increasing magnitude and frequency of saw mismatch was observed.

Finally, ways in which the sawn timber in a sawmill could be graded and sorted more efficiently was investigated. It was found that by using a grading method based on multivariate techniques it is possible to increase the proportion of higher sawn timber grades by up to 10 percentage points, which may increase sawmill profitability.
Preface

The work of this thesis has been carried out at the Division of Wood Science and Technology, Luleå University of Technology, Skellefteå, under the supervision of Professor Dick Sandberg, Professor Anders Grönlund and Professor Johan Oja. Thank you for your guidance and support during this time. Your encouragement made my work enjoyable and challenging.

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Last, I wish to thank my family for all your support.

Skellefteå, November 2014

Anders Berglund
List of publications

Paper I

Paper II

Paper III

Paper IV

Paper V

Paper VI

Paper VII

Paper VIII
Contributions to the papers

Paper I
Berglund had the main responsibility for simulations, data analysis and article writing. Guidance and feedback were provided by the co-authors.

Paper II
Berglund and Johansson shared the responsibility for simulations, data analysis and article writing. Skog contributed with simulations, data analysis, guidance and feedback.

Paper III
Breinig performed simulations and data analysis and wrote the article. Berglund implemented errors in knot detection for the simulation and contributed with data analysis and article writing. The other co-authors contributed with guidance and feedback.

Paper IV
Fredriksson had the main responsibility for simulations, data analysis and article writing. Berglund contributed with data analysis and writing the article. Broman was responsible for data collection and provided guidance and feedback.

Paper V
Johansson and Berglund shared the responsibility for data collection, statistical modelling and article writing. Skog contributed with statistical modelling, guidance and feedback.

Paper VI
Berglund had the main responsibility for data collection, data analysis and article writing. Dahlquist helped with software and hardware development. Guidance and feedback were provided by both co-authors.

Paper VII
Berglund had the main responsibility for data collection, data analysis and article writing. Grönlund contributed with guidance and feedback.

Paper VIII
Berglund had the main responsibility for data collection, data analysis and article writing. Guidance and feedback were provided by the co-authors.
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This doctoral thesis comprises a summary together with articles published in scientific journals and conference proceedings that were authored during the years 2011 to 2014. The work performed during this time in various areas of the sawmill process is described in the summary, which is traditional in its outline and describes the background, materials and methods and results together with a discussion and finally the conclusions drawn from this work.

This introductory chapter presents an overview of the field of work as well as the background to this thesis. It begins with a description of sawmill production in Sweden and continues with a description of the sawmill process, from standing tree to sawn timber. This is followed by a section describing the properties of logs entering the sawmill and why the sawing of these can be complicated. The sawing of logs results in sawn timber, and the next section is therefore devoted to wood features on sawn timber and how they affect the properties of sawn timber. The next section presents examples of how the information about the properties of logs and sawn timber can be used to control and optimize the sawmill process. This is followed by two sections describing various methods to characterize, grade and optimize the breakdown of logs as well as methods to characterize and grade sawn timber.

Finally in this chapter, the objectives and limitations of this thesis are presented.
1.1 Sawmill production in Sweden

The sawmill industry is of great importance for Swedish economy. The export of sawn timber has increased from 6 to 12 million m$^3$ during 1980-2011 reaching a value of SEK 22 billion (Swedish Forest Agency, 2013). The volume of sawn timber produced has increased from 11 to 16 million m$^3$ during the same period. This increase has been possible by e.g., the introduction of a high degree of automation in Swedish sawmills, leading to a modern industry with high productivity. During the last 30 years, the number of sawmills in Sweden producing more than 10,000 m$^3$ sawn timber per year has decreased from slightly below 300 to 135. The production of sawn timber in Sweden has been concentrated to larger sawmills, specialized in a certain species and group of products. The ten largest companies in Sweden are producing 60% of the annual production of sawn timber in Sweden and the 20 largest companies are producing 80% of the annual production.

Sweden’s land area is 40.8 million hectares of which 23.1 million hectares (57%) is productive forest land (Swedish Forest Agency, 2013). The total standing volume is about 3 billion m$^3$, of which 39% is Scots pine (*Pinus sylvestris* L.), 42% Norway spruce (*Picea abies* (L.) Karst.) and 12% birch (*Betula spp.*) (Figure 1.1). The total harvest in 2011 was 88.4 million m$^3$ standing volume equivalent to 71.9 million m$^3$ solid volume under bark. Of the total net volume, 47% was used for sawn timber, 44% for pulpwood and 9% for fuel or other applications (Figure 1.2).

![Figure 1.1: Distribution of wood species in Swedish forests (Swedish Forest Agency, 2013; Swedish Wood, 2013).](image-url)
1.2. Main steps in the sawmill process

The sawmill process (Figure 1.3) is the process of turning logs into sawn timber and this is complex despite years of technical development. One reason is the large variability of the raw material. The properties of logs are difficult to predict and this makes the process difficult to control. Secondly, the final product is the result of several process steps, possibly performed by different actors and involving many decisions. This section presents a brief review of the main steps in the sawmill process and is to a large extent based on the material written by Grönlund (1992). The two commercially most important species in Sweden are Scots pine and Norway spruce, and these two species are the main focus throughout this thesis.

Figure 1.2: Use of timber in Sweden year 2011 (Swedish Forest Agency, 2013; Swedish Wood, 2013).
1.2.1 Log sorting

Today’s forestry harvesters cut, de-limb and perform bucking of trees in the forest, so that they then be transported to a sawmill by a truck. The sawlogs are typically 3 to 6 m in length with a top diameter of 120 to 400 mm. Logs that arrive at a sawmill pass first through the log sorting station, which has two purposes. The first is to set a price for the log that the sawmill should pay the forest owner, which depends on log volume,
grade and species. The second is to sort the log into one of a number of sawing classes that make the breakdown of the log more efficient, i.e. to get as much volume of sawn timber out of each log as possible.

Today the price of logs is determined by automatic measurements of log volume combined with manual visual grading. Each individual log is graded with respect to the rules specified by the Swedish Timber Measurement Council (2007) with the mission of making objective and unbiased measurements of sawlogs. A log’s grade is based on properties visible on the surface area.

The sawing class is governed by the species and top diameter of the log. For some sawmills, the sawing class is also dependent on additional properties such as taper and crook and if known also internal features such as knottiness and heartwood content. The log is measured automatically with either different optical equipment or X-ray equipment. The different sawing classes group logs with similar top diameters. The top diameter ranges of the sawing classes are typically in intervals of 10 to 20 mm and they are set in order to have an efficient breakdown, and with respect to market demand, sawmill facilities and logistics.

1.2.2 Log sawing

The logs are processed sawing class by sawing class, batches of logs being continuously fed from a specific sawing class to the saw intake. This makes it possible to use a sawing pattern adapted for each specific sawing class. It also minimizes the repositioning of the saw blades as far as possible. The handling of the sawn timber is also easier, since the number of different dimensions that are produced simultaneously is reduced.

In most sawmills, the logs are turned on their way to the saw intake so that the top end of the log comes first. Before the intake, the logs are debarked and the butt end is reduced. The logs are then automatically measured in order to determine the orientation of the log and to position the log in the best possible way for sawing. The log position can be adjusted in three different ways, by parallel, skew and rotational offsets as shown in Figure 1.4.

The best log position has traditionally been the position that maximizes the volume yield, which is one of the key parameters for a sawmill. It is a measure of how much of the log volume that is turned into high val-
ued sawn products compared to the less valued chips and sawdust. Volume yield can be defined in different ways, but in this thesis it is defined as the volume of dry, trimmed and edged sawn timber divided by the log volume under bark. The volume yield varies depending on sawing class and sawing pattern, but it is typically in the range of 40 to 60%.

![Figure 1.4: The different ways to position a log in front of the first saw, (a) rotation, (b) skew and (c) parallel displacement.](image)

There are many different techniques for processing a log. The most common sawing technique applied in Sweden is cant sawing, which is illustrated in Figure 1.5a. Today’s sawing machines are also capable of curve sawing in order to obtain a higher volume yield. This means that the saw blades follow the curvature of the log as illustrated in Figure 1.5b. Curve sawing is only carried out in the second saw. In this thesis, unless otherwise specified, the applied sawing technique is cant sawing combined with curve sawing.

When a crooked log is to be sawn, the best rotational position with respect to volume yield is in general the horns down position, and for this reason the horns down position is often used in Sweden when reference is made to the rotational positioning of a log. The horns down position is defined as the position in front of the first saw where the largest curvature of the log is directed upwards as illustrated in Figure 1.5c. The advantage
is that the crook does not effect the sawing in the first saw, but is instead handled by the curve sawing in the second saw.

![Diagram of sawmill process]

Figure 1.5: (a) Cant sawing is the most common sawing technique in Sweden. The first sawing machine saws 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. (b) Curve sawing, seen from a view above the cant. The saw blades in the second saw follow the curvature of the cant. (c) Horns down position, the log is positioned in front of the first saw so that the largest curvature is directed upwards (Fredriksson, 2014).

The sawing pattern, i.e. position and number of saw blades (dashed lines in Figure 1.5a), determines the width and thickness of the sawn timber as well as the number of pieces of sawn timber produced. The larger pieces of sawn timber originating from the centre of the log are called centre boards while the smaller pieces of sawn timber closer to the log periphery are called side boards. After sawing, side boards are edged where the intent is to find the width and grade that maximizes the value
of each side board. It is important to choose a sawing pattern for each sawing class that maximizes the volume yield.

1.2.3 Green sorting

After sawing, the sawn timber is taken to the green sorting by a transverse conveyor. Here the sawn timber moves in a direction perpendicular to its lengthwise extent, as shown in Figure 1.6. This enables scanning and sorting of the sawn timber according to dimensions and sometimes also according to grade. The advantage of sorting the sawn timber according to dimensions and grade is that it is possible to adapt the upcoming drying according to the properties of the sorted groups.

![Figure 1.6: Transverse transport of sawn timber in the green sorting line.](image)

1.2.4 Drying

Sawn timber is usually dried in either a batch kiln or a progressive kiln. The main principles are however similar. The heat and moisture transporting media is air which flows around the sawn timber under the action of large fans while the steam from the sawn timber is ventilated. Both batch kilns and progressive kilns in general work in the low temperature region with temperatures of 40 to 80 °C. The difference is mainly that in a batch kiln, the sawn timber is dried by changing the climate for the whole batch with time. In a progressive kiln, the sawn timber enters the dryer at one end and is transported to the other end throughout the drying process. Since the sawn timber contains more moisture at the beginning of the drying process than towards the end, the climate will be more humid
1.2. Main steps in the sawmill process

early in the drying process than at the end. In Swedish sawmills, about as large volume is dried in batch kilns as in progressive kilns.

1.2.5 Trimming

The intention when trimming sawn timber is the same as that of edging side boards. The aim is to find the length and grade that maximizes the value of each piece of sawn timber and to cut the length accordingly. The sawn timber passes the trimming plant after drying since the sawn timber shrinks during the drying process and may become distorted or cracked. This can then be taken into account when trimming the sawn timber.

After trimming, the sawn timber is sorted according to dimensions and grade, either manually or automatically according to a standard that specifies the requirements of each grade. The dry and trimmed sawn timber is finally packaged and sold to a customer or used for further processing by the sawmill itself or by another actor.

1.2.6 Cross-cutting and finger-jointing

The dried and trimmed sawn timber can be sold to a customer who uses it for further processing, or further processing can be carried out by the sawmill itself. Cross-cutting of sawn timber combined with finger-jointing is one example of further processing which is important for the content of this thesis. Cross-cutting is normally done for two reasons, to remove unwanted features of a piece of sawn timber and to adapt the sawn timber to a specified length. Cross-cutting can be combined with finger-jointing, where the ends of the wooden pieces that were cut are milled to finger-joints (Figure 1.7). The finger-jointed components are glued together into desired end-products. The aim of a finger-jointing process is to maximize product volume yield and minimize waste, while maintaining an acceptable end-product quality.

Wood scanners and software for calculating cross-cutting positions on sawn timber have now been used in sawmills for some years. These scanners are used to detect biological and geometrical deviations in the sawn timber, and this makes it possible to remove undesired defects for finger-jointed products using cross-cut saws. The positions of the cuts are governed by an optimization software that maximizes the value of the end-
products produced from each piece of sawn timber. This optimization process means that price and grading rule settings of the different end-products need to be considered, as well as the positions of detected defects. Examples of biological features that can be undesirable for an end-product are knots, wane, cracks, bark, pitch pockets and top ruptures.

![Finger-joint](image)

*Figure 1.7: Illustration of a finger-joint (Swedish Wood, 2013).*

### 1.3 Properties of sawlogs

The external and internal features of sawlogs entering a sawmill are governed by e.g. growth location, soil conditions, genes and climate of the standing tree. It is the diversity of the logs that makes the sawing of logs into sawn timber complex, since the process needs to be adapted to the properties of each individual log. In this section properties of logs that are important from a sawmill perspective and relevant to this thesis are presented.

#### 1.3.1 Crook and taper

Crook and taper are two properties of the log that are commonly used to describe log shape and these properties affect the sawing of logs into sawn timber to a great extent.

A crooked log is more difficult to process since, if the saw blade is to follow a straight line, a crooked log results in a lower volume yield. If instead a crooked log is subjected to curve sawing, the saw blades are forced to follow a specific curve radius in order to increase the volume
1.3. Properties of sawlogs

yield. This means that large forces affect the stability of the saw blade and increase the risk of deviances in the dimensions of the sawn timber.

A log with large taper narrows down quickly from the butt end towards the top end. It is difficult to find a suitable sawing pattern for such a log, since there is a greater volume of wood in the butt end than in the top end. There is a trade off between using the wood in the butt end against the risk of having wane on the sawn timber at the top end.

1.3.2 Density, heartwood and sapwood

The density of wood is dependent on the density of the wood fibres and on the moisture (water) content. The difference between a green piece of wood and a dry piece of wood can be felt when handling the wood. The outermost wood in Scots pine and Norway spruce is called sapwood while the innermost is called heartwood. The sapwood conducts water from the soil to the branches and leaves, while the heartwood cells are closed to free water transport and chemically transformed to be more resistant to decay (Forest Products Laboratory, 1999). In a cross-section of a Scots pine log, the border between heartwood and sapwood can be observed with the naked eye, since the heartwood is darker in colour than the sapwood (Figure 1.8), especially in wood that has been exposed to sunlight. It is much more difficult to see the border between heartwood and sapwood in a Norway spruce log, since the heartwood has the same colour as the sapwood.

![Figure 1.8: End of a Scots pine log showing difference in colour between the inner heartwood and the outer sapwood.](image)
1.3.3 Knots

Tree branches are not only present on the outside of the stem. In fact they start to grow from the centre of the tree, from the pith. Knots are the parts of the branches that have been incorporated by the stem. For Scots pine and Norway spruce, a tree that is no longer in need of its branch stops providing it with water and nutrients, and this causes the death of the branch. A knot can therefore have a sound and dead part, depending on whether or not the branch was living or dead when it was incorporated by the stem (Figure 1.9). Since the dead part of a knot is partially or completely dried out, it has a lower density than the sound part of the knot. Branches of Scots pine and Norway spruce generally fall of from the lower parts of the tree first and this process then continues upwards. For this reason, the top log contains mostly knots that are entirely sound whereas the middle log and butt log also contain knots that are partially dead (Figure 1.10). The outer parts of the butt log can be free of knots as all knots have been incorporated by the stem.

![Radial profile of a knot illustrating the sound and dead part of a knot.](image)

*Figure 1.9: Radial profile of a knot illustrating the sound and dead part of a knot.*
1.4. Properties of sawn timber

The properties of the sawlogs also affect the properties of the sawn timber. This sections contains a description of important properties of sawn timber from a sawmill perspective.

1.4.1 Knots

As knots are present within the tree, they are also visible on the sawn timber. The influence of knots on the appearance and strength of sawn timber depends on their size, location, shape and whether they are sound or dead (Figure 1.11). The shape of the knot depends on the position of the saw blade in relation to the knot orientation in the log. If a knot is sawn at
a right angle to its extension the result is a round knot. An elliptical knot is the result if the knot is sawn diagonally to the branch extension, while a “spike” knot is the result if a knot is sawn in the lengthwise direction of the branch. The knots are in general dark in colour compared with the surrounding wood. Knots reduce the strength of sawn timber since the fibres around the knot are distorted (Figure 1.12). The discontinuity of the wood fibres leads to stress concentrations as well as checks that often occur around the knots when the sawn timber is dried.

![Figure 1.11: An example of (a) a sound knot and (b) a dead knot, on a piece of sawn timber.](image)

![Figure 1.12: Illustration of fibre distortion in the vicinity of a knot (Swedish Wood, 2013).](image)
1.4.2 Wane

When a log is sawn into sawn timber, the applied sawing pattern (position of the saw blades) may temporarily lie partially outside the cross-section of the log. This causes wane on the sawn timber as shown in Figure 1.13, meaning that the outer surface of the log is present on the edges of the sawn timber. There are many reasons for why this can occur. One is that the sawing pattern used is too large for the log being processed, which most often occurs close to the top end of the log where the log diameter is the smallest. Another is that the log has a large crook which is difficult for the saw blades to follow when sawing. Positioning errors in the sawing machine can also lead to wane on the sawn timber produced.

Figure 1.13: Wane is the presence of bark or the absence of wood on the corners of a piece of sawn timber.

1.4.3 Nominal size and green target size

When logs are cant sawn, the sawn timber produced has a rectangular cross-section. Important concepts are then the nominal size and green target size. Nominal size is the dried size of the sawn timber used when setting the volume of sawn timber for which the customer is paying, whereas the green target size is the larger size aimed at in the sawing. The green target size compensates for deviation in sawing and of shrinkage and distortion during drying to ensure that the final size of the sawn timber is not less than the nominal size. The green target size is therefore chosen carefully since it is not good for the delivered sawn timber to exceed the nominal size too much. The sawmill will then deliver sawn timber volume that is not being paid for.
1.4.4 Saw mismatch

In Sweden, circular sawing machines with double arbors are commonly used today, mainly for their production capacity since they are capable of sawing large logs at high feed speeds. Since the sawing machine has two arbors the log is sawn from two directions, and the saw blades have a certain overlap as illustrated in Figure 1.14.

![Circular sawblades in a double arbor sawing machine with a certain overlap](Cristóvão, 2013)

In a double arbor sawing machine, it is important that the saw blades are aligned with each other in the axial direction. Tool wear or large lateral forces exerted on the saw blades can mean that the saw blades become misaligned. Misaligned saw blades will result in sawn timber having a surface profile with saw mismatch, as illustrated in Figure 1.15. Saw mismatch is not desired by the sawmill customer since it may result in a larger planer allowance and it has a negative effect on the appearance of the sawn timber. Typically the saw mismatch varies in the range of 0 to 1 mm, but single pieces of sawn timber can have saw mismatch that is greater than 1 mm.
1.4. Properties of sawn timber

1.4.5 Warp

Sawn timber can show warp after sawing as well as after drying, because of several different wood features. Warp or distortion on sawn timber is in general divided into four types, cup, bow, spring, and twist, as shown in Figure 1.16.

Figure 1.15: (a) Cross-section of sawn timber having saw mismatch and (b) an illustration showing that the saw mismatch spreads along the lengthwise direction of the sawn timber.

Figure 1.16: (a) Cup, (b) bow, (c) spring, and (d) twist are the four different shape distortions that sawn timber can exhibit. Cup is measured as the largest deviation within the width of the sawn timber. Bow, spring and twist are measured as the largest deviation from a straight line 2 m in length.
Cup is caused by a combination of the annual ring orientation in the cross-section of the sawn timber and differences in radial and tangential shrinkage when the sawn timber is dried (Sandberg, 1997). Compression wood causes bow or spring depending on the location of the compression wood in the sawn timber (Warensjö and Rune, 2004). Bow and spring are more common in sawn timber from a log with large crook, since the amount of compression wood is generally higher in these logs (Gjerdrum et al., 2001). Spiral grain results in twisted sawn timber (Forsberg and Warensjö, 2001).

1.5 Methods to characterize, grade and optimize breakdown of sawlogs

There are destructive and non-destructive methods for characterizing the properties of sawlogs. Destructive methods consist of making knots and other defects visible by cutting the logs into cross-sections, veneers or flitches. In this way, outer shape, knots and other wood features can be measured and described. The literature contains several such studies e.g. in Finland (Usenius and Song, 1996), New Zealand (Todoroki, 1996) and U.S.A (Harless et al., 1991; Oceña, 1992). The drawback of these methods is that they are very time-consuming when the log needs to be cut into thin flitches or cross-sections. Nor is it possible to build a model of the log and then produce sawn timber for which different properties can be measured, e.g. appearance or strength.

From a sawmill perspective it is necessary to measure log properties and predict the properties of the sawn timber before sawing the log, non destructive methods are therefore used in sawmills to measure external and internal properties of sawlogs.

In Swedish sawmills, sawlogs are measured and graded for production optimization and also to determine the payment between forest owner and sawmill. For production optimization, the logs are sorted primarily according to species and top diameter and sometimes also with respect to log quality. The purpose is to maximize the volume of sawn timber, which has been the best way of maximizing the value of the sawn timber.

Sorting of sawlogs with respect to log quality requires a measurement system that can predict the quality of the sawn timber. Such a prediction
can be made by inspecting the log end (see Section 1.5.1) or by measuring the outer shape using a 3D-scanner (see Section 1.5.2). The prediction can be improved even more when information about the internal properties of the log can be obtained by using a discrete X-ray scanner (see Section 1.5.3). An industrial computed tomography (CT) scanner has recently entered the market, making it possible to obtain a full reconstruction of internal log properties (Giudiceandrea et al., 2011, 2012), and such a machine should make the quality sorting of logs even more accurate than discrete X-ray scanning.

Measurements of outer shape by a 3D-scanner makes it possible to optimize the sawing of the log with respect to volume yield. Since the position of internal features such as knots cannot be precisely determined, it is only possible to maximize the volume of the sawn timber produced. In order to improve the quality and therefore the value of the sawn products, full information about the the external and internal features of each sawlog needs to be obtained. This is now possible through the recently developed industrial CT scanner.

1.5.1 Log end inspection

One way to estimate the quality of a log is by inspecting the log ends and the log surface. The rules defined by the Swedish Timber Measurement Council (2007) are based on a visual inspection of the log ends and log surface with regard to different wood features. Several methods have been evaluated to aid the log grader and perform some inspections automatically, and some of them have been tested under industrial conditions, e.g. Enarvi (2006) and Norell and Borgefors (2008) using digital cameras to sort out defect-free logs and to detect the pith. Inspection of the log ends can also be carried out in order to sort the log for production optimization. Gjerdrum and Holbo (2004) estimated the heartwood diameter from infrared images taken on one of the log ends. The difficulty in automating the inspection of log ends is that they are often covered with dirt or snow making them difficult to analyse with an image processing algorithm under industrial conditions.
1.5.2 Optical three-dimensional scanning

Optical three-dimensional scanning is used to obtain a model of the log outer shape. The principle behind these 3D-scanners is laser triangulation where the emitting laser, the camera and the laser beam projected on an object form a right-angled triangle, as shown in Figure 1.17a. The position of the reflected laser beam within the field of view of the camera makes it possible to determine the incidence angle of the reflected laser beam. The distance from the object to the laser as well as to the camera can then be calculated by use of geometry, which means that it is possible to map the shape of the object by sweeping a laser beam across it.

To be able to scan the entire circumference of a log, three or four laser triangulation units need to be positioned around the log to make measurements on all sides (Figure 1.17b). The log is transported lengthwise through the scanner and by combining the data from all the triangulation units, the outer shape of the log can be obtained.

![Figure 1.17](image)

*Figure 1.17: (a) Principle of laser triangulation. The distance between laser and object $(d_1, d_2)$ can be calculated from the position of the reflected laser beam within the field of view of the camera $(x_1, x_2)$. (b) Illustration of 3D log scanner with three laser triangulation units positioned around the log to scan all sides. A laser line is projected around the log and the outer shape can be determined one cross-section at a time during lengthwise transport (Skog, 2013).*
If the outer shape of the log is known, parameters such as log taper and bumpiness (knots seen on the log outer surface) can be calculated and used to predict log quality (Grace, 1994; Jäppinen and Nylander, 1997), but still the quality of the log cannot be predicted perfectly since information about the interior of the log is not available.

### 1.5.3 X-ray scanning

Several different techniques have been used to obtain information about the internal properties of wood e.g. gamma rays (Hagman, 1993), X-rays (Lindgren, 1991), nuclear magnetic resonance (NMR) (Chang et al., 1989; Soest, 1996), microwaves (Kaestner and Bååth, 2000), ultrasound (Han and Birkeland, 1992; Sandoz, 1996), vibration (Skatter and Dyrseth, 1997) and longitudinal stress waves (Ross et al., 1997). A summary of these different methods can be found in Grundberg (1999) and Skatter (1998b).

For scanning sawlogs, X-rays and gamma rays have proven to be suitable methods since they are able to penetrate a sawlog and produce an image of its interior (Grundberg et al., 1990; Grundberg, 1999). X-rays have the advantage over gamma rays that they are created by a power source which can be switched on and off, and the intensity of the radiation does not decline with time as it does for gamma radiation as a consequence of radioactive decay. Due to these practical as well as safety aspects, X-ray scanning has proven to be the preferable scanning method.

The principle of X-ray scanning is that a beam of high energy photons generated by an X-ray tube is sent through the object of interest. The transmitted radiation is collected by a detector resulting in an X-ray image, also called radiograph. As a result of interactions between the photons and the material, the intensity of the radiation declines according to the exponential attenuation law. For a beam of monoenergetic photons of energy $I_0$, passing through a homogeneous material, the transmitted intensity, $I$, is

$$I = I_0 \cdot e^{-\mu t}$$

where $t$ is the thickness of the material, and $\mu$ is the linear X-ray attenuation coefficient which in turn depends on the material and the photon energy and is given by

$$\mu(E) = \rho \cdot \mu_m(E),$$

where $\rho$ is the mass density of the material, and $\mu_m(E)$ is the mass attenuation coefficient of the material for a particular photon energy $E$. The mass attenuation coefficient describes how much the material is absorbing the radiation of a particular energy.
where $\rho$ is the material density, $\mu_m$ is the mass attenuation coefficient and $E$ is the photon energy level.

Since wood is an inhomogeneous material, $\mu$ varies throughout the material. However, by calculating $\mu_m$ according to the procedure described by Tsai and Cho (1976) it was shown by Lindgren (1991) that $\mu_m$ is approximately constant for dry wood and that $\mu_m$ of green wood varies only slightly with differences in moisture content. This means that most of the variation in $\mu$ is due to density variations in the wood. If the photon energy range of the X-ray source is known and the transmitted X-ray intensity is measured using a detector, it is possible to estimate the density of the material by integrating Equation 1.1 over the energy spectrum with $I_0$ and $\mu$ as functions of the photon energy.

**Discrete industrial X-ray scanning**

Discrete industrial X-ray scanning means that sawlogs are scanned in a sawmill from a fixed number of directions, typically one to four. By moving the log on a conveyor and feeding it through the scanner, the X-ray attenuation can be measured cross-section by cross-section. The data obtained lead to an estimate of the density throughout the log.

This process is illustrated in Figure 1.18, which shows the most commonly used two-directional X-ray scanner, and Figure 1.19 shows two examples of the resulting X-ray images. Dark areas represent areas of low attenuation (low density), while bright areas represent areas of high attenuation (high density). The X-ray images clearly show the heartwood border, the position of knot whorls and the knot volume in the log. Variables extracted from the X-ray data have been successfully used to predict numerous sawlog properties, e.g. species (Grundberg and Grönlund, 1996), knot structure (Pietikäinen, 1996; Grundberg and Grönlund, 1998), heartwood content (Skatter, 1998a; Oja et al., 2001), stiffness (Oja et al., 2001) and strength (Oja et al., 2005).

The lack of resolution in the rotational direction however makes it impossible to detect the exact position of knots, heartwood/sapwood border, rot, pitch pockets and checks. It has been suggested that at least six measurement directions are required in order to detect knots that are larger than 1 cm in diameter (Sikanen, 1989).
1.5. Methods to characterize, grade and optimize breakdown of sawlogs

Figure 1.18: An illustration of a two-directional discrete X-ray scanner using two X-ray sources and producing two mutually perpendicular radiographs (Grundberg and Grönlund, 1997). As the log is fed through the scanner the transmitted X-ray intensity is measured one cross-section at a time using two detector arrays.

Figure 1.19: Two mutually perpendicular X-ray radiographs from an industrial X-ray log scanner. Dark areas represent areas of low attenuation (low density), while bright areas represent areas of high attenuation (high density). The metal carriers are filtered out and therefore appear as white areas in the images (Skog, 2013).
Industrial computed tomography scanning

Computed tomography (CT) scanning is a type of X-ray scanning where the X-rays are sent through the object from several directions and was first introduced for medical purposes. From 1972 until the mid 1980’s, the X-ray power was transferred to the X-ray tube using high voltage cables, so the rotating gantry moved 360° in one direction and then rotated back 360° back in the other direction to scan a second slice (Cierniak, 2011). Between each slice, the gantry came to a complete stop while the scanned object moved forward by an increment equal to the slice thickness. Using the multiple scans from different directions, a three-dimensional image showing the density of each slice could be reconstructed.

In the mid 1980’s, it became possible for electric power to be transferred from a stationary power source to the rotating gantry without high voltage cables. This enabled CT scanners to rotate continuously without having to slow down to start and stop. This type of a spiral or helical CT scanner has been continually developed. The first design was single-slice computed tomography (SSCT), where a fan-beam of radiation was emitted and passed through the object before it reached an array of X-ray detectors arranged in a row. The second design, multi-slice computed tomography (MSCT), instead contains between 8 and 34 rows of detectors making it possible to acquire projections simultaneously for the subsequent reconstruction of up to four slices. This resulted in an eightfold increase in the rate of acquisition of the reconstructed images. MSCT assumed that the fan beams were parallel which made it difficult to increase the number of rows in the detector array. With the development of cone-beam computed tomography (CBCT) where the beams are not parallel (Figure 1.20), there was a substantial increase in the width of the detector array, and new reconstruction algorithms that were specially designed for systems with a conical beam of radiation were developed.
1.5. Methods to characterize, grade and optimize breakdown of sawlogs

Figure 1.20: CT scanning of sawlogs using a cone beam X-ray source and a matrix detector (Johansson, 2013).

CT scanners were traditionally developed and used mainly within medicine, but it has also been possible to use medical CT scanners for scanning logs. There are numerous research studies using CT to study the properties of logs, e.g. Lindgren et al. (1992); Davis and Wells (1992). The CT images obtained show many features of a log clearly since these features correspond to a change in density level (Figure 1.21). Knots and green sapwood have a higher density than green heartwood, which makes it easier to separate knots and sapwood from heartwood. It is more difficult to separate knots from green sapwood, especially if the knots are sound (Johansson et al., 2013).

CT scanning of logs has also enabled the development of computer software to study how different log properties and production parameters affect the sawing process in a sawmill e.g. Björklund and Julin (1998); Todoroki and Rönnqvist (1999); Chiorescu and Grönlund (2000); Pinto et al. (2005). Computer software for the virtual sawing of logs based on CT data is useful since a log breakdown can be simulated in a large number of ways. This makes it possible to evaluate how different production parameters e.g. log properties, log sorting, sawing pattern, log positioning, prices for sawn timber and machine settings affect the sawing process. It is also much more time-consuming and expensive to evaluate different production parameters and settings by sawing real logs in a sawmill. A simulation model is an attempt to model, as accurately as possible, a real
system. However the most important factor when simulating log breakdown is perhaps not the absolute results of the simulation, but rather to be able to compare how different production parameters affect the results in a relative sense.

![Cross-section images of: (a) Scots pine log, (b) a whorl of sound knots in a Scots pine log and (c) a Norway spruce log. Dark grey pixels show low density heartwood while bright grey pixels show high density sapwood or knots. In the spruce log, intermediate wood results in a less distinct transition between heartwood and sapwood (Skog, 2013).](image)

Despite the speed of the CBCT scanners with 2D matrix detectors, no reconstruction algorithm was fast enough for CT scanning of logs during sawmill production at the required feed speed. Rinnhofer et al. (2003) investigated the use of a CT scanner developed for airport security in a sawmill. Using the airport CT scanner, the breakdown of sawlogs was optimized and the value of the sawn products could then be increased. Nevertheless the scanning speed was only 1.5 m/min, which is too slow for practical use in a sawmill where the feed speeds are typically 70 to 130 m/min, i.e. 50 to 90 times larger.

Since it was not possible at that time to obtain the required feed speeds by using CT scanning, Seger and Danielsson (2003) simulated the use of discrete X-ray scanning with two fixed source-detector systems placed at 90° relative to each other. Each system consisted of a cone beam X-ray source and a 2D matrix detector, which had not been evaluated for discrete X-ray scanning before. The logs moved through this arrangement at 120 to 180 m/min lengthwise on a conveyor belt, while cone-beam projec-
tions were acquired by each of the source-detector systems. Their results indicated that the knots could be reconstructed with sufficient accuracy to allow optimization. Heartwood on the other hand could barely be distinguished from sapwood. This type of solution is nevertheless interesting since it is more cost-efficient in a sawmill than using a CT scanner.

In 2004, however, a fast spiral cone beam reconstruction algorithm developed by Katsevich (2004) enabled the development of the first sawmill high-speed CT scanner which entered the market in 2012 (Giudiceandrea et al., 2011, 2012). This industrial CT scanner supports conveying speeds up to 150 m/min and provides full three-dimensional density information about each log during sawmill production.

1.6 Methods to characterize and grade sawn timber

The sawn timber in a sawmill shows almost the same diversity as the sawlogs. Since the sawn timber originates from different logs and from different positions within the log, the variation in appearance and strength properties is also large. For the sawmill to be able to describe what they can sell and for the customer to gain a perception of what is being purchased, it is necessary to agree on some quality restrictions on the sawn timber as a guideline.

These quality restrictions are defined by visual grading rules separating the sawn timber into different grades, with respect to either appearance or bending strength. Both for visual appearance grading and visual strength grading, knots and wane on the sawn timber are the most important features and the majority of visual grading rules are related to these features. Other features are also restricted e.g. cracks, pitch pockets, bark pockets, scars, slope of grain, top rupture and compression wood.

The first visual appearance grading rules valid throughout Sweden were formulated in “Guiding principles for grading of Swedish sawn timber” in 1960, and since then several new editions have been printed (Swedish Sawmill Managers Association, 1982). These visual grading rules were based on numerous printed visual grading rules in northern Sweden from 1880 and thereafter and were formulated to unite the grading of sawn timber in Sweden. The sawn timber is divided into seven different grades.
denoted I to VII, where grade I is considered to be the best grade and grade VII to be waste. It is quite common to group together grades I to IV which are then denoted as U/S (unsorted).

The difficulty with the visual grading rules in “Guiding principles for grading of Swedish sawn timber” was that they were subjective. The idea was that the grading rules would describe the quality of the delivered sawn timber as a whole and not to evaluate single defects on the sawn timber. Consequently, the problem was that the sawmill could always claim that the delivered timber fulfilled the requirements as a whole, while the buyer could instead claim the opposite.

This problem was the main reason why the visual appearance grading rules were reformulated in Sweden into the “Nordic timber grading rules” (Swedish Sawmill Managers Association, 1994). The intention now was to have defect restrictions that were absolute and easy to interpret, since all single defects have to be within specified limits for each grade. In the Nordic timber grading rules, sawn timber is divided into four different grades A, B, C and D where A is the best grade and D is waste. Grade A can also be further subdivided into grades A1 to A4. In practice each sawmill typically has its own sets of visual appearance grading rules adapted to different raw material, dimensions of sawn timber, markets and customers.

There are also visual strength grading rules and these rules are rather different than visual appearance grading rules. Visual strength grading rules valid in Sweden are specified in the Nordic standard INSTA142 (Swedish Standards Institute, 2010) and as for visual appearance grading rules, knots and wane are the most important features. The visual strength grading rules separate the sawn timber into four strength grades T0, T1, T2, and T3 where T3 is the highest strength class and T0 is the lowest. In Sweden, it is mainly sawn timber of Norway spruce that is strength graded since sawn timber of Scots pine is preferably used for carpentry and furniture.

Strength grading of sawn timber can also be performed by a machine and in such case machine strength grading rules are applied. The sawn timber is separated into strength classes based on requirements for characteristic bending strength, average modulus of elasticity (MOE) in bending and characteristic density. These requirements are specified in the European standard EN338 (European Committee for Standardization (CEN),
2009) for a moisture content (MC) of 12% for Norway spruce. The grades are denoted with capital letter $C$ followed by two digits that indicate the characteristic bending strength in MPa. This characteristic value corresponds to the 5th percentile bending strength of all pieces graded into the class. This means that 5% of the sawn timber in a given class is allowed to be weaker than the value indicated by the class designation. Visual strength grades T0, T1, T2 and T3 correspond to the machine strength grades C14, C18, C24 and C30.

1.6.1 Manual grading

Manual grading of sawn timber has been the traditional way of visually appearance grading and strength grading sawn timber in sawmills, but it is less widely used in larger Swedish sawmills nowadays. In a sawmill, a manual grader visually inspects the sawn timber and typically has between 2 and 3 seconds to make a decision regarding the grade. During this time, the grader needs to consider visual defects on all sides of the sawn timber. The sawn timber should also be trimmed and value optimized, meaning that the grader should know the price of all the grades in order to maximize the value by trimming and removing undesired defects from the sawn timber. It is not difficult to understand why this is a tiresome and monotonous task, when thousands of pieces of sawn timber are produced in a sawmill every hour. The manual grading should be objective but it is difficult for different manual graders to be completely consistent. Grundberg and Grönlund (1997) showed that only 57% of 934 pieces of sawn timber were given the same grade by two different manual graders performing appearance grading according to the Nordic timber grading rules.

1.6.2 Automatic grading

Visual appearance and strength grading

To improve both efficiency and repeatability, automatic visual grading systems have been used in Nordic sawmills for nearly three decades. These systems scan individual pieces of sawn timber from all sides and the images obtained are processed and analysed. Each piece of sawn timber is
then assigned a grade automatically, based on the detected surface defects and specified grade requirements. The systems are configurable and can grade sawn timber with respect to both appearance and strength. Nowadays automatic visual grading systems can be found in many parts of the process, for example in the green sorting and final grading. For appearance grading, the limiting number of grades that can be used is related to logistics and handling equipment rather than to the automatic grading systems themselves.

**Machine strength grading**

Machine strength grading means that machines are used to assign the sawn timber to a strength class by using various technologies to predict the bending strength of the sawn timber. The common factor is the ability of the machines to measure a number of properties of the sawn timber and to use these to predict the strength properties of the piece and assign the sawn timber to the appropriate strength class. Many strength-grading machines measure the MOE and use it to predict the bending strength or, as it is also called, the modulus of rupture (MOR). The MOE can be determined by measuring the natural frequency of the log caused by longitudinal vibration (Skatter and Dyrseth, 1997) or ultra-sound (Sandoz, 1989). The average MOE of the log is then correlated with the average MOE of the sawn timber from that log. Some machines make natural frequency measurements directly on the sawn timber (Giudiceandrea, 2005). X-ray technology can also be used to predict MOR by measurements on logs (Oja et al., 2005) or directly on the sawn timber (Giudiceandrea, 2005). In both cases, parameters related to density and knots are used to predict the MOR. An extensive description of machines, standards and techniques used for strength grading has been presented by Oscarsson (2014).
1.7 Problem statement

The possibility of scanning logs for internal features in the sawmill using industrial CT scanners enable decisions regarding sorting and breakdown of each log that have not been possible with present techniques. In the present work, some possible applications of utilizing an industrial CT scanner in a sawmill have been investigated.

One example is to optimize the position of the log when sawing with respect not only to the volume but also to the value of the sawn timber, which has not previously been possible. Since information about the external and internal features of each sawlog can be obtained the whole breakdown process can be simulated and optimized i.e. sawing, trimming and edging of side boards. If the log is positioned in such a way that it results in sawn timber with good appearance or high strength, the value of the sawn timber and the sawmill profitability can be increased. In Paper I, the potential gain in value by applying an optimized rotational position for value yield was investigated with respect to the appearance of sawn timber. The work continued in Paper II, where the potential gain in value when an optimized rotational position for producing high-strength sawn timber was applied.

When a breakdown optimization based on CT data is applied, the optimization process is affected by uncertainties. One uncertainty is the positioning error of the sawing machine, and the effect of a rotational error was therefore investigated in Paper I and Paper II. Another uncertainty is the effect of errors in the feature detection algorithms applied on the CT images. Since knots are one of the most important features of sawn timber for grading, the extent to which errors in knot detection affect the gain in value in a rotational optimization was investigated in Paper III.

An industrial CT scanner could also be used to sort logs for different end-uses, and in this work one such example was studied. It is quite common for sawmills in Sweden to either deliver sawn timber for subsequent cross-cutting in combination with finger-jointing or to do this themselves. The optimization of sawing volume yield and the optimization of cross-cutting volume yield are performed separately, and this leads to a sub-optimization of each process. The main reason is that hitherto it has not been possible to connect, online in a sawmill, the log breakdown simulations with the subsequent simulations of cross-cutting of sawn timber,
since the latter depends on the exact position of defects in the sawn timber. If the log breakdown based on CT data was available in the sawmill, it would be possible to simulate the whole chain from sawlog to the cross-cut and finger-jointed end-product online during sawmill production. A first step towards realizing such a method has been developed in Paper IV where a simulation based on CT data of the whole chain from sawlog to the cross-cut and finger-jointed end-product is validated against a real scenario. The advantage of such a simulation of the whole chain is that it shows how industrial CT could be used to identify suitable sawlogs for a given end-use.

Another possible use of an industrial CT scanner is to predict the bending strength of sawn timber with a greater accuracy than today’s visual and machine strength grading equipment. The problem with visual strength grading and machine strength grading equipment is that the prediction models used for MOR are rather weak. An extensive study was carried out by Hanhijärvi and Ranta-Maunus (2008) where they tested and combined different measurement techniques to predict MOR, and the results show that, with the techniques available for sawmills today it is difficult to predict the bending strength of sawn timber. For Norway spruce, Hanhijärvi and Ranta-Maunus (2008) obtained the largest coefficient of determination, $R^2 = 0.64$, when using a combination of natural frequency and X-ray measurements on the sawn timber. For Scots pine, the results obtained using the same methods were slightly better, $R^2 = 0.69$, but it should be kept in mind that these measurements were carried out in a laboratory and not in a sawmill. It is possible that industrial CT scanning of sawlogs can improve the prediction models for the bending strength of sawn timber, and this was investigated in Paper V.

A traditional way to increase sawmill profitability is to find ways of increasing the volume yield. One way of accomplishing this is by reducing the saw blade thickness, which would mean a lot for the profitability of many Swedish sawmills. For example, it was shown in a simulation study by Flodin and Grönlund (2011) that decreasing the saw blade thickness by 1 mm increased the volume yield by up to 3 percentage points.

Nevertheless, sawmills in Sweden are in general doubtful about using thinner saw blades to reduce the kerf width. They are afraid of a poorer sawing accuracy and precision, as well as more frequent saw-blade failures (Steele et al., 1992; Maness and Lin, 1995). The saw mismatch is not
nowadays measured continuously in Swedish sawmills. Large deviations in green target sizes are detected and necessary actions can be taken, but an increase in the presence and magnitude of saw mismatch will pass unnoticed. In Paper VI and Paper VII, a method of measuring and evaluating the presence of saw mismatch in a sawmill was developed.

Another field of interest in this work has been how the appearance grading of the sawn timber produced can be made more efficient with respect to customer-adaptation. This is interesting since customization of the appearance grading rules is becoming increasingly important in order to deliver the sawn timber that the customer desires (European confederation of woodworking industries, 2004). Sawmill profitability can be increased if the sawn timber is graded correctly and fulfils the demands of the customer. In Sweden today, automatic visual grading is more common than manual grading, but the configuration of automatic visual grading systems takes time and there are many parameters that can be changed for each grade, so that changes are rarely made (Lycken, 2006; Lycken and Oja, 2006).

A common belief in the sawmill industry is that a customer tends to tolerate a few defects that are slightly larger than those allowed on a piece of sawn timber, if the other sections on that piece of sawn timber are better than the average for that grade. The opposite is also commonly true, i.e. that a customer may find a piece of sawn timber unsatisfying because the general impression is not representative of the assigned grade, even though all the defects are within the allowed limits.

This shows the difficulty with grading rules like the Nordic timber grading rules, with strict requirements with regard to allowed defect size and defect frequency. The consequence of these strict rules is that pieces of sawn timber that a customer would accept may be downgraded to a lower grade merely because a few grading rules are exceeded. There are also pieces of sawn timber that a user does not accept, even though all the grading rules are fulfilled. This affects both sawmill profitability and customer satisfaction in a negative way. Paper VIII presents an automatic method to grade sawn timber that can more easily be adapted to customer preferences than the currently used automatic visual grading systems, and at the same time increase sawmill profitability.
1.8 Research question and objectives

The processing of sawlogs into sawn timber is complicated by the diversity of the raw material. The main question to be answered in this thesis is how the sawing of logs into sawn timber can be performed more efficiently with respect to choice of raw material, volume and value yield in the sawing and in the grading of the sawn timber produced.

More specifically, the objectives of this thesis were:

1) To investigate whether data obtained from a CT scanner can be used to optimize the breakdown of sawlogs with respect to the appearance of the sawn timber (Paper I), as well as the bending strength of the sawn timber (Paper II) to increase the value of the sawn timber.

2) To investigate the effect that errors in knot detection algorithms used on CT images has on log breakdown optimization using CT data (Paper III).

3) To develop and validate a simulation software for the cross-cutting of sawn timber and to investigate how the total volume yield in the sawlog, sawn timber, finger-jointed end-product chain varies for different logs (Paper IV).

4) To develop a model that can predict the bending strength of sawn timber based on CT data with greater accuracy than existing models based on log outer shape and discrete X-ray scanning (Paper V).


6) To develop an automatic grading method that can more easily be adapted to customer preferences than currently used automatic grading systems and at the same time increase sawmill profitability (Paper VIII).

These objectives are related to different parts of the sawmill process as illustrated in Figure 1.22. Objectives 1 to 4 are related to industrial CT scanning which is linked to log sorting and log sawing. Objective 5 concerns the measurement of saw mismatch, performed on the sawn timber
at the green sorting. Finally, objective 6 is related to grading of the sawn timber at the green sorting or the trimming plant.

Figure 1.22: Overview of the different operations in the sawmill process (Swedish Wood, 2013) and the parts of the sawmill process to which the objectives of this thesis are related.
1.9 Limitations

The studies performed in this work have focused on two species: Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) Karst.). The work has been based on data obtained from the scanning of logs or on real wood material.

The choice of tree species, sawing technique, grading and other operations are typical for the Swedish sawmill industry. This makes the results applicable and particularly of interest to Swedish sawmill industry, even though there are similarities with other softwood species and with sawmill operations in other parts of the world.

For the grading of sawn timber, only knots and wane have been considered. These features are the most important with respect to the appearance and strength of a piece of sawn timber.

There are many possible further processing activities. In this thesis, cross-cutting combined with finger-jointing was studied.
Chapter 2

Materials and Methods

In this work, the following materials and methods have been used.

1) Simulation of log breakdown optimization of Scots pine and Norway spruce using CT data of sawlogs from the Swedish pine stem bank (Grundberg et al., 1995) as well as from the European spruce stem bank (Berggren et al., 2000).

2) Simulations of log breakdown optimization of a data set consisting of CT data from 57 Norway spruce sawlogs collected in Germany.

3) Simulation of log breakdown and cross-cutting of 18 Scots pine logs from a sawmill in northern Sweden.

4) Destructive bending strength tests on sawn timber from 59 Norway spruce logs in the European spruce stem bank.

5) Measurements of saw mismatch using laser triangulation on 20 pieces of Norway spruce sawn timber in a laboratory, and also in a sawmill in northern Sweden where approximately 390,000 pieces of sawn timber were measured during 14 days of sawmill production.

6) Appearance grading of sawn timber based on multivariate prediction models calibrated using 323 pieces of Scots pine sawn timber that were randomly selected from a sawmill in northern Sweden.
2.1 The Swedish pine and European spruce stem banks

The Swedish pine stem bank (Grundberg et al., 1995) and the European spruce stem bank (Berggren et al., 2000) are collections of CT-scanned logs with a large diversity in log properties because of differences in geographical origin and growth conditions. The Swedish pine stem bank consists of 716 Scots pine logs from Sweden and the European spruce stem bank consists of 750 Norway spruce logs mainly from Sweden, but also some from Finland and France. The trees were selected thoroughly to obtain a diversity representative of logs from Scandinavian forests.

All the logs were CT scanned at Luleå University of Technology in Skellefteå using a medical Siemens Somatom AR.T CT scanner (Siemens Healthcare, 2014). The scanning was performed in the green condition, but a slice was cut off from the butt end of the log and conditioned to 9% moisture content and then CT scanned again. In this way, the green density was known for the entire log while the dry density could be calculated for the CT slices in the butt end. The scans were performed every 10 mm and the full resolution images from these scans were 512 × 512 pixel images with 12 bit depth. For the 12 bit depth images, one intensity number corresponds approximately to a CT number, i.e. to a density level of 1 kg m$^{-3}$. The width of the beam was 5 mm and to achieve the highest resolution the width and height of the reconstructed image varied between 350 and 450 mm, depending on log size. This means that each pixel in the CT image described a voxel element of volume between 0.68 × 0.68 × 5 mm$^3$ and 0.88 × 0.88 × 5 mm$^3$. From the CT images, it has been possible to describe external and internal log properties such as log outer shape, pith location, heartwood/sapwood border and knots. The knots are described by 9 parameters for Scots pine and 10 parameters for Norway spruce, specifying the knot geometry, position, and direction in the log (Oja, 2000).
2.2 Simulation of log sawing

In this work, the computer software Saw2003 developed by Nordmark (2005) has been used to simulate the sawing of CT-scanned logs. The description of log outer shape, pith location and knots from these logs can be loaded into the software and used to simulate sawing. The edging and trimming of side boards and the trimming of centre boards is implemented in the software and carried out with respect to the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). The grading is carried out only with respect to knots and wane on the sawn timber since these are the most important wood features to consider and that are described in the software. The breakdown simulations are controlled by setting the properties of the simulated sawing machine (e.g., kerf width), the sawing patterns for the different sawing classes, and the prices for centre and side boards of different grades.

2.3 Log breakdown optimization based on CT data

In this thesis, the manner in which information of log outer shape and knots from CT data can be utilized to optimize the log rotation of each log in a sawmill has been investigated. Simulations of log breakdown optimization have been carried out using Saw2003 with respect to both appearance grading (Paper I) and visual strength grading of sawn timber (Paper II). Breakdown optimization focused on appearance grading was carried out on the entire Swedish pine and European spruce stem bank, whereas for the breakdown optimization focused on visual strength grading, 677 logs from the European spruce stem bank were used. This since it is mainly Norway spruce that is used for strength grading in Sweden. In the simulations, sawing patterns were specified according to Table 2.1 for both appearance and strength grading and prices were set according to Table 2.2 for appearance grading and Table 2.3 for visual strength grading. For the simulations focused on the visual strength grading of sawn timber, all the centre boards were graded by an external trimming software according to the visual strength grading rules, INSTA142 (Swedish Standards Institute, 2010).
### Materials and Methods

#### Table 2.1: Sawing patterns used in the log breakdown simulations depending on the top diameter of the log. All values are nominal target values.

<table>
<thead>
<tr>
<th>Sawing class</th>
<th>Sawing pattern (mm)</th>
<th>Top diameter range (mm)</th>
<th>First saw (mm)</th>
<th>Second saw (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>38 by 75 by 2</td>
<td>0–129</td>
<td>19, 75, 19</td>
<td>19, 38, 38, 19</td>
</tr>
<tr>
<td>2</td>
<td>38 by 100 by 2</td>
<td>130–149</td>
<td>19, 100, 19</td>
<td>19, 38, 38, 19</td>
</tr>
<tr>
<td>3</td>
<td>50 by 100 by 2</td>
<td>150–169</td>
<td>19, 100, 19</td>
<td>19, 50, 50, 19</td>
</tr>
<tr>
<td>4</td>
<td>50 by 125 by 2</td>
<td>170–184</td>
<td>19, 125, 19</td>
<td>25, 50, 50, 25</td>
</tr>
<tr>
<td>5</td>
<td>63 by 125 by 2</td>
<td>185–194</td>
<td>19, 125, 19</td>
<td>19, 63, 63, 19</td>
</tr>
<tr>
<td>6</td>
<td>50 by 150 by 2</td>
<td>195–209</td>
<td>19, 150, 19, 19</td>
<td>19, 25, 50, 50, 25, 19</td>
</tr>
<tr>
<td>7</td>
<td>63 by 150 by 2</td>
<td>210–219</td>
<td>19, 150, 19, 19</td>
<td>19, 25, 63, 63, 25, 19</td>
</tr>
<tr>
<td>8</td>
<td>50 by 175 by 2</td>
<td>220–229</td>
<td>19, 175, 19, 19</td>
<td>19, 25, 50, 50, 25, 19</td>
</tr>
<tr>
<td>9</td>
<td>63 by 175 by 2</td>
<td>230–249</td>
<td>19, 175, 19, 19</td>
<td>25, 25, 63, 63, 25, 25</td>
</tr>
<tr>
<td>10</td>
<td>63 by 200 by 2</td>
<td>250–264</td>
<td>19, 200, 19, 19</td>
<td>25, 25, 63, 63, 25, 25</td>
</tr>
<tr>
<td>11</td>
<td>75 by 200 by 2</td>
<td>265–284</td>
<td>19, 200, 19, 19</td>
<td>19, 25, 75, 75, 25, 19</td>
</tr>
<tr>
<td>12</td>
<td>75 by 225 by 2</td>
<td>285–304</td>
<td>19, 225, 19, 19</td>
<td>19, 25, 75, 75, 25, 19</td>
</tr>
<tr>
<td>15</td>
<td>63 by 200 by 4</td>
<td>345–384</td>
<td>25, 32, 200, 32, 25</td>
<td>19, 25, 63, 63, 63, 25, 19</td>
</tr>
<tr>
<td>16</td>
<td>75 by 200 by 4</td>
<td>385–449</td>
<td>25, 32, 200, 32, 25</td>
<td>19, 25, 75, 75, 75, 75, 25, 19</td>
</tr>
</tbody>
</table>

#### Table 2.2: Relative prices per m³ used in the simulations for appearance-graded sawn timber with the price for centre boards of grade B as reference, and with different levels of price differentiation between grades.

<table>
<thead>
<tr>
<th>Grade</th>
<th>Relative price per m³</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Centre boards</td>
<td></td>
</tr>
<tr>
<td>Grade A</td>
<td>108</td>
</tr>
<tr>
<td>Grade B</td>
<td>100</td>
</tr>
<tr>
<td>Grade C</td>
<td>81</td>
</tr>
<tr>
<td>Sideboards</td>
<td></td>
</tr>
<tr>
<td>Grade A</td>
<td>138</td>
</tr>
<tr>
<td>Grade B</td>
<td>88</td>
</tr>
<tr>
<td>Grade C</td>
<td>78</td>
</tr>
</tbody>
</table>
2.3. Log breakdown optimization based on CT data

Table 2.3: Relative prices per m³ that were used in the simulations for visually strength-graded sawn timber with the price for centre boards of grade T2 as reference.

<table>
<thead>
<tr>
<th>Board type</th>
<th>Centre boards</th>
<th>Side boards</th>
<th>Chips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade</td>
<td>T3 T2 T1 T0 Reject</td>
<td>A B C -</td>
<td></td>
</tr>
<tr>
<td>Relative price per m³</td>
<td>106 100 68 68 68</td>
<td>100 100 68 18</td>
<td></td>
</tr>
</tbody>
</table>

Breakdown of each log was simulated for rotational positions \( \theta = [-90°, 90°] \), where \( \theta = 0° \) corresponds to the horns down position. The simulated sawing leads to value and volume yield as functions of log rotational position, \( \theta \), as shown in Figure 2.1. This made it possible to investigate the gain in value that can be achieved both by appearance grading and strength grading if each log were rotated and processed in its value optimizing position instead of in the conventional horns down position.

![Figure 2.1](image)

Figure 2.1: (a) The value of sawn timber and chips and (b) the volume yield when simulating log breakdown for one example log in rotational positions \( \theta \in [-90°, 90°] \). The value is relative to the value in the horns down position (100%), where the horns down position corresponds to an angle of rotation of 0°.

The increase in value, \( V \), of the sawn timber when applying the value maximizing log rotation for each log compared to the horns down position
can be presented in various ways. One way is to calculate the relative increase in total value for all the logs in the value maximizing position relative to the horns down position according to

$$V_{rel}^{tot}_{maxval} = \frac{\sum_{i=1}^{N} V_i(\theta_i^{maxval}) - \sum_{i=1}^{N} V_i(0)}{\sum_{i=1}^{N} V_i(0)},$$  \hspace{1cm} (2.1)$$

where $V_{rel}^{tot}_{maxval}$ is the relative increase in total value for all logs, $\theta_i^{maxval}$ is the rotational position of log $i$ relative to the horns down position that maximizes the value, and $N$ is the number of logs.

Another way is to calculate the relative increase in value between the value maximizing position and the horns down position for each individual log and then take the average according to

$$\overline{V}_{rel}^{ind}_{maxval} = \frac{1}{N} \sum_{i=1}^{N} \frac{V_i(\theta_i^{maxval}) - V_i(0)}{V_i(0)},$$  \hspace{1cm} (2.2)$$

where $\overline{V}_{rel}^{ind}_{maxval}$ is the average of the relative value increase between the value maximizing position and the horns down position for all logs, $\theta_i^{maxval}$ is the rotational position of log $i$ relative to the horns down position that maximizes the value, and $N$ is the number of logs.

The impact that a rotational error would have on a rotational optimization was investigated both for appearance grading and visual strength grading. For appearance grading a normally distributed rotational error, $\mathcal{N}(0^\circ, 5^\circ)$, was added to the value maximizing position of each log and the way in which the value optimization was affected by this was investigated according to

$$V_{tot}^{maxval} = \frac{\sum_{i=1}^{N} V_i(\theta_i^{maxval} + \mathcal{N}(0^\circ, 5^\circ)) - \sum_{i=1}^{N} V_i(0)}{\sum_{i=1}^{N} V_i(0)},$$  \hspace{1cm} (2.3)$$

This is however a naive way of investigating the effect of a rotational error. A better method would have been to apply a Gaussian filter on the value function in order to obtain the expected value function when a rotational error is present and use this to calculate the value maximizing position. This method was used in the study of log rotation optimization with respect to visual strength grading (Paper II) using a Gaussian filter with windows size $6\sigma - 1 = 6 \cdot 5 - 1 = 29$ degrees.
The studies in which log rotational optimization is performed with respect to appearance grading and visual strength grading assume a completely accurate detection of knots in the CT images. Since this is not possible in a real application (Johansson et al., 2013), it was of interest to study how errors in knot detection affect the value yield in a rotational log breakdown optimization (Paper III). In order to do this, 57 Norway spruce sawlogs were collected from a stand in south western Germany and CT scanned using a Microtec CT.LOG scanner (Microtec, 2014). The scanner was set to a resolution of 5 mm in the longitudinal direction, with a slice image size of 768 by 768 pixels for a circular imaging area of 800 mm in diameter. The resolution in the cross-section plane was approximately 1 mm²/pixel. The CT images were processed for log outer shape and knots, using software for wood feature extraction developed by Johansson et al. (2013). Log breakdown optimization was simulated using Saw2003 in the same way as in the previous studies (Figure 2.1) and with respect to the appearance grading of the sawn timber. In this case however, the reference rotation $\theta = 0^\circ$ corresponds not to the horns down position but instead to the value maximizing position based on log outer shape. It is current practice in most high-production softwood sawmills in Germany to control the rotation of a log solely on the basis of its outer shape. The sawing patterns used were the same as in the previous studies (Table 2.1).

Three types of systematic and random errors were analysed: errors added to the knot diameter, to the radial position of the dead knot border, and to the rotational position of a knot. For each error type, both systematic and random errors were tested with different specified error levels as shown in Table 2.4. Absolute errors were specified for dead knot border and knot rotational position. Knot diameter error levels were defined as relative values based on the maximum diameter of each knot because it was assumed that the inaccuracy in knot diameter measurement was dependent on knot size. For the specification of the error levels, evaluation results from the work by Johansson et al. (2013) were taken as orientation with the range of the error levels tested covering and to some extent exceeding the magnitude of errors reported there. All errors were tested separately, i.e., there was no combination of different error types of systematic and random errors because the priority of this study was to identify the critical magnitudes of those error types that have the largest effect on their own before examining the interactions of different errors.
The errors were also evaluated for different price scenarios, as previously shown in Table 2.2.

Table 2.4: Error levels tested for the different types of systematic and random errors imposed on the knot description.

<table>
<thead>
<tr>
<th>Error type</th>
<th>Systematic errors</th>
<th>Random errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knot diameter (%)</td>
<td>-50, -25, -10, 10, 25, 50</td>
<td>10, 25, 50</td>
</tr>
<tr>
<td>Dead knot border position (mm)</td>
<td>-30, -20, -10, 10, 20, 30</td>
<td>10, 20, 40, 60</td>
</tr>
<tr>
<td>Rotational position (degrees)</td>
<td>-6, -4, -2, -1, 1, 2, 4, 6</td>
<td>4, 8</td>
</tr>
</tbody>
</table>

2.4 Simulation of cross-cutting of sawn timber

A cross-cutting simulation software capable of interacting with the virtual sawn timber simulated by Saw2003 has been developed and the results have been compared to those of an industrial scanner for cross-cutting sawn timber (Paper IV). The advantage of such a software is that this enables the possibility to use CT data of sawlogs to simulate sawing and then pass on the resulting virtual sawn timber for simulation of cross-cut optimization as well. In this way, the whole chain from log to finger-jointed end-product can be simulated.

An overview of this cross-cutting simulation study is shown in Figure 2.2. The material used was 18 Scots pine logs from two different sawing classes that were selected at the logyard of a sawmill in the north of Sweden. They were measured by a RemaLog optical 3D scanner (RemaSawco, 2014) and log dimensions were recorded. The top diameters ranged from 156 to 214 mm, and the lengths from 3.4 to 4.9 m. The logs were of three different types: butt logs, middle logs and top logs, six logs being taken from each type to study the effect of log type on volume yield in the cross-cutting process. Of these six logs, three were taken from one sawing class and three from another to give six different groups of logs.
2.4. Simulation of cross-cutting of sawn timber

The logs were scanned with a medical Siemens Somatom AR.T CT scanner (Siemens Healthcare, 2014). The results from the scanning were \(512 \times 512\) pixel image stacks of each log, with a voxel size of \(0.68 \times 0.68 \times 5.34\) mm\(^3\). A knot detection algorithm developed by Johansson et al. (2013) was used on the image stacks, which resulted in a parametrized description of the knots in the log. The outer shape of the logs was also obtained from the CT-image stacks. When scanning the logs, the rotational position of each log was marked on the butt end of the log by drawing an arrow. The reason was to be able to simulate sawing of the logs in the same position as in a real sawmill.
The logs were sawn at the sawmill into sawn timber of nominal dimension 50 × 100 mm. Only the centre boards were used in this study, since only these boards were cross-cut and finger-jointed. In the first saw, images of the butt end of each log were recorded using a video camera during sawing. This made it possible to estimate the rotational position for each log that was sawn, as shown in Figure 2.3. The real sawn timber was scanned using an industrial cross-cut optimization scanner, WoodEye (Innovativ Vision, 2014). The camera images were used for detection and classification of features on the sawn timber, which were stored and used for subsequent cross-cutting decisions. The cross-cut saw produced pieces for subsequent finger-jointing, with flexible lengths between 170 and 550 mm and quality requirements according to Table 2.5. Pieces of length 170 to 285 mm were valued differently from pieces of length 285 to 550 mm, for the sake of optimization. When the value of 170 to 285 mm pieces was set to 100, the relative value of pieces 285 to 550 mm was 103. The reasoning behind this was to produce more of longer lengths, which were easier to handle in the production process.

![Image](image.png)

Figure 2.3: The arrow visible in the butt end of the log made it possible to simulate sawing of the logs in approximately the same log rotational position as that in which they were sawn in the sawmill.

Using the video camera recording from the sawing, the breakdown of the sawlogs could be simulated in the same rotational position as in the sawmill using Saw2003. Price levels are irrelevant in the simulation, since
Table 2.5: Quality specifications for the finger-jointed product used in this study. Length and width of features are defined using the sawn timber, i.e. feature length is size in the lengthwise direction of the sawn timber.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Maximum length (mm)</th>
<th>Maximum width (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sound knot</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Dead knot</td>
<td>Not allowed</td>
<td>Not allowed</td>
</tr>
<tr>
<td>Wane</td>
<td>5</td>
<td>2.5</td>
</tr>
</tbody>
</table>

no trimming was carried out on the centre boards. The complete lengths of the centre boards were used in the cross-cutting and finger-jointing process. The resulting virtual sawn timber from the simulations was used in a developed cross-cutting optimization software, which is based on the principles described by Rönqvist and Astrand (1998). The software classifies knots and wane as allowed or not allowed, in the same way as an industrial cross-cutting optimizer. This preprocessing divides the sawn timber into zones from which products can be cut out or considered as waste. The cross-cut decisions are made on the basis of these results, optimizing the value of the product mix made from each piece of sawn timber. The value for each product is fixed and defined beforehand as the value per meter of material produced.

To validate the cross-cutting simulation program, the cross-cutting volume yield for each piece of sawn timber was calculated, both for the results of the cross-cutting simulation program and the real process. The cross-cutting volume yield $Y_{cc}$ was defined as

\[ Y_{cc} = \frac{L_{out}}{L_{in}}, \]

where $L_{in}$ is the length of input material (each piece of sawn timber) and $L_{out}$ is the total length of output material (cross-cut pieces). The cross-cutting volume yield depends only on the length of the input and output material since the dimension of the sawn timber is constant when performing cross-cutting for finger-jointing.
Materials and Methods

The total volume yield for each log was also calculated for the results of the cross-cutting simulation program and the real process. The total volume yield $Y_{tot}$ was defined as

$$Y_{tot} = \frac{V_{crosscut}}{V_{log}},$$

(2.5)

where $V_{crosscut}$ is the total dry volume of output material (cross-cut pieces) from one log and $V_{log}$ is the volume of the green log. The log volume was the volume measured by the 3D scanner at the sawmill.

2.5 Prediction of strength of sawn timber based on CT data

Models for the prediction of bending strength were developed using 59 Norway spruce logs that originated from the European spruce stem bank. The rotational positions when sawing these logs have been documented and destructive bending strength tests were carried out on the centre boards. Only centre boards were tested since spruce side boards are not generally strength-graded in Sweden. Using data from the CT images and the bending strength tests, multivariate models for predicting bending strength (MOR) were created. Each step is explained in detail in the following sections.

2.5.1 Bending strength tests

The logs were cut using cant sawing with curve sawing in the second saw and the rotational position of each log was documented. Depending on log diameter, the sawing resulted in 2 or 4 centre boards which were then dried to a moisture content of 12% and planed to dimensions of $45 \times 95$ mm, $45 \times 120$ mm, or $45 \times 145$ mm.

Destructive bending strength tests were performed on all inner centre boards (Figure 2.4) according to the European standard EN408 (European Committee for Standardization (CEN), 2003). The number of specimens and logs for each dimension of the sawn timber are presented in Table 2.6. On some pieces of sawn timber, the identification tag was lost during storage of the sawn timber and these pieces were excluded from the tests.
2.5. Prediction of strength of sawn timber based on CT data

To create prediction models for bending strength of sawn timber, variables are needed that can explain the variability in MOR. This section presents an overview of the variables used for the four different prediction models. These are variables that can be extracted from logs by (1) a 3D scanner, (2) a 3D scanner combined with a discrete X-ray scanner, and (3) a CT scanner with knowledge of the rotational position in which the logs were sawn. The fourth prediction model corresponds to a CT scanner, but without any knowledge of the rotational position when sawing. Table 2.7 summarises the number of variables used in each model. Detailed

![Diagram of sawing pattern](image)

Figure 2.4: The sawing pattern shown has four centre boards, but only the inner, grey shaded boards, were used in the current study. In cases where only two centre boards were obtained, both of them were used.

<table>
<thead>
<tr>
<th>Dimension (mm)</th>
<th>No. of pieces of sawn timber</th>
<th>No. of logs</th>
</tr>
</thead>
<tbody>
<tr>
<td>45 × 95</td>
<td>41</td>
<td>21</td>
</tr>
<tr>
<td>45 × 120</td>
<td>46</td>
<td>25</td>
</tr>
<tr>
<td>45 × 145</td>
<td>26</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 2.6: Number of pieces of sawn timber used for each dimension of sawn timber and the number of logs from which the sawn timber originated.

2.5.2 Variable extraction

To create prediction models for bending strength of sawn timber, variables are needed that can explain the variability in MOR. This section presents an overview of the variables used for the four different prediction models. These are variables that can be extracted from logs by (1) a 3D scanner, (2) a 3D scanner combined with a discrete X-ray scanner, and (3) a CT scanner with knowledge of the rotational position in which the logs were sawn. The fourth prediction model corresponds to a CT scanner, but without any knowledge of the rotational position when sawing. Table 2.7 summarises the number of variables used in each model. Detailed
descriptions of the variables and how they were extracted are given in the following sections.

Table 2.7: Number of variables used in each model divided into different groups. CT* denotes the CT model where the rotational position of the logs during sawing was unknown.

<table>
<thead>
<tr>
<th>Model</th>
<th>Variable groups</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Outer shape</td>
</tr>
<tr>
<td>3D</td>
<td>65</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>65</td>
</tr>
<tr>
<td>CT</td>
<td>65</td>
</tr>
<tr>
<td>CT*</td>
<td>65</td>
</tr>
</tbody>
</table>

**Outer shape**

The software *Quality On-line* (SP Wood Technology, 2014) was used to extract 65 variables describing the outer shape of each log. These outer shape variables describe the log in terms of e.g. length, crook, taper, ovality and bumpiness of both the whole log and divided into different parts of the log.

**Discrete X-ray**

Discrete X-ray variables were extracted from the CT images by simulating a two-directional X-ray scanner. This simulation was conducted in MATLAB (MathWorks, 2014) and 189 variables were extracted describing the log based on discrete X-ray data. These X-ray variables describe some of the internal features of the log such as density, number of knot whorls, distance between knot whorls and heartwood content.
2.5. Prediction of strength of sawn timber based on CT data

CT

The variables extracted exclusively from the CT data can be split into three groups:

1. 3D shape of the heartwood volume,
2. density variables, and
3. knot variables.

The shape of the heartwood volume can be extracted from CT images, and it was already available for each log in the European spruce stem bank. Using the information about the heartwood border, another 65 variables were extracted analogous to the outer shape variables using Quality Online (SP Wood Technology, 2014).

An important predictor of the bending strength of sawn timber is the dry density of the wood (Johansson et al., 1992; Hanhijärvi and Ranta-Maunus, 2008). The moisture content in clear heartwood for Norway spruce varies only slightly, typically in the range of 34 to 40% (Esping, 1992). From this follows that changes in heartwood density measured by a CT scanner correspond to changes in dry density. Three density variables were extracted by obtaining the average intensity value of the clear heartwood pixels for each cross-section of the CT image stack. This procedure resulted in a vector consisting of average pixel intensities for every 10 mm of the log. The variables extracted from this vector were average value, standard deviation, and the 20th percentile. The proportion of heartwood in the logs was also included in this group.

Out of the 183 variables obtained using CT data, 114 of the variables were associated with the knot distribution within the log. Table 2.8 shows how these knot related variables were calculated using different parts of the CT cross-sections of the log. Most variables were extracted from the position in the log where each piece of sawn timber was processed. The rotational position was known for the logs, but the skew and lateral positions of the logs were not documented when the sawing was carried out. Therefore an approximation regarding the lateral position of the cross-sections of the sawn timber was used in the CT images. This approximation was that, for each CT slice, the corresponding cross-section of the sawn timber was centred next to the pith as shown in Figure 2.5.
Table 2.8: The number of knot variables used in the study divided into groups. The cross-section position tells which part of the log cross-section that was used, i.e. the whole cross-section (global), only the piece of sawn timber (sawn timber), or the part of the piece of sawn timber lying downwards in the bending strength tests (sawn timber tension). The lengthwise position specifies if only the knots in the middle 2.5 m were considered (middle) or if there was no such restriction (global).

<table>
<thead>
<tr>
<th>Cross-section position</th>
<th>Lengthwise position</th>
<th>No. of variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>Global</td>
<td>19</td>
</tr>
<tr>
<td>Global</td>
<td>Middle</td>
<td>19</td>
</tr>
<tr>
<td>Sawn timber</td>
<td>Global</td>
<td>28</td>
</tr>
<tr>
<td>Sawn timber</td>
<td>Middle</td>
<td>10</td>
</tr>
<tr>
<td>Sawn timber tension</td>
<td>Global</td>
<td>28</td>
</tr>
<tr>
<td>Sawn timber tension</td>
<td>Middle</td>
<td>10</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>114</td>
</tr>
</tbody>
</table>

Figure 2.5: The position of the cross-section of the sawn timber in a CT slice was assumed to be next to the pith and centred (the width of the sawn timber is denoted \( w \)). This approximation was only required when extracting knot variables from the CT images.

2.5.3 Multivariate models

The multivariate partial least squares (PLS) method was used to predict the bending strength (MOR) of the sawn timber. PLS is a good method when a large number of variables are involved in relation to the number of observations (Wold et al., 2001). It is also suitable when the predic-
2.5. Prediction of strength of sawn timber based on CT data

tor variables are correlated with each other and for noisy data. A PLS regression model can be analysed by plots such as score plots, loadings, and variable importance on projection (VIP) plots (Eriksson et al., 2006). These plots are important for the interpretation of a PLS model and make the model easier to understand and validate.

Three multivariate PLS models were created for each dimension of sawn timber using variables obtained by 3D scanning, 3D and discrete X-ray scanning, and CT scanning. Since both 3D variables and discrete X-ray variables can be obtained from CT images, all the 3D and discrete X-ray variables were included in the CT model as described in Table 2.7. A fourth model was also created that was identical to the CT model, but in which a random rotational position was used to extract the rotation-specific knot variables. The purpose of this fourth model was to investigate whether knowledge of the position in the log from which the sawn timber was sawn contributed to bending strength predictability, i.e. to affirm the quality of the rotation-dependent CT variables. Models were created for each dimension of sawn timber separately since the intention was to predict variations in bending strength for sawn timber of the same dimension using a specific sawing pattern and not for sawn timber of different dimensions using different sawing patterns.

The software used was Simca 13.0.3 (Umetrics, 2014) and a manual variable reduction was performed in the software on each of the models in order to maximize the goodness of prediction ($Q^2$). The $Q^2$ is based on cross-validation (Martens and Naes, 1989) which means that $n$ models are built, each excluding a part, $(1/n)$, of the observations, when creating a training set to build a model. Each model can then be tested on the observations that were excluded when the model was built. These observations are called the test set. The $Q^2$ shows the proportion of variance in the test sets that is explained by the model. This means that $Q^2$ is a measure of the model’s ability to predict new observations that are not included when the model is built. In the current study, the number of observations for each dimension of sawn timber was rather low (Table 2.6), which means that the samples could not be split into a test set and a validation set. To circumvent this problem when analysing the results, emphasis was put on the $Q^2$ rather than on the goodness of fit ($R^2$).

Special care was taken in the variable reduction step to ensure that sufficient work was performed for each model to achieve as high a $Q^2$ as
Possible. The main reason for maximizing the $Q^2$ instead of the $R^2$ or the root mean square error (RMSE) was the desire to create a model to predict bending strength of new observations and not merely to predict the bending strength of a specific data set.

The exact procedure was to start by maximizing the $Q^2$ for the model based on 3D variables, which resulted in a PLS model with a reduced number of variables. To maximize the $Q^2$ for the discrete X-ray model, the remaining 3D variables were added to all of the discrete X-ray variables. A PLS model was then again created by variable reduction leaving a reduced number of 3D and discrete X-ray variables. Finally, these variables were added to all the CT variables and a final variable reduction was carried out. This procedure made it possible to evaluate the differences in predictability of bending strength between using 3D scanning, discrete X-ray combined with 3D scanning and CT scanning. For the model with CT variables extracted from a random rotational position, the variable reduction step was performed in a manner analogous to that of the ordinary CT model, i.e. producing a model with its own set of variables and coefficients.

Variable reduction was carried out by removing variables one by one starting with the ones having the lowest VIP values. If the $Q^2$ was increased the variable was removed, otherwise the next variable in the VIP plot was considered. This procedure was repeated until the removal of no variable increased the $Q^2$.

### 2.6 Saw mismatch measurements

A method to measure saw mismatch in a sawmill using laser triangulation has been developed and evaluated (Paper VI). The measurement unit was developed in order to measure saw mismatch in the green sorting line of a sawmill, where the sawn timber is transported transversally according to Figure 1.6 in Section 1.2. A laser line strikes the surface of the sawn timber across the grain direction. Any occurrence of saw mismatch on the sawn timber means that the reflection of the laser line is displaced in the field of view of the camera as shown in Figure 2.6. This displacement is proportional to the magnitude of the saw mismatch on the sawn timber.

The measurement unit was evaluated by selecting 20 pieces of sawn timber of final dimensions $38 \times 125$ mm, with lengths between 3.4 and 5.3
2.6. Saw mismatch measurements

Figure 2.6: Illustration of the measurement set-up, $\alpha$ is the angle between the laser beam and the normal to the surface and $d$ is the displacement of the laser beam in the field of view of the camera due to saw mismatch.

m and with different frequencies and magnitudes of saw mismatch. The saw mismatch of each piece of sawn timber was measured five times on each side face at 1 cm intervals. The saw mismatch was also measured manually using a depth gauge with a specially designed holder for measuring saw mismatch. The manual measurements were carried out on the pith side, 50 cm from the top end by five different persons, and these were used to compare and evaluate the performance of the laser triangulation measurement.

The industrial partner required a measurement system that would be simple and cost-effective and able to detect saw mismatch exceeding 0.5 mm. In order to detect every piece of sawn timber having a saw mismatch exceeding 0.5 mm, it would be necessary to measure saw mismatch on both sides of the sawn timber and along the whole length. However, the purpose of measuring saw mismatch in a sawmill is not to detect whether the saw mismatch exceeds 0.5 mm for every single piece of sawn timber, but rather to detect a trend in the sawing process where a large number of pieces of sawn timber start to have saw mismatch that would become a problem for the customer. Since the laser triangulation units will be installed at selected positions in the green sorting line of a sawmill, the question is how many units are needed to detect such a trend. This was investigated using the measured saw mismatch of the 20 pieces of sawn timber and by simulating the use of the following numbers of laser
triangulation units (Figure 2.7): (1) Two laser triangulation units, one on each side face, centred 50 cm from the top end of the sawn timber. (2) Four laser triangulation units, two on each side face, centred 50 and 150 cm from the top end of the sawn timber. (3) Six laser triangulation units, three on each side face, centred 50, 150, and 200 cm from the top end of the sawn timber. (4) Eight laser triangulation units, four on each side face, centred 50, 150, 200, and 400 cm from the top end of the sawn timber.

Further tests were carried out by installing one laser triangulation unit in the green sorting line of a sawmill (Paper VII). Measurements of saw mismatch were carried out and recorded over a period of 14 days during which a wide range of sawing classes were processed. The saw mismatch of each piece of sawn timber was measured on the upward side face at a distance of 50 cm from the butt end of the sawn timber. During the 14 day period, saw mismatch was measured on approximately 390,000 pieces of sawn timber.
2.6. Saw mismatch measurements

The intention was to be able to relate the frequency and magnitude of saw mismatch to saw blade properties, such as the operating time, saw blade thickness, number of resharpenings, collar size, etc., but it was unfortunately not possible to track in the sawmill system when saw blades were replaced and resharpened. Instead, the presence and magnitude of saw mismatch was related to the cant height, feed speed, and average top diameter of the processed logs. These process parameters are also believed to affect the magnitude and presence of saw mismatch, however they are strongly correlated with each other.

The measured saw mismatch data were filtered with a sliding window using three different types of filters. To describe these different types of filtering, consider the vector $X$ as containing the measured saw mismatch data for $N$ pieces of sawn timber:

$$X = (x_1, x_2, \ldots, x_N).$$  \hfill (2.6)

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:

$$W_j = (x_{i-(S-1)}, \ldots, x_i) \quad \forall i \in \{S, S+1, \ldots, N\}$$

$$\forall j \in \{1, 2, \ldots, (N - (S - 1))\}. \hfill (2.7)$$

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

$$W_{j_y} = (x \in W_j | x > y \text{ mm}) \quad \forall j \in \{1, 2, \ldots, (N - (S - 1))\}. \hfill (2.8)$$

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

$$Y_1(j) = \frac{\text{length}(W_{j_y})}{S} \quad \forall j \in \{1, 2, \ldots, (N - (S - 1))\}, \hfill (2.9)$$

where each element is the proportion 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

$$Y_2(j) = \bar{W}_{j_y} \quad \forall j \in \{1, 2, \ldots, (N - (S - 1))\} \hfill (2.10)$$
where 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

$$Y_3(j) = P_{95}(W_j).$$  \hspace{1cm} (2.11)

where each element is the 95th percentile of the values within the sliding window.

The resulting response variables for these different type of filters were used in a PLS regression, where cant height, feed speed, and average top diameter of the processed logs were used as predictors. Different threshold values of $y$ for $Y_1$ and $Y_2$ were evaluated, $y = 0.1, 0.3, 0.5, 0.7, 0.9, 1.1$ and $1.3$ mm as well as different window sizes for all three response variables $W_j = 50, 100, 300$ and $500$ pieces of sawn timber. The PLS model using the response variable that results in the largest goodness of prediction, $Q^2$, was considered to be the most suitable since its variance can be predicted to the greatest extent by variables which are believed to have an effect on the magnitude and presence of saw mismatch.

2.7 Customer-adapted grading

An automatic method for appearance grading has been developed that is more easily adapted to customer preferences than the currently used rule-based automatic systems (Paper VIII). For the study, 323 pieces of Scots pine sawn timber were randomly selected at a sawmill in northern Sweden. The dimensions of the sawn timber were $38 \times 150$ mm and the length varied between 3.4 and 5.6 m. The logs were sawn with four centre boards from each log ($38/50/50/38) \times 150$ mm, and in this study the outer centre boards were used.

An expert in customer preferences for the North African market served as an example of an important customer, i.e. a customer who regularly purchases significant volumes of sawn timber. The North African market was chosen because it is a large market for Scots pine sawn timber to which both lower and higher qualities of sawn timber are delivered.

The expert visually inspected and graded the 323 pieces of sawn timber into grades A, B, and C according to the preferences of North African customers. The expert was instructed to consider only knots and was not
allowed to trim the sawn timber in any way to enhance its grade. Grade D was not considered, since grade D does not have the same characteristic knottiness as grades A, B and C. Sawn timber is assigned to grade D because of one or several extreme wood features, so that it is easier to separate grade D using automatic visual grading systems than it is to separate grades A, B, and C, which are more closely related.

Each piece of sawn timber was also scanned by a rule based automatic grading system, a *Finscan Boardmaster* (Finscan, 2014), in the final grading where the individual pieces of sawn timber are scanned on all sides during cross transport. Knots and other wood features were detected in the images obtained and the sawn timber was graded according to grading rule settings. These settings were based on the Nordic timber grading rules, but were adapted with respect to the sawmill’s experience of customer preferences on the North African market. As before, only knots and no other features were taken into account in the grading and no trimming was allowed. The rule-based automatic grading was also performed with respect to knot distribution on the entire piece of sawn timber.

From the *Finscan Boardmaster* scanning, 1566 variables related to knot size and knot distribution were extracted for each piece of sawn timber according to Table 2.9. These variables were then used to train multivariate PLS models for predicting grade, in accordance with the grading made by the North African market expert. The advantage of multivariate grading over rule-based grading is that PLS models can more easily be calibrated with respect to customer preferences. Also, unlike rule-based grading, PLS models grade according to the overall impression of the knots on a piece of sawn timber.

The sawn timber was graded into grades A, B and C using two different PLS models. The first PLS model separated the sawn timber of grade C from grades A and B and a threshold value $L_C$ was used to control the separation to some extent as shown in Figure 2.8. In a second step, the sawn timber not assigned to grade C was separated into grades A or B by a second PLS model. This separation can also be controlled using a threshold value $L_A$. The choice of threshold values is discussed further in Section 3.5.
**Table 2.9:** The 58 variables (marked x) related to knots that were extracted for each of the four surfaces on the sawn timber. Knot size was measured according to guidelines in the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Knot type</th>
<th>Sound &amp; dead</th>
<th>Sound</th>
<th>Dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total no. of knots</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Mean knot size (mm)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>St.dev. knot size (mm)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Maximum knot size (mm)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Ratio Knot area (mm²) / Surface area (mm²) (%)</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio sound knots (%)</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio dead knots (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sound knots per m (No./m)</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dead knots per m (No./m)</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ratio of knots ≤ 9 mm</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 10 – 19 mm (%)</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&quot; 20 – 29 mm (%)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 30 – 39 mm (%)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 40 – 60 mm (%)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 60 – 80 mm (%)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; ≥ 80 mm (%)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>No. of knots ≤ 9 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 10 – 19 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 20 – 29 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 30 – 39 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 40 – 60 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; 60 – 80 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>&quot; ≥ 80 mm (No./m)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>
2.7. Customer-adapted grading

PLS model I
\( \hat{y}_i > L_C, L_C \in [0, 1] \)

Yes
Board grade C

No

PLS model II
\( \hat{y}_i > L_A, L_A \in [0, 1] \)

Yes
Board grade A

No
Board grade B

Figure 2.8: Decision tree using two PLS models for the automatic grading of sawn timber into grades A, B and C.
This chapter presents the main results of this thesis. Section 3.1 presents the results obtained when using CT data to simulate log breakdown optimization with respect to appearance-graded and visually strength-graded sawn timber. Results showing how errors in knot detection affect such an optimization are also included. Section 3.2 summarizes the results of the cross-cut simulation study, where a simulation of cross-cutting based on CT data was compared with the results obtained using an industrial scanner for cross-cutting sawn timber. Section 3.3 shows how CT data can be used to predict the bending strength of sawn timber, where predictions based on CT data are compared with predictions obtained using only log outer shape data and using log outer shape data combined with discrete X-ray data. Section 3.4 presents the results of measurements of saw mismatch on 20 pieces of sawn timber in a laboratory as well as the result of measurements in a sawmill. Finally, Section 3.5 shows how the appearance grading of sawn timber can more easily be calibrated and adapted to customer preferences using a multivariate method.

3.1 Log breakdown optimization based on CT data

As mentioned in the introduction, the CT scanning of logs at conveying speeds up to 150 m/min makes it possible to optimize the position of the log when sawing. For the first time, this can be performed with respect
not only to log outer shape but also to internal features. This should make it possible to, instead of optimizing the volume yield, now optimize the value of the sawn timber using information about the external and internal features of the sawlog.

3.1.1 Appearance of sawn timber

The results obtained from a simulation of a rotational breakdown optimization with respect to the value of appearance-graded sawn timber using 1466 logs from the Swedish pine and European spruce stem banks are summarized in Table 3.1. The relative value increase based on the total value (Equation 2.1) was 13% for both Scots pine and Norway spruce when choosing the log rotation that maximizes the value of each log was chosen instead of the horns down position. The relative value increase based on each individual log (Equation 2.2) was on average 16% for both Scots pine and Norway spruce.

When a normally distributed rotational error, $\mathcal{N}(0^\circ, 5^\circ)$, was added to the value maximizing position, the relative value increase according to Equation 2.1 decreased to 6% for both species, and the average relative value increase according to Equation 2.2 decreased to 8% for both species.

If a Gaussian filter was applied to evaluate the effect of a rotational error, the relative value increase according to Equation 2.1 became 8% for Scots pine and 7% for Norway spruce, and the relative value increase according to Equation 2.2 was on average 9% for both species.

The effect of the rotational step length (number of simulated log rotations) on the average relative value increase compared to the horns down position is shown in Figure 3.1. If a rotational error is present, the average relative value increase is as shown in Figure 3.2. The impact on the average relative value increase of price differences between quality grades is presented in Figure 3.3.

Figure 3.4 shows the effect that systematic errors in the measurement of knot diameter and in the radial position of the dead knot border had on the average relative value increase when the log rotation for 57 Norway spruce sawlogs from Germany were optimized. For these logs, the reference point ($0^\circ$) is not the horns down position but instead the volume-maximizing rotational position. The effects of a normal distribution of random errors with different standard deviations are shown in Figure 3.5. In Figures 3.1
3.1. Log breakdown optimization based on CT data

to 3.5, the average relative value increase is based on the individual logs according to Equation 2.2.

Table 3.1: Relative increase in value when applying to each log the rotational position that maximizes the value of the sawn timber in the Swedish pine and European spruce stem banks, compared to the horns down position. Definitions of \( V_{rel}^{tot\text{maxval}} \), \( V_{rel}^{ind\text{maxval}} \) are given in Equations 2.1 and 2.2.

<table>
<thead>
<tr>
<th></th>
<th>Scots pine</th>
<th>Norway spruce</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( V_{rel}^{tot\text{maxval}} )</td>
<td>( V_{rel}^{ind\text{maxval}} )</td>
</tr>
<tr>
<td>Ideal</td>
<td>13%</td>
<td>16%</td>
</tr>
<tr>
<td>Error added</td>
<td>6%</td>
<td>8%</td>
</tr>
<tr>
<td>Gaussian filter</td>
<td>8%</td>
<td>9%</td>
</tr>
</tbody>
</table>

Figure 3.1: The average relative value increase when applying the rotational position that maximizes the value of the sawn timber for each log in the (a) Swedish pine and (b) European spruce stem banks compared to the horns down position. The different rotational step lengths evaluated are 1°, 5°, 10°, 20°, 45° and 90°.
Figure 3.2: The average relative value increase when applying the rotational position that maximizes the value of the sawn timber for each log in the (a) Swedish pine and (b) European spruce stem banks, compared to the horns down position, when a normally distributed rotational error $N(0^\circ, 5^\circ)$ is introduced using a Gaussian filter with window size 29°. The different log rotational step lengths evaluated are 1°, 5°, 10°, 20°, 45° and 90°.

Figure 3.3: The average relative value increase when applying the rotational position that maximizes the value of the sawn timber for each log in the (a) Swedish pine and (b) European spruce stem bank, compared to the horns down position. The price differences (low, normal, high) between the quality grades are specified in Table 2.2.
3.1. Log breakdown optimization based on CT data

Figure 3.4: The average relative value increase between rotational optimization taking into account internal knottiness and conventional outer-shape-based optimization with different levels of price differentiation as functions of (a) a systematic error in knot diameter and (b) a systematic error in the radial position of the dead knot border. The different price differentiations between grades are defined in Table 2.2.

Figure 3.5: The average relative value increase between optimization taking into account internal knottiness and conventional outer-shape-based optimization for different levels of price differentiation as functions of (a) a normally distributed random error in knot diameter and (b) a normally distributed random error in the radial position of the dead knot border. The different price differentiations between grades are defined in Table 2.2.
3.1.2 Strength of sawn timber

The results of a simulated breakdown optimization of 677 logs from the European spruce stem bank with respect to visual strength grading are presented in Table 3.2. The average relative value increase based on each individual log (Equation 2.2) was 11% when the rotational position was optimized with respect to the value of the visually-strength graded sawn timber. The results were the same if the optimization was carried out with respect to the value of the centre boards or with respect to the value of all products i.e. centre boards, side boards and chips. There was no effect on the average change in volume yield when considering only centre boards while the average volume yield increased with 2 percentage points when considering all the products. The relative value increase and volume yield change distributions when the log rotation is optimized with respect to the value of the centre boards are presented in Figure 3.6a and Figure 3.6b respectively.

When a Gaussian filter was applied to the value function to simulate the effect of a normally distributed rotational error $\mathcal{N}(0^\circ, 6^\circ)$, the average relative value increase was 6% when considering only centre boards and 5% when considering all the products. There was still no effect on the average change in volume yield when considering only centre boards while the average volume yield increased with 1 percentage point when considering all the products. Figure 3.6c shows the centre board grade distribution for the rotational position that gives the optimum value of the centre boards and for the horns down position.
3.1. Log breakdown optimization based on CT data

Table 3.2: Average relative value increase in percent and average volume yield change in percentage points (pp) with reference to the horns down position and when choosing the log rotational position that maximizes the value of the centre boards as well as the total value of all the products (centre boards, side boards and chips). Ideal values and values with an applied rotational error, $Z \in N(0^\circ, 6^\circ)$, are presented. $N$ is the number of logs in each sawing class (SC) used in the simulations. The average relative value increase and the average change in volume yield over all logs are weighted averages.

<table>
<thead>
<tr>
<th>SC</th>
<th>N</th>
<th>Centre boards</th>
<th>All products</th>
<th>Centre boards</th>
<th>All products</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average relative value increase (%)</td>
<td>Average volume yield change (pp)</td>
<td>Average relative value increase (%)</td>
<td>Average volume yield change (pp)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ideal</td>
<td>With error</td>
<td>Ideal</td>
<td>With error</td>
</tr>
<tr>
<td>1</td>
<td>86</td>
<td>8</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>64</td>
<td>9</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>63</td>
<td>9</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>46</td>
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<td>0</td>
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<td>15</td>
<td>6</td>
<td>1</td>
<td>0</td>
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<td>7</td>
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<td>0</td>
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</tr>
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<td>14</td>
<td>6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>22</td>
<td>12</td>
<td>6</td>
<td>1</td>
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</tr>
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<td>14</td>
<td>18</td>
<td>13</td>
<td>6</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>677</td>
<td>11</td>
<td>6</td>
<td>0</td>
<td>0</td>
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</tbody>
</table>
Figure 3.6: (a) Relative value increase in percent and (b) volume yield change in percentage points when the log breakdown is simulated in the rotational position that maximizes the value of the strength-graded centre boards and compared with the horns down position. (c) The distribution of the strength-graded centre boards for the horns down position and for the rotational position that maximizes the value of the centre boards.
3.2 Simulation of cross-cutting of sawn timber

The results of a cross-cutting simulation software based on CT data have been compared with the results obtained with an industrial scanner for cross-cutting sawn timber. Figure 3.7a shows the cross-cutting volume yield (Equation 2.4) given by the simulation program plotted against the cross-cutting volume yield obtained with the industrial WoodEye scanner and optimizer. The correlation coefficient ($r$) was 0.86 while the RMSE was 13 percentage points.

The total volume yield from the sawing and cross-cutting (Equation 2.5) of the 18 logs is shown in Figure 3.7b, where the log types are indicated. The correlation coefficient between the total volume yield using the simulation software and the total volume yield using the industrial WoodEye scanner was 0.93 and the RMSE was 4 percentage points.

![Figure 3.7: Comparison of the volume yield results given by the cross-cut simulation software and the industrial WoodEye scanner and optimizer. (a) Cross-cutting volume yield (Equation 2.4) for all pieces of sawn timber and (b) total volume yield from sawing and cross-cutting (Equation 2.5) of 18 logs. In (b), squares correspond to butt logs, triangles correspond to middle logs and circles correspond to top logs.](image-url)
3.3 Prediction of strength of sawn timber based on CT data

The results of bending strength predictions using PLS models based on variables obtained by 3D scanning, 3D scanning combined with discrete X-ray scanning, and 3D scanning combined with discrete X-ray scanning and CT scanning are shown in Table 3.3 and in Figure 3.8. It is clear that the values of $R^2$, $Q^2$, and RMSE were best for the CT models and worst for the 3D models for all three dimensions of sawn timber evaluated. The differences between the 3D model and the discrete X-ray model were larger than those between the discrete X-ray model and the CT model. The goodness of prediction for the two smallest dimensions were similar with all the models, but the models could not explain the variance to the same extent for the dimension $45 \times 145$ mm.

Table 3.3: The results of predicting the bending strength using the four PLS models in terms of goodness of fit ($R^2$), goodness of prediction ($Q^2$) and RMSE. The number of principal components (PC) and the number of variables used in the models are also specified. CT* denotes the CT model where the rotational position of the logs when sawing was unknown.

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension (mm)</th>
<th>No. of PCs</th>
<th>$R^2$</th>
<th>$Q^2$</th>
<th>RMSE (MPa)</th>
<th>No. of variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D</td>
<td>$45 \times 95$</td>
<td>1</td>
<td>0.69</td>
<td>0.63</td>
<td>6.1</td>
<td>14</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>$45 \times 95$</td>
<td>2</td>
<td>0.82</td>
<td>0.78</td>
<td>4.8</td>
<td>17</td>
</tr>
<tr>
<td>CT</td>
<td>$45 \times 95$</td>
<td>2</td>
<td>0.86</td>
<td>0.83</td>
<td>4.2</td>
<td>19</td>
</tr>
<tr>
<td>CT*</td>
<td>$45 \times 95$</td>
<td>2</td>
<td>0.82</td>
<td>0.79</td>
<td>4.7</td>
<td>21</td>
</tr>
<tr>
<td>3D</td>
<td>$45 \times 120$</td>
<td>1</td>
<td>0.56</td>
<td>0.49</td>
<td>7.9</td>
<td>7</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>$45 \times 120$</td>
<td>2</td>
<td>0.77</td>
<td>0.73</td>
<td>5.9</td>
<td>10</td>
</tr>
<tr>
<td>CT</td>
<td>$45 \times 120$</td>
<td>2</td>
<td>0.89</td>
<td>0.83</td>
<td>4.0</td>
<td>19</td>
</tr>
<tr>
<td>CT*</td>
<td>$45 \times 120$</td>
<td>3</td>
<td>0.84</td>
<td>0.77</td>
<td>4.9</td>
<td>25</td>
</tr>
<tr>
<td>3D</td>
<td>$45 \times 145$</td>
<td>1</td>
<td>0.53</td>
<td>0.48</td>
<td>5.9</td>
<td>3</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>$45 \times 145$</td>
<td>1</td>
<td>0.62</td>
<td>0.57</td>
<td>5.3</td>
<td>17</td>
</tr>
<tr>
<td>CT</td>
<td>$45 \times 145$</td>
<td>1</td>
<td>0.73</td>
<td>0.66</td>
<td>4.5</td>
<td>16</td>
</tr>
<tr>
<td>CT*</td>
<td>$45 \times 145$</td>
<td>1</td>
<td>0.64</td>
<td>0.59</td>
<td>5.1</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 3.4 shows the number of variables left after the variable reduction. Of the discrete X-ray variables, no group of variables were found
3.3. Prediction of strength of sawn timber based on CT data

![Graphs showing R², Q², and RMSE for each PLS model dimension of the sawn timber. X-ray denotes the model using both discrete X-ray and 3D variables, while CT* denotes the CT model where the rotational position of the logs during sawing was unknown. Lines are drawn to ease the interpretation.](c)

Figure 3.8: The (a) R², (b) Q², and (c) RMSE for each PLS model dimension of the sawn timber. X-ray denotes the model using both discrete X-ray and 3D variables, while CT* denotes the CT model where the rotational position of the logs during sawing was unknown. Lines are drawn to ease the interpretation.

It is more important than others for the three timber dimensions: the variables left after reduction vary depending on the dimension. It is therefore difficult to generalize as to which of the discrete X-ray variables were removed when creating the CT models. Seen over all the dimensions of sawn timber for the CT models with known rotational position, 73% of all the CT knot variables left after reduction were calculated using the knot volume at the position of each piece of sawn timber in the log cross-section. The proportion before variable reduction was 58%. For the CT models with a random rotational position, 54% of the knot variables left after the reduction were of this type. Knot variables associated with the actual piece of sawn timber were thus more important when applying the correct rotational position than when applying the random position.
Table 3.4: Variables used in the prediction models and whether they were based on data obtained from 3D scanning, discrete X-ray scanning or CT scanning. The CT variables were divided into subgroups according to whether they were related to the heartwood (HW), density ($\rho$) or knots within the log. CT* denotes the CT model where the rotational position of the logs during sawing was unknown.

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension (mm)</th>
<th>Number of variables by group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3D</td>
<td>Discrete X-ray</td>
</tr>
<tr>
<td>3D</td>
<td>45 x 95</td>
<td>14</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 x 95</td>
<td>3</td>
</tr>
<tr>
<td>CT</td>
<td>45 x 95</td>
<td>2</td>
</tr>
<tr>
<td>CT*</td>
<td>45 x 95</td>
<td>2</td>
</tr>
<tr>
<td>3D</td>
<td>45 x 120</td>
<td>7</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 x 120</td>
<td>0</td>
</tr>
<tr>
<td>CT</td>
<td>45 x 120</td>
<td>0</td>
</tr>
<tr>
<td>CT*</td>
<td>45 x 120</td>
<td>0</td>
</tr>
<tr>
<td>3D</td>
<td>45 x 145</td>
<td>3</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 x 145</td>
<td>3</td>
</tr>
<tr>
<td>CT</td>
<td>45 x 145</td>
<td>2</td>
</tr>
<tr>
<td>CT*</td>
<td>45 x 145</td>
<td>2</td>
</tr>
</tbody>
</table>

3.4 Saw mismatch measurements

3.4.1 Measurement precision and repeatability

The means of the five repeated measurements of saw mismatch using laser triangulation are plotted against the means of the manual measurements by five independent persons in Figure 3.9a. The manual measurements and the laser triangulation measurements agreed well, the correlation coefficient ($r$) was 0.77 and the RMSE was 0.3 mm. The standard deviations of the five replicate measurements are shown in a histogram in Figure 3.9b. For 13 out of the 20 pieces of sawn timber, the standard deviation was smaller for the laser triangulation measurement than for the manual measurement.

Figure 3.10 shows a plot of the lengthwise position of maximal saw mismatch on the sapwood side plotted against that on the pith side. The maximal saw mismatch clearly does not occur at the same position on the
two side faces. The correlation coefficient between these two variables was as low as 0.19.

Figure 3.9: (a) Means and (b) standard deviations of five replicate measurements of saw mismatch on 20 pieces of sawn timber using laser triangulation and manually using a depth gauge.

Figure 3.10: The position of maximal saw mismatch on the sapwood side plotted against the position of maximal saw mismatch on the pith side. The position was measured as the distance from the maximal saw mismatch to the top end of the sawn timber. The straight line is the identity line $y = x$ drawn as reference.
The results obtained when evaluating the number of laser triangulation units that are required to detect a saw mismatch exceeding 0.5 mm are presented in Table 3.5. The results show that the detection of pieces of sawn timber having a saw mismatch exceeding 0.5 mm increases with increasing number of laser triangulation units. If eight laser triangulation units (four on each side face) would have been placed at discrete positions along the length of the sawn timber, 19 out of 20 defective pieces of sawn timber would have been detected, but with only two laser triangulation units (one on each side face), 15 out of 20 defective pieces of sawn timber would have been detected.

Table 3.5: The number of pieces of sawn timber where the detected maximum saw mismatch exceeded 0.5 mm when different numbers of laser triangulation units were used for the evaluation of 20 pieces of defective sawn timber.

<table>
<thead>
<tr>
<th>No. of laser triangulation units</th>
<th>No. of detected pieces of sawn timber</th>
<th>Proportion of defective pieces detected (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>15/20</td>
<td>75</td>
</tr>
<tr>
<td>4</td>
<td>15/20</td>
<td>75</td>
</tr>
<tr>
<td>6</td>
<td>18/20</td>
<td>90</td>
</tr>
<tr>
<td>8</td>
<td>19/20</td>
<td>95</td>
</tr>
</tbody>
</table>
3.4.2 Measurements in sawmill

Measured saw mismatch in a sawmill during one day of production is shown in Figure 3.11. In Figure 3.11a the unfiltered data is presented, while Figures 3.11b to 3.11d show three different types of filter applied as described in Equations 2.9 to 2.11. It is clear that a filter is necessary if it is to be possible to detect a trend of increasing or decreasing saw mismatch in the data. The results when predicting variability in saw mismatch for each response variable and for different thresholds and filter window sizes are shown in Table 3.6. Results are presented in terms of the goodness of prediction ($Q^2$). The response variable defined according to Equation 2.9 apparently resulted in the largest goodness of prediction using a window size of 500 pieces of sawn timber and a threshold value for saw mismatch of 0.5 mm. It is clear that the choice of window size and threshold value is important in order to be able to detect variability of saw mismatch in a sawmill using laser triangulation. The centred and scaled PLS regression coefficients using two principal components for the PLS model with the best goodness of prediction are shown in Figure 3.12. All the predictive variables, i.e. average log top diameter, cant height and feed speed were positively correlated with the saw mismatch response variable defined according to Equation 2.9. This means that an increase in the average log top diameter, cant height and feed speed will lead to an increasing occurrence of saw mismatch on the sawn timber.
Figure 3.11: Saw mismatch measurements during one day of production made with a laser triangulation unit placed 50 cm from the butt end of the sawn timber. (a) Unfiltered data. (b) Ratio filtering according to Equation 2.9 using a threshold value of 0.3 mm and a window size of 100 pieces of sawn timber. (c) Average filtering according to Equation 2.10 with a window size of 100 pieces of sawn timber. (d) Filtering using the 95th percentile according to Equation 2.11 with a window size of 100 pieces of sawn timber.
### 3.4. Saw Mismatch Measurements

Table 3.6: Goodness of prediction, $Q^2$, for the three filtered response variables using different threshold values and window sizes (number of pieces of sawn timber). (a) Ratio filtering according to Equation 2.9, (b) average filtering according to Equation 2.10, and (c) filtering using the 95th percentile according to Equation 2.11.

<table>
<thead>
<tr>
<th>Threshold (mm)</th>
<th>Window size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
</tr>
<tr>
<td>0.1</td>
<td>0.00716</td>
</tr>
<tr>
<td>0.3</td>
<td>0.108</td>
</tr>
<tr>
<td>0.5</td>
<td>0.115</td>
</tr>
<tr>
<td>0.7</td>
<td>0.0921</td>
</tr>
<tr>
<td>0.9</td>
<td>0.0709</td>
</tr>
<tr>
<td>1.1</td>
<td>0.0555</td>
</tr>
<tr>
<td>1.3</td>
<td>0.00935</td>
</tr>
</tbody>
</table>

(a)

<table>
<thead>
<tr>
<th>Threshold (mm)</th>
<th>Window size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50</td>
</tr>
<tr>
<td>0.1</td>
<td>0.0932</td>
</tr>
<tr>
<td>0.3</td>
<td>0.0165</td>
</tr>
<tr>
<td>0.5</td>
<td>0.000965</td>
</tr>
<tr>
<td>0.7</td>
<td>0.00193</td>
</tr>
<tr>
<td>0.9</td>
<td>0.00474</td>
</tr>
<tr>
<td>1.1</td>
<td>0.00889</td>
</tr>
<tr>
<td>1.3</td>
<td>0.0133</td>
</tr>
</tbody>
</table>

(b)

<table>
<thead>
<tr>
<th>Window size</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
</tr>
<tr>
<td>0.0392</td>
</tr>
</tbody>
</table>

(c)
Figure 3.12: The significant ($\alpha = 0.05$), centred and scaled regression coefficients of the PLS model with the largest goodness of prediction.
3.5 Customer-adapted grading

Multivariate prediction models for the grading of sawn timber were calibrated with respect to the preferences of an important customer on the North African market. A comparison between the grading by this customer expert and the rule-based grading performed by the *Finscan Boardmaster* (Finscan, 2014) on 323 pieces of sawn timber is shown in Table 3.7. Out of the total 323 pieces of sawn timber, the customer expert graded 24% of the pieces of sawn timber as grade A, 44% as grade B and 32% as grade C, whereas the rule-based grading gave 24% as grade A, 31% as grade B and 45% as grade C. According to the expert, the rule-based grading correctly graded 62% of the 323 pieces of sawn timber, but underestimated 25% and overestimated 13%.

![Table 3.7: The numbers and proportions of the 323 pieces of sawn timber assigned to each grade by rule-based automatic grading (column-wise) and by the customer expert (row-wise). The consistency with the customer expert was also calculated.](image)

In order to try to improve the grading, a multivariate approach was investigated. The multivariate grading was based on two PLS models as described in Figure 2.8. The PLS model I separated sawn timber of grade C from grade A and B and had a goodness of fit ($R^2$) of 0.70 and a
Results

goodness of prediction ($Q^2$) of 0.43. This means that 70% of the variance in the grades of the sawn timber is explained by the model and 43% of the variance can be predicted according to cross-validation. The $R^2$ value for the PLS model II was 0.66 and the $Q^2$ value was 0.49. The separation between the grades of the sawn timber in a principal component coordinate system is illustrated by the score plot shown in Figure 3.13. The separation between grade A (squares) and grade C (triangles) is clear while there are mixed zones between grades A and B (circles) and between grades B and C.

![Score plot showing the different grades according to the customer expert, and their formation in the coordinate system of the first two principal components, $t[1], t[2]$. Squares correspond to grade A, circles to grade B and triangles to grade C.](image)

A multivariate grading of the 323 pieces of sawn timber using the two PLS models and threshold limits $L_A = 0.28$ and $L_C = 0.78$ is compared with the grading by the customer expert in Table 3.8. The grade distribution for the multivariate grading was 32%, 51%, 17% for grades A, B, C, respectively and, according to the expert, the multivariate grading cor-
rectly graded 76% of the sawn timber. The proportion of underestimated sawn timber had decreased to 2%, but the proportion of overestimated sawn timber had increased to 22%.

Table 3.8: The numbers and proportions of the 323 pieces of sawn timber assigned to each grade predicted by the two PLS models (column-wise) and by the customer expert (row-wise). The threshold limits used for separating the grades of the sawn timber were $L_A = 0.28$ and $L_C = 0.78$. The consistency with the customer expert was also calculated for the different grades according to the PLS models.

<table>
<thead>
<tr>
<th>Grade</th>
<th>PLS A</th>
<th>PLS B</th>
<th>PLS C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Expert</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>73(23%)</td>
<td>5(2%)</td>
<td>0(0%)</td>
<td>78(24%)</td>
</tr>
<tr>
<td>B</td>
<td>26(8%)</td>
<td>117(36%)</td>
<td>0(0%)</td>
<td>143(44%)</td>
</tr>
<tr>
<td>C</td>
<td>4(1%)</td>
<td>42(13%)</td>
<td>56(17%)</td>
<td>102(32%)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>103(32%)</td>
<td>164(51%)</td>
<td>56(17%)</td>
<td>323(100%)</td>
</tr>
</tbody>
</table>

Correct grade: \(\frac{73+117+56}{323} = 76\%\)

Underestimated grade: \(\frac{5+0+0}{323} = 2\%\)

Overestimated grade: \(\frac{26+4+42}{323} = 22\%\)

Correct or underestimated grade: \(\frac{73+117+56+5+0+0}{323} = 78\%\)

The result of a multivariate grading of the 323 pieces of sawn timber using the same two PLS models but with a different configuration of threshold limits $L_A = 0.34$ and $L_C = 0.41$ is shown in Table 3.9. The grade distribution when using this configuration of threshold limits was 28%, 41%, 31% for grades A, B, C, respectively, and according to the expert, 87% of the sawn timber was now graded correctly. At the same time, the proportion of underestimated and overestimated sawn timber were only 5% and 8% respectively.
Table 3.9: The numbers and proportions of the 323 pieces of sawn timber assigned to each grade by the two PLS models column-wise and by the customer expert row-wise. The threshold limits used for separating the grades of the sawn timber were $L_A = 0.34$ and $L_C = 0.41$. The consistency with the customer expert was also calculated for the different grades according to the PLS models.

<table>
<thead>
<tr>
<th>Grade</th>
<th>PLS</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Expert</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>71(22%)</td>
<td>6(2%)</td>
</tr>
<tr>
<td>B</td>
<td>16(5%)</td>
<td>118(36%)</td>
</tr>
<tr>
<td>C</td>
<td>2(1%)</td>
<td>9(3%)</td>
</tr>
<tr>
<td>Total</td>
<td>89(28%)</td>
<td>133(41%)</td>
</tr>
</tbody>
</table>

Correct grade: $(71+118+91)/323 = 87\%$

Underestimated grade: $(6+1+9)/323 = 5\%$

Overestimated grade: $(16+2+9)/323 = 8\%$

Correct or underestimated grade: $(71+118+91+6+1+9)/323 = 92\%$
4.1 Use of CT scanning in a sawmill

Industrial CT scanning in sawmills has two advantages over present-day technology. A CT scanner can be used both to optimize the log position when sawing with respect to the value of the sawn timber, and to sort logs with respect to the value of the sawn timber or other value-added products.

It was clear from the studies of the optimized positioning of sawlogs based on CT data that there is a potential for a value increase if each log is rotated individually, with respect to both appearance grading (Table 3.1) and visual strength grading (Table 3.2).

Increased rotational step length (Figure 3.1), positioning errors in log rotation (Figure 3.2), smaller price differences between grades (Figure 3.3) and errors in the extraction of knots (Figures 3.4 and 3.5) all have a negative effect on the value increase. When the rotational step length is increased, rotational positions with a greater value return will be overlooked. Rotational errors in the sawing machine make it difficult to target specific log rotations with a greater value. Larger price differences will lead to a greater average relative value increase since it will be more profitable to obtain the higher grades of sawn timber when more is being paid for them. Systematic and random detection errors in knot diameters and dead knot borders will reduce the average relative value increase in a rotational optimization compared to the situation when knot detection is completely accurate.
In Figure 3.6a it can be observed that relative value increases for individual logs optimized for visual strength grading are in the interval 0 to 50%. Figure 3.6b shows that volume yield was affected negatively as well as positively when optimizing the log rotation for value. However, for most logs the volume yield did not change more than about 1 percentage point. Figure 3.6c shows that the main reason for the increase in value of the visually strength graded sawn timber was because of a shift of centre board grades mainly from grade T1 at the horns down position to grade T2 at the value optimized position.

Despite practical limitations it seems that the potential value increase can be reached, which is important to point out since an industrial CT scanner requires a large investment. For a sawmill to justify an investment in a CT scanner, it must be possible to increase profitability. Optimization of log breakdown is one example of how an industrial CT scanner can add value to the process.

A practical issue when curve sawing a crooked log and deviating from the horns down position is that the sawn timber may become warped during the drying process. Fredriksson et al. (2014) investigated the effect that a deviating log rotation had on the warp of the sawn timber after drying. Half of their 177 studied logs were sawn in the horns down position while the other half were rotated perpendicular to the horns down position when sawing. The latter position is considered to be the worst position for curve sawing, with respect to distortions in the sawn timber after drying, especially for curved logs. These authors found that for logs with a bow height less than 15 mm, an unconventional rotational position did not cause excess spring on the sawn timber. Bow and twist were not affected by the rotational position at all. Sawlogs with a bow height exceeding 15 mm account for about 40% of the sawlogs in Sweden (Grönlund, 1992), which means that 60% of the sawlogs can be rotated more freely without any excessive risk of spring in the sawn timber. The significance of the “horns down” position can also be discussed for a log with a bow height less than 15 mm. Such a log seems to be rather straight to the human eye, which also supports the observation that these are the logs that can be rotated more freely.

Another possible utilization of an industrial CT scanner is for sorting logs with respect to the value of the sawn timber or other value-added processed products. In the work described in this thesis, the possibility of
4.1. Use of CT scanning in a sawmill

Sorting logs suitable for finger-jointing was investigated. Figure 3.7b shows a comparison between the developed cross-cut simulation software based entirely on CT data and the industrial WoodEye scanner and optimizer with regard to the total volume yield of sawing and cross-cutting. The results obtained by the two methods were highly correlated \((r = 0.92)\), showing that it is possible to simulate the total volume yield of log sawing and cross-cutting before sawing the logs by using CT data. Since this is a finger-jointing process with only one finger-jointed end-product (Table 2.5), maximizing the total volume yield of sawing and cross-cutting is equal to maximizing the value of the finger-jointed end-product. The differences in total volume yield were large between different logs, which shows that an industrial CT scanner can be used to identify logs that are suitable as well as unsuitable for a specific end use. In Figure 3.7b, it is clear that the total volume yield is lower for the butt logs, since dead knots were not allowed at all on the finger-jointed end-product, and these are more frequent in the butt logs than in the middle and top logs.

It is also possible that industrial CT scanning can be used to predict the strength of sawn timber prior to sawing with a higher accuracy than existing models based on log outer shape and discrete X-ray scanning. The development of prediction models for the bending strength of sawn timber based on CT data showed that the coefficient of determination \((R^2)\) and the goodness of prediction \((Q^2)\) increase, and that the RMSE decreases for all dimensions of sawn timber when variables based on CT data are added to prediction models for bending strength (Table 3.3). However, the number of pieces of each dimension only enabled the use of a training set and no test set. Since only a training set was used there is a risk that the prediction models were optimized for the specific sawn timber in this study, i.e. the models were over-fitted. The model optimizations were focused on the \(Q^2\) value to mitigate such a possible effect, but nevertheless the number of observations were limited so it is important to emphasize the relative changes in the \(R^2\), \(Q^2\) and RMSE values between models rather than the absolute numbers.

The goodness of prediction achieved in Table 3.3 is higher than that achieved in a previous study by Brännström et al. (2007). For the model with discrete X-ray and 3D variables, the \(Q^2\) values were between 0.57 and 0.78 in Table 3.3 compared to 0.44 in Brännström et al. (2007). One explanation for this is that the prediction models developed within this work
use discrete X-ray variables as well as 3D variables, whereas Brännström et al. (2007) based their models solely on discrete X-ray variables. Another difference is that the CT scanning in this work was carried out in a laboratory environment in contrast to the discrete X-ray scanning which was performed by Brännström et al. (2007) in the log sorting at a sawmill where more noise is expected. The number of observations included per dimension of sawn timber was also less in the present work than in Brännström et al. (2007), and this increases the risk of over-fitting the models. These three features combined make it inadvisable to directly compare the results of the current study than with that of Brännström et al. (2007).

If a CT scanner is purchased, it is important for the sawmill to ensure that the competence and ambition to utilize the machine is well established within the company. As with discrete X-ray scanning, these types of equipment require continuous maintenance and calibration to make the most out of the investment. As industrial CT scanners become more frequent, manufacturers of sawing machines will probably be put under pressure to decrease the positioning errors as much as possible. It will also be a driving force for researchers and engineers to continue improving detection algorithms for the extraction of wood features from CT images, since this will have a direct impact on sawmill revenue.

Regarding the placement of a CT scanner in a sawmill, in my opinion the most likely place for a Swedish sawmill is in the log yard. This is where it should be easiest to adapt the material flow and make room for such a large installation, and the CT scanner can then be used for log sorting with respect to quality and different end uses. The results presented in this thesis, show how CT information can be used to sort logs with respect to sawing and subsequent cross-cutting and finger-jointing. However, it may also be possible to optimize the log position when sawing if the CT information about each log can be traced when the logs arrive at the sawing machines. There are a number of alternative methods for tracing measurement data of sawlogs. Two well-known non-contact methods are barcode identification and radio frequency identification (RFID). Barcode identification is used in almost every supermarket checkout counter, where the bars are optically read by a laser scanner. For RFID, an antenna picks up the RFID tag when it is within the antenna’s reading range (Finkenzeller, 2010). For traceability in forestry and sawmills, RFID is
4.2. Saw mismatch measurements

Saw mismatch is an important parameter to monitor if the saw blade thickness is to be reduced to increase volume yield. For this reason it is important to develop a measurement principle that works in a sawmill environment.

The results obtained when saw mismatch was measured on 20 pieces of sawn timber showed that laser triangulation measurements of saw mismatch were well correlated with manual measurements (Figure 3.9a). The RMSE was strongly affected by the measurements on 3 of the 20 pieces of sawn timber, where the laser triangulation measurement and the manual measurement deviated significantly from each other. The reason for this was that the laser triangulation unit did not detect the saw mismatch, but detected other surface unevenness instead. The manual measurement correctly measured the saw mismatch despite the surface unevenness. The standard deviation of the five repeated measurements on the 20 pieces of sawn timber show that the repeatability of the laser triangulation measurement was better than that of the manual measurement for a majority of the 20 pieces of sawn timber.

The correlation between maximal saw mismatch on the pith side and on the sapwood side proved to be weak ($r = 0.19$), indicating that a displacement of the cant (Figure 1.5a) was not the reason for the occurrence of saw mismatch on these 20 pieces of sawn timber. Had this been the case, the correlation between maximal saw mismatch on the two side faces would have been stronger.

The results presented in Table 3.5 indicate that it should be sufficient to measure mismatch on both side faces of the sawn timber at a specific position to detect a trend towards increasing saw mismatch. Nevertheless,
the measurement of saw mismatch in a sawmill is performed on only side of the sawn timber at a specific position. The reasoning behind this is that since the sawn timber passes randomly with pith side or sapwood side facing upwards on the conveyor, measurements will still be made randomly on both the pith side and sapwood side of the sawn timber. There are also other practical advantages in installing the camera with the lens face downwards, since difficulties with chips and dust covering the lens are then avoided.

The saw mismatch measurements in a sawmill resulted in the detection of a trend towards an increase in the frequency and size of saw mismatch over one day of production (Figure 3.11). This is interesting since it is possible that saw mismatch is a powerful indicator that the saw blades are becoming unstable or dull and that they should be replaced before a complete saw blade failure occurs. Such information would facilitate the use of thinner saw blades since it would then be easier to avoid production disruptions because of saw blade failure.

The PLS model that had the highest goodness of prediction ($Q^2$) when predicting saw mismatch was using the response variable defined according to Equation 2.9. The goodness of prediction was then about 0.135 and the window size used was set to 500 pieces of sawn timber with a threshold value of 0.5 mm (Table 3.6). This result means that 13.5% of the variance in this response variable can be predicted by the PLS model using average log top diameter, cant height and feed speed as predictor variables. The goodness of prediction was not so dependent of window size, since the value of $Q^2$ for a given threshold value was fairly constant with different window sizes. The choice of threshold value is more important and it appears that a threshold value in the interval 0.3 to 0.5 mm is the best choice in this case.

The PLS coefficients (Figure 3.12) show that the cant height, average log top diameter and feed speed are all positively correlated with the saw mismatch. This means that increasing feed speed in the sawmill as well as increasing log size both tend to increase the size and frequency of saw mismatch. It should be pointed out that a goodness of prediction of 13.5% is a small value, it is probably the differences in frequency and size of saw mismatch between different sawing classes that is predicted by the strongly correlated predictor variables. Still it is interesting that all variables are positively correlated with the saw mismatch, even though the
feed speed is negatively correlated with the cant height and the average log top diameter.

To improve the prediction of the variability in saw mismatch, additional variables need to be considered. It is of interest to investigate whether properties related to the saw blades can explain more of the variability in saw mismatch. If so, this could provide useful information for how to reduce the thickness of saw blades without increasing the risk of saw mismatch as well as saw blade failure. Properties of saw blades that are interesting to look at in this context would be for example the collar size and number of saw teeth on the saw blade. One can also speculate on how many times a saw blade should be resharpened or equipped with new tooth tips, or if it is better to switch to a new saw blade earlier. To accomplish this, a fixed laser triangulation unit integrated into the sawmill data system must be installed so that the properties of the saw blades can be thoroughly varied and recorded.

4.3 Customer-adapted grading

Customer-adapted grading using multivariate methods for the grading of sawn timber can be a complement to rule-based grading. The results obtained have shown that it is possible to have satisfied customers at the same time as sawmill revenues are increased when using multivariate grading methods.

It is clear that, according to the expert, the total proportion of correctly graded sawn timber is higher with multivariate grading using grading limits $L_A = 0.28$ and $L_C = 0.78$ (Table 3.8) than with rule-based grading (Table 3.7). The total proportion of correctly graded sawn timber was 76% with multivariate grading and 63% with rule-based grading. The multivariate grading also had a larger proportion of higher grade sawn timber 32% and 51% for grades A and B, respectively, compared with 24% and 31% for rule-based grading. The proportion of grade A increased by 8 percentage points and the proportion of grade B increased by 20 percentage points using multivariate grading instead of rule-based grading.

To evaluate customer satisfaction, a good measure is the proportion of sawn timber that is graded correctly or where the grade has been underestimated. For a customer, a correct grade is of expected quality and
A discussion paper analyzed the impact of grading sawn timber using multivariate methods compared to traditional rule-based systems. An underestimated grade can mean the customer purchases timber of higher quality at a lower price. Using multivariate grading with specific threshold values, the customer expert found that 78% of timber was correctly or underestimated graded compared to 87% with rule-based methods. The customer would prefer to purchase more timber of apparently higher grade at a lower price with rule-based grading.

Using threshold limits $L_A = 0.28$ and $L_C = 0.78$, the multivariate grading led to a higher proportion of higher grades, but at the expense of customer satisfaction. The expert observed a 28% and 41% proportion of grade A and B timber, respectively, compared to 24% and 31% with rule-based grading. The proportion of grade A increased by 4 percentage points, and the proportion of grade B increased by 10 percentage points using multivariate grading with less challenging threshold limits $L_A = 0.34$ and $L_C = 0.41$.

Customer satisfaction improved with the configuration of threshold limits, showing a 92% proportion of correctly or underestimated grades compared to 87% for rule-based grading. The customer would buy more high-grade timber at a lower price with multivariate grading.

Economically, a sawmill producing 400,000 m$^3$ annually and current prices of €198, €170, and €142 for grades A, B, and C, respectively, could benefit. With an important customer purchasing 100,000 m$^3$, this sawmill has a high customer satisfaction rate. The sawmill's annual production is 25% of the sawmill's annual production. The economic benefits include more high-grade timber purchased at a lower price.
had a grade distribution of 24%, 31% and 45% for grades A, B and C respectively (Table 3.7). Using the multivariate models with grading limits \( L_A = 0.28 \) and \( L_C = 0.78 \) the grade distribution was 32%, 51% and 17% (Table 3.8). Using the grading limits \( L_A = 0.34 \) and \( L_C = 0.41 \), the distribution was 28%, 41% and 31% (Table 3.9). Assume that each of the three grading strategies was used to grade the 100,000 m³ of sawn timber for the important customer and that the grade distributions were the same as for the 323 pieces of sawn timber. Grading using \( L_A = 0.28 \) and \( L_C = 0.78 \), the sawmill would increase their revenue by €1,008,000 annually compared with rule-based grading. This corresponds to a 6% annual increase of revenue compared with rule-based grading. Grading using \( L_A = 0.34 \) and \( L_C = 0.41 \), the sawmill would increase their revenues by €504,000 compared with rule-based grading. This corresponds to a 3% annual increase of revenues compared with rule-based grading. This rough calculation example shows the economical benefit of introducing multivariate grading in a sawmill. Choosing threshold limits (\( L_A \) and \( L_C \)) for grade separation is a trade off between increased sawmill revenue and customer satisfaction. To which extent the proportion of higher grades can be increased to increase sawmill profitability depends on customer preferences and on the current market situation. In times of high market demand, customers’ quality requirements tend to be more tolerant than when the market demand is low.

To calibrate PLS models for multivariate grading, as with any other statistical method, a reliable and representative data set is essential (Eriksson et al., 2000). In the present case, this depends on how well the customer expert has described customer preferences on the North African market. Knowledge of how large the training set needs to be in order to have a representative data set is limited in this context. In the present work, 323 pieces of sawn timber were used as training set where 78 pieces of sawn timber were of grade A, 143 of grade B and 102 of grade C according to the customer expert. The experience was that this was satisfactory, even though more pieces of grade A in the training set would have been preferred. Lycken and Oja (2006) suggested that 100 pieces of sawn timber of each grade would be necessary to calibrate a model and this seems reasonable. There is no upper limit for the number of pieces of sawn timber of each grade that can be used in a training set. The limiting factor is that the work load to perform such a manual grading must be feasi-
ble. Another question is to what extent the same models can be used on similar dimensions of sawn timber or whether separate models need to be calibrated for different dimensions of sawn timber. The advantage is that once data relating to customer preferences has been collected and multivariate models created, these models can be used for a longer time and threshold limits can be adjusted as desired.
The main question asked of the work described in this thesis was how the sawing of logs into sawn timber can be performed more efficiently with respect to the choice of raw material, volume and value yield in the sawing and in the grading of the sawn timber produced. The work is focused on the two commercially most important species in Sweden, the softwoods Scots pine and Norway spruce.

The first objective was to investigate whether data from a CT scanner can be used to optimize the breakdown of sawlogs with respect to the appearance and bending strength of the sawn timber. Simulations of rotational optimization of sawlogs have shown that there was an average relative value increase in reference to the horns down position of 16% for appearance graded sawn timber and 11% for visually strength graded sawn timber. When a rotational error was introduced, the average relative value increase dropped to 9% for appearance grading and 6% for visual strength grading. This leads to the conclusion that it is possible to optimize the log rotation of sawlogs to obtain a higher value of appearance graded and strength graded sawn timber by using information from a CT scanner, also when considering a typical rotational error of a sawing machine.

The second objective was to investigate the effect that errors in knot detection algorithms had on a rotational optimization based on CT data. The conclusion is that the value of the sawn timber when performing a rotational optimization is effected negatively of errors in knot detection and that the gain in value of a rotational optimization is increased if im-
Conclusions

proving the knot detection. It is most important to improve the detection of the knot diameter followed by the detection of the dead knot border.

The third objective was to develop and validate a simulation software for the cross-cutting of sawn timber and to investigate how the total volume yield in the sawlog, sawn timber, finger-jointed end-product chain varies for different logs. The high correlation between the total volume yield simulated using CT data and the total volume yield obtained from an industrial scanner leads to the conclusion that a CT scanner can be used for log sorting with respect to sawing and subsequent cross-cutting and finger-jointing. Sawlogs that would result in a poor total volume yield in the upcoming cross-cutting optimization can be identified, and instead used for other applications and other customers.

The fourth objective was to develop a model that can predict the bending strength of sawn timber based on CT data with a greater accuracy than existing models based on log outer shape and discrete X-ray scanning. The coefficient of determination ($R^2$) and the goodness of prediction ($Q^2$) increase, and the RMSE decreases for all evaluated dimensions of sawn timber when variables based on CT data are added to prediction models for bending strength. The conclusion is that the prediction of bending strength of sawn timber is performed with greater accuracy using CT scanning of sawlogs than with discrete X-ray scanning combined with 3D-scanning, even when there are uncertainties in the sawing pattern position.

The fifth objective was to develop a method for measuring and evaluating saw mismatch in a sawmill. The high correlation between the laser triangulation measurement of saw mismatch and the manual measurement of saw mismatch as well as the improved repeatability using laser triangulation lead to the conclusion that laser triangulation measurement of saw mismatch is comparable with manual measurement. The measurement of saw mismatch in a sawmill using laser triangulation also leads to the conclusion that saw mismatch can be a powerful indicator that the saw blades are becoming unstable or dull and should be replaced before a complete saw blade failure occurs.

The sixth objective was to develop an automatic grading method that more easily is adapted to customer preferences than currently used automatic grading systems and at the same time increase sawmill profitability. The conclusion is that by grading sawn timber using a multivariate method
it is possible to increase the proportion of higher sawn timber grades by up to 10 percentage points while customer satisfaction is maintained, which means a possibility to increase sawmill profitability.

All in all, this thesis shows how different scanning techniques and different types of computer modelling can be used to utilize the raw material in a sawmill more efficiently. CT scanning of sawlogs can be used to increase the value of the sawn timber by a more efficient log sorting and sawing optimization, but also to enhance predictions of the bending strength of sawn timber. Laser triangulation is used to measure saw mismatch in sawmills which can be an indicator of unstable or dull saw blades. Multivariate prediction models are used to grade the sawn timber more efficiently which means that it is possible to increase sawmill profitability.
Future work in the field of industrial CT scanning should include taking the step from simulation studies to real practice by investigating the potential of this new technology in a Swedish sawmill. Purchasing an industrial CT scanner is a large investment and will have to be a joint venture between Swedish industry and academia. If this is possible, the potential for rotational optimization with respect to both appearance grading and strength grading could be verified and the greater possibilities of sorting sawlogs for different end-uses. Installing a CT scanner would also require a decision as to where to install it in a sawmill. Placing the CT scanner in the log sorting station would mean that it could be used for log sorting and possibly also sawing optimization, provided the sawlog can be recognized at the sawing machine and information showing how to optimize the log breakdown can be traced. Placing the CT scanner close to the sawing machine would mean that it can definitely be used for sawing optimization, but not for log sorting. A demonstration unit showing the potential of industrial CT scanning would probably put pressure on sawing machine manufacturers and lead to improvements in log positioning as well as in wood feature extraction algorithms.

The work involving models for predicting bending strength of sawn timber also needs to be continued. It was observed that there is a contribution from variables extracted from CT data in the development of these prediction models. Further studies should include variables that are focused on individual knots in the sawn timber, and whether these are subject to compressive or tensile stress. In our study, it was not possible
to keep track of the exact position of individual knots. To accomplish this, it would be better to CT-scan sawn timber instead of using data from CT-scanned logs. Uncertainties in log position when sawing the logs could then be eliminated.

When measuring saw mismatch, it is essential to be able to relate the properties of the saw blades to the frequency and magnitude of saw mismatch. To achieve this, a good tracking system for when different saw blades have been used must be developed. Such an investigation would facilitate our understanding of how and when problems with saw mismatch occur.

The further development of customer-adapted grading using multivariate methods involves tests in a sawmill during ongoing production. This would provide access to a larger material of sawn timber and also an opportunity to evaluate this type of method for other markets and customers than the one investigated in this thesis. It is also necessary to standardize the procedure for calibrating the multivariate models against a new customer or market. To accomplish this, the way in which the calibration procedure is affected by the dimensions of the sawn timber and by the number of pieces of sawn timber used to calibrate the models must be investigated. The question of trimming optimization when using this multivariate method also needs to be studied, although this has not been considered in this thesis.


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Paper I

Improved log rotation using information from a 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.

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 (Pinus 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 Swedish stem bank (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 Rönqvist, 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 (Swedish Sawmill Managers Association, 1994). 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 sawing class (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.

<table>
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<th>SC</th>
<th>Sawing pattern (mm)</th>
<th>Top diameter lower limit (mm)</th>
<th>Top diameter upper limit (mm)</th>
<th>First saw (mm)</th>
<th>Second saw (mm)</th>
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<td>449</td>
<td>25, 200, 25</td>
<td>19, 25, 63, 25</td>
</tr>
<tr>
<td>16</td>
<td>75 by 200 by 4</td>
<td>449</td>
<td>449</td>
<td>25, 200, 25</td>
<td>19, 25, 75, 25</td>
</tr>
</tbody>
</table>
2. Materials and methods

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 $[-180^\circ, 180^\circ)$, where the rotation angle of $0^\circ$ 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 $0^\circ$ and a typical standard deviation of $5^\circ$. Note that from now on, if not specified, the normal price differences between the quality grades have 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 (Swedish Sawmill Managers Association, 1994), boards classified as grade D are chipped.

<table>
<thead>
<tr>
<th></th>
<th>PINE &amp; SPRUCE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Centre boards grade A</td>
<td>194</td>
</tr>
<tr>
<td>Centre boards grade B</td>
<td>180</td>
</tr>
<tr>
<td>Centre boards grade C</td>
<td>146</td>
</tr>
<tr>
<td>Side boards grade A</td>
<td>247</td>
</tr>
<tr>
<td>Side boards grade B</td>
<td>157</td>
</tr>
<tr>
<td>Side boards grade C</td>
<td>140</td>
</tr>
</tbody>
</table>

The simulations resulted in value as a function of log rotation for each log, as shown in Figures 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. Partial least squares discriminant analysis (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 $5^\circ$ wide, but not wider than $20^\circ$. 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 ±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°).
The distribution of log rotation for greatest profit return for the 408 selected logs. The rotation angle of $0^\circ$ corresponds to the horns down position.

The predictors used in the PLS-DA were:

- Volume ($V$) [$m^3$ sub]
- 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

$$ T = \frac{D_{BUTT} - D_{TOP}}{L}. $$

(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
2. Materials and methods

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

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

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

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}.](image)

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
3. Results and discussion

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 $1^\circ$, $5^\circ$, $10^\circ$, $20^\circ$, $45^\circ$ and $90^\circ$.](image)

Figure 8 shows the mean of the value increase and the mean of the yield increase when a normally distributed rotational error with mean $0^\circ$ and standard deviation of $5^\circ$ 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.
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.

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.
3. Results and discussion

![Graph showing mean value and yield increase with standard deviation 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 ±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
4. Summary and 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.

References


Value optimized log rotation for strength graded boards using computed tomography

Authors:
Anders Berglund, Erik Johansson, Johan Skog

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Abstract

A possible application for an industrial computed tomography scanner in a sawmill is for finding an optimal rotational position of logs with respect to knots and outer shape. Since a computed tomography scanner is a great investment, it is important to investigate potential profitability of such an investment for different production strategies. The objective of this study was to investigate the potential value increase of the sawn timber of Norway spruce (Picea abies (L.) Karst.) by rotating logs to their optimum position prior sawing compared with sawing all logs in horns down position. The production strategy evaluated by log breakdown simulation in this case study was to produce strength graded timber of the center boards, while the side boards were appearance graded. This case study showed an average value increase with respect to the value of center boards, side boards and chips of 11%.

1 Introduction

An industrial CT scanner for the sawmill industry (Giudiceandrea et al., 2011) leads to questions regarding production strategies, and how to increase the profit return if making the investment of such a scanner. A CT scanner will make three dimensional information about the inner properties, e.g. knots, of the log available at production speed. One way to utilize this information is to optimize the rotational position of each log that is processed at the saw line. The idea is to find the rotational position of each log that results in the most high-valued products.

In earlier work by Berglund et al. (2013), log breakdown was simulated for about 800 Norway spruce logs and 600 Scots pine logs from mainly Sweden and Finland, but also France. This made it possible to investigate the profitability in an improved log rotation when using CT data to optimize the rotational position. In that study, all sawn timber was appearance graded according to the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). Consideration was given only to knots and wane when determining the board grade. An increased average value recovery of 13% was found using the log rotation for greatest profit.
return for each log. An introduced rotational error of the sawing machine reduced the increased average value yield to 6%.

Some sawmills produce and sell strength graded timber instead of, or in addition to, appearance graded timber. It would be useful to investigate the profitability of using a CT scanner at the saw line to optimize this breakdown process. Since internal features of logs, such as knots, can be detected, there should be a possibility for rotating logs to avoid edge knots and arris knots and thereby increasing the share of high strength boards. Such an investigation would be useful when evaluating if the results of Berglund et al. (2013) are applicable to sawmills producing strength graded timber or if the obtained value recovery mainly depends on the grading rules.

When using timber in load-bearing constructions, strength and stiffness of the material have to be within ensured limits (Johansson, 2003). Using wood for construction is somewhat different compared with other engineering materials such as steel or concrete, where strength and stiffness of the material more easily can be controlled. To control mechanical properties of wood and to ensure dimensional strength of a construction, wood is graded according to grading rules. There are two methods under use to measure board strength, namely visual strength grading and machine strength grading.

Visual strength grading, as the name implies, ensures that the visible defects on a board does not exceed the limits specified by the grading rule. Visual strength grading in Scandinavia is performed according to the Nordic standard (Swedish Standards Institute, 2010). The Nordic standard pertains to Scots pine (Pinus sylvestris L.), Norway spruce (Picea abies (L.) Karst.), Sitka spruce (Picea sitchensis (Bong.) Carr.), Silver fir (Abies alba Mill.), Douglas fir (Pseudotsuga menziesii (Mirb.) Franco) and Larch (Larix decidua Mill., Larix eurolepis, Larix kaempferi (Lamb.) Carr.). Timber graded according to this standard is sorted into classes T3, T2, T1 and T0.

The objective of this work was to investigate, by log breakdown simulations, how the log rotation affects the value outcome of visually strength graded timber according to the Nordic standard (Swedish Standards Institute, 2010). The production strategy of this case study was from the perspective of a sawmill in northern Sweden processing Norway spruce (Picea abies (L.) Karst.) to produce strength graded timber of the cen-
ter boards, while the side boards are graded according to the appearance grading in the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). The reason for grading the center boards by visual grading is that visual grading can be taken under consideration prior to sawing using an industrial CT scanner since internal features like knots can be detected (Johansson et al., 2013).

2 Materials and methods

2.1 The European spruce stem bank

The material used in this study comes from the European spruce stem bank (ESSB) (Berggren et al., 2000), which consists of data from about 800 Norway spruce \((Picea abies \text{ (L.) Karst.})\) logs. The logs origin from 31 plots in different geographic locations, where the largest share is from Sweden, but also plots from Finland and France are represented.

When collecting these logs, six trees were chosen in each plot; 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 of the stand, with class limits at half a standard deviation above and below this mean (Björklund and Moberg, 1999). The diversity of the logs in the ESSB with respect to diameter, outer shape and knot structure makes them good examples of logs in the Scandinavian countries, and thereby suitable for the objective of this study.

The logs were scanned using a medical CT scanner (Siemens SOMATOM AR.T) and the resulting CT images show the log outer shape, as well as internal features such as 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). All logs were scanned every 10 mm and the resulting images of each CT slice had \(512 \times 512\) pixels with 12 bit gray scale values.

The description of log outer shape and knots in the ESSB makes it possible to simulate log breakdown of these logs.
2.2 Log breakdown simulation

Log breakdown simulation has the advantage that it can be carried out in a relatively short time frame and the input data can be processed an infinite number of times. This makes relative studies possible by comparing different methods or strategies on the same material. These reasons have made it widely used in the field of wood technology (Björklund and Julin, 1998; Todoroki and Rönqvist, 1999; Nordmark, 2005).

In this work the Saw2003 software (Nordmark, 2005) was used since it is developed to interact with the data in the ESSB. This software has been validated both with respect to value and yield in previous studies (Chiorescu and Grönlund, 2000). Within the software, the outer shape of the log is described by a cross section every 100 mm whereas knots are described using full information from the CT images (every 10 mm). The software performs simulation of cant sawing with curve sawing in the second saw, 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 center boards.

![Figure 1: Cant sawing. The first sawing machine cuts the log into side boards and a cant. The cant is then rotated by 90° and cut by the second sawing machine into side boards and center boards. Side boards are further processed by edging and trimming, while trimming is the only operation on center boards.](image-url)
The breakdown simulations are controlled by setting the sawing patterns for the different log top diameter classes, the properties of the simulated sawing machine (e.g. kerf width), the grading rule settings, and the prices for center and sideboards of different grades. In the simulation of the sawing process, trimming and edging is value optimized with respect to the specified prices of the sawn timber. Only knots and wane are considered in this optimization.

**Grading**

In general, spruce side boards are not strength graded in Sweden due to the small cross section. Side boards of spruce are also demanded for other types of products, such as outdoor claddings for example. Consequently, the side boards in this study were appearance graded using Saw2003. The grading of the simulated boards in Saw2003 is carried out according to appearance grading rules for knots and wane specified in the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). Knots and wane are the most important features for board grading in Scandinavia and this is why the majority of grading rules are related to these features. The Nordic timber grading rules separate the boards into three different grades, A, B and C, where grade A is considered as the best grade and grade C the worst. Consequently, market prices for grade A are higher than prices for grade B, etc. Boards not fulfilling the requirements for either of these grades are turned into chips in the simulation.

The center boards were outputted from Saw2003 and strength graded and trimmed according to the visual grading described in the Nordic standard (Swedish Standards Institute, 2010) using the software MATLAB version R2012b. Timber graded according to the Nordic standard is divided into sorting classes T3, T2, T1 and T0 with corresponding strength classes C30, C24, C18 and C14. The numbers in these strength class names correspond to bending strength in MPa.

The grading was simplified and only carried out with respect to knots and wane on the boards since these defects are most important for appearance graded and strength graded timber. Information regarding other wood features such as annual ring width, splits, rot, resin pockets, top rupture etc. was not accounted for. Additionally, for the strength grading according to Swedish Standards Institute (2010), an arris knot lying
completely or partly within wane should according to the standard be measured as an edge knot, but it was still measured as an arris knot. No special consideration was given to splay knots occurring as a consequence of top rupture.

The strategy investigated in this study was to produce center boards of sorting class T3 or T2. The center boards that did not fulfil the requirements for grade T3 or T2 were sold at a lower price.

**Sawing patterns, machine properties and prices**

The sawing patterns used in the simulations are shown in Table 1 where the logs, depending on their top diameter, were sorted into their respective SC. The sawing allowance, e.g. shrinkage as well as deviations in the sawing, used in the simulation 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.

The prices per volume unit of sawn timber used were relative with respect to center boards of grade T2. In Table 2 the relative prices are presented for each grade. There is a steep drop from strength grades T3/T2 down to strength grade T1/T0/Reject. This is because spruce logs in northern Sweden in general are of high quality. If the sawn boards do not fulfil the requirements for strength grades T3/T2, they are used for products sold at a significantly lower price. The price drop from appearance grade A and B down to grade C, is because spruce side boards of grades A and B are used for construction purposes, while side boards of grade C are used for packaging. The prices are representative for a sawmill in northern Sweden producing strength graded center boards and appearance graded side boards, according to industrial contacts. Unfortunately it was not possible to give a reference for prices of sawn timber in northern Sweden since these are not published due to competition between sawmills.
2. Materials and methods

Table 1: The logs are sorted into a SC with respect to their top diameter. The first saw determines the width of the center boards and the thickness of the side boards in the first saw. The second saw determines the thickness of the center boards and additional side boards. All measures are nominal target values.

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<th>Top diameter range (mm)</th>
<th>First saw (mm)</th>
<th>Second saw (mm)</th>
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<tbody>
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<td>130–149</td>
<td>19, 100, 19</td>
<td>19, 38, 38, 19</td>
</tr>
<tr>
<td>2 50 by 100 by 2</td>
<td>150–169</td>
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<td>25, 50, 50, 25</td>
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<td>4 63 by 125 by 2</td>
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<td>14 63 by 200 by 4</td>
<td>345–384</td>
<td>25, 32, 200, 32, 32</td>
<td>25, 25, 63, 63, 63, 63, 25, 19</td>
</tr>
</tbody>
</table>

Table 2: Price list with price differentiation between board grades. The prices are relative with the price for center boards grade T2 as reference.

<table>
<thead>
<tr>
<th>Board type</th>
<th>Center boards</th>
<th>Side boards</th>
<th>Chips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grade</td>
<td>T3</td>
<td>T2</td>
<td>T1</td>
</tr>
<tr>
<td>Price/m³</td>
<td>106</td>
<td>100</td>
<td>68</td>
</tr>
</tbody>
</table>
2.3 Simulation runs

Simulation of curve sawing of all logs in the ESSB was performed in each angle of rotation in the interval \([-90^\circ, 90^\circ]\), where the rotation angle of 0° corresponds to the horns down position. 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). This log positioning prior to sawing is common practice in the Scandinavian sawmills when applying curve sawing.

The outcome of the simulations are two functions: the value recovery, \(V\), and the volume yield, \(Y\), of the boards as functions of rotation angle. These are defined as

\[
V = f(\theta), \quad \theta \in [-90^\circ, 90^\circ], \\
Y = g(\theta), \quad \theta \in [-90^\circ, 90^\circ],
\]

where \(\theta\) is the log rotation angle and \(\theta = 0^\circ\) is set as the horns down position. The value function, \(V\), and yield function, \(Y\), with respect to the strength graded center boards of one example log are shown in Figure 2. In the case where strength graded center boards, side boards and chips are considered, the value and yield functions look similar to the respective functions in Figure 2.

Let \(\theta_{i}^{\text{max}}\) be the rotational position of log \(i\) relative to horns down that maximizes the value. If there are \(N\) logs, the average value recovery relative to horns down is

\[
V_{\text{rel}}^{\text{max}} = \frac{1}{N} \sum_{i=1}^{N} V_{i}(\theta_{i}^{\text{max}}) \frac{V_{i}(0)}{V_{i}(0)}. 
\]

The average yield change for these choices of \(\theta\) is calculated as

\[
\Delta Y_{\text{rel}}^{\text{max}} = \frac{1}{N} \sum_{i=1}^{N} (Y_{i}(\theta_{i}^{\text{max}}) - Y_{i}(0)).
\]
2. Materials and methods

2.4 The effect of an error to the angle of rotation

A rotational error in a sawing machine is in this article assumed to be normally distributed $Z \sim \mathcal{N}(\mu, \sigma)$, where $\mu$ is the expected value and $\sigma$ is the standard deviation. In this study, the values of $\mu$ and $\sigma$ were chosen as $\mu = 0^\circ$ and $\sigma = 6^\circ$, which are typical error levels for rotational error of a circular sawline in a Scandinavian sawmill (Heinola sawmill solutions, 2014). An estimate of the expected value and yield function of a sawing machine with a rotational error from a distribution $Z \sim \mathcal{N}(0^\circ, 6^\circ)$ was obtained using a Gaussian filter with $\sigma = 6^\circ$ and window size $W_S = 6\sigma - 1 = 6 \cdot 6 - 1 = 35^\circ$. Figure 3 shows an example of the effect of applying the Gaussian filter on the same value and yield functions as in Figure 2.

Figure 2: The value function (a) and yield function (b) with respect to the strength graded center boards of a log. The value is relative to the value at the horns down position where the rotation angle of $0^\circ$ corresponds to the horns down position.
Figure 3: The filtered value function (a) and the filtered yield function (b) obtained by applying a Gaussian filter to the value and yield function shown in Figure 2a and Figure 2b. The Gaussian filter had a standard deviation of $\sigma = 6^\circ$ and a window size of $W_S = 35^\circ$. The rotation angle of $0^\circ$ corresponds to the horns down position.

3 Results

3.1 Center boards

Table 3 shows the resulting average value increase and yield change for center boards when simulating log breakdown in the value optimizing log rotation compared with the horns down position. The corresponding value for each SC is also shown as well as the results when a rotational error from a distribution $Z \in N(0^\circ, 6^\circ)$ is present.

For an ideal rotation, the average value increase for all SC was 11% compared with 6% with a rotational error. The corresponding change in volume yield was 0 percentage points in average both for an ideal rotation and with a rotational error. Histograms of center board value increase and yield change for the optimizing log rotation in reference to horns down are shown in Figure 4a and 4b. Figure 4c presents center board grade distribution for the rotational position that results in the optimum value of the center boards and for the horns down position. There was a shift of center board grades mainly from grade T1 at horns down position to grade T2 at the value optimized position.
Table 3: Average value increase in percent and average yield change in percentage points in reference to horns down position and when choosing the log rotational position that maximizes the value of the center boards as well as the total value of all products (center boards, side boards and chips). Values both for an ideal and with an applied rotational error, $Z \in \mathcal{N}(0^{\circ}, 6^{\circ})$, are presented. $N$ is the number of logs in corresponding SC used in the simulations. The average value increase and average yield increase over all logs are the weighted means.

<table>
<thead>
<tr>
<th>SC</th>
<th>N</th>
<th>Center boards</th>
<th></th>
<th>All products</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average value increase (%)</td>
<td>Average yield increase (pp)</td>
<td>Average value increase (%)</td>
<td>Average yield increase (pp)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>86</td>
<td>Ideal</td>
<td>8</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>64</td>
<td>Ideal</td>
<td>9</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>63</td>
<td>Ideal</td>
<td>9</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>46</td>
<td>Ideal</td>
<td>9</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>7</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>55</td>
<td>Ideal</td>
<td>10</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>8</td>
<td>5</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>37</td>
<td>Ideal</td>
<td>11</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>6</td>
<td>3</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>35</td>
<td>Ideal</td>
<td>15</td>
<td>6</td>
<td>1</td>
<td>0</td>
<td>12</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>68</td>
<td>Ideal</td>
<td>14</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>7</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>47</td>
<td>Ideal</td>
<td>17</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>14</td>
<td>7</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>57</td>
<td>Ideal</td>
<td>11</td>
<td>6</td>
<td>1</td>
<td>0</td>
<td>11</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>43</td>
<td>Ideal</td>
<td>11</td>
<td>6</td>
<td>1</td>
<td>1</td>
<td>9</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>36</td>
<td>Ideal</td>
<td>14</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>13</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>22</td>
<td>Ideal</td>
<td>12</td>
<td>6</td>
<td>1</td>
<td>0</td>
<td>9</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>18</td>
<td>Ideal</td>
<td>13</td>
<td>6</td>
<td>0</td>
<td>1</td>
<td>10</td>
<td>5</td>
<td>2</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>677</td>
<td>11</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>11</td>
<td>5</td>
<td>2</td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 4: Value increase in percent (a) and change in volume yield in percentage points (b) compared with the horns down position when simulating log breakdown in the rotational position that maximizes the value of the strength graded center boards. The grade distribution of the strength graded center boards for the horns down position and for the rotational position that maximizes the value of the center boards are shown in (c).
3.2 Center boards, side boards and chips

Results when considering the total value of center boards, side boards and chips are also shown in Table 3. The average value increase for an ideal rotation and with a rotational error applied were 11% and 5% respectively. Change in volume yield was 2 percentage points in average for an ideal rotation and 1 percentage point in average with a rotational error present. Histograms of value increase and yield change are presented in Figure 5a and 5b. The grade distribution of the center boards for this case is shown in Figure 5c.

![Figure 5: Value increase in percent (a) and change in volume yield in percentage points (b) compared with the horns down position when simulating log breakdown in the rotational position that maximizes the total value of the strength graded center boards, appearance graded side boards and chips. The grade distribution of the strength graded center boards for the horns down position and for the rotational position that maximizes the total value are shown in (c).](image-url)
Comparing the optimal rotational position between Figure 4c and 5c, it is clear that the grade distributions of the center boards were almost unaffected when adding side boards and chips as parameters to the optimization. To better understand this result, tests were performed showing that for 281 out of the 677 logs (42% of the logs), the optimal rotational positions with and without the addition of side boards and chips were identical. It is expected that the optimal rotational position would be the same for a large share of logs, since the volume of center boards is higher in relation to the volume of the side boards and thus affects the choice of optimal rotational position to the greatest extent. For the remaining 396 logs (58% of the logs), there were just minor changes in the center board grade distribution even though there were changes in rotational position.

Discussion

A major discussion point is how the results of this simulation study can be applied to a Scandinavian sawmill sawing Norway spruce. This requires an understanding of how grading rules and price scenario affect the results. Also, practical considerations such as errors in log positioning and knot detection in CT images are important. In this section, these topics will be discussed together with the effects other wood properties and defects have on the results.

The results of this study are consistent with the results obtained by Berglund et al. (2013), where the boards were appearance graded according to the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). Both that set of grading rules and the strength grading rules used in this study (Swedish Standards Institute, 2010) are based on knots visible on board surfaces. There are, however, some distinct differences between the two standards. For example, whether the knots are sound or dead and the position of knots are assessed differently depending on which of the two standards that is used. This implies that the production strategy of using a CT scanner to rotate logs to their optimal position is robust for grading rules focused on knots.

Another result from Berglund et al. (2013) is that when increasing the price differentiation between grades, the value increase between horns down and the optimal rotational position becomes higher. This would
3. Results

likely be the effect in the current study as well. The grade distributions in Figure 4c and 5c would be skewed toward T3 and T2 since it would be more profitable to produce boards of higher quality. Prices of sawn timber used in this study were obtained through industrial contacts, but prices vary both through time and between sawmills. However, the prices used in this study are a good reference point when investigating the profitability using different price levels.

No sawing machine is perfect when it comes to the positioning of the log when sawing. There are positioning errors in rotation, skew and lateral directions. From the simulations in this work, it is evident that a rotational error in the sawing machine reduces the average value increase, but that it is still profitable to rotate each log individually to obtain a higher value recovery. This means that a reduction in rotational error of the saw line results in a higher value recovery for a sawmill with a production strategy similar to the case in this study. This fact should put pressure on the manufacturers of sawing machines to reduce the positioning errors as much as possible. There are also errors in the detection of log features in the CT images, causing for example knots to be detected as larger or smaller than in reality. For appearance and visual strength grading rules, the detection of knots is the most important wood feature for the grade of the sawn boards. It was found in a study by Breinig et al. (2013) that knot detection errors of higher magnitudes than those reported by Johansson et al. (2013) still resulted in an improvement of value recovery when simulating a rotational optimization.

Another practical issue is that when curve sawing a crooked log and deviating from the horns down position, the sawn timber might be warped during the drying process. To better understand this, Fredriksson et al. (2014) investigated the effect that a rotational optimization would have on the warp of the sawn timber after drying. Half of their 177 studied logs were sawn in the horns-down position while the other half was sawn rotated perpendicular to horns down position. The later position is considered as the worse position when applying curve sawing and with respect to board distortions after drying, especially for curved logs. They found that for straight logs, with a bow height less than 15 mm, an unconventional rotational position did not cause excess spring in the boards. Bow and twist were not affected by the rotational position at all.
A limitation of the current study is that some defects and properties affecting the strength grade in Swedish Standards Institute (2010) are omitted in the current study. These include annual ring width, spiral grain and splay knots due to top ruptures. Splay knots is the most important defect of the three and if such knots appear on board surfaces, they have a large impact on strength grading. If splay knots would be included in the simulations of this study, it is reasonable to expect that the difference in value would increase between the optimal rotational position and horns down. In other words, rotational optimization would be even more beneficial. The reasoning behind this is that for logs with top ruptures, the calculated total value of all sawn products would be lower if those top ruptures would be accounted for when grading the boards. This applies to both horns down and the optimal rotational position, but in the latter case, information of top ruptures can be included in the optimization process. If horns down rotational position is used, the placement of splay knots will be purely random. When it comes to annual ring width and spiral grain, these properties and defects would likely have a limited impact on the results of this study. These properties do not vary in the same way as knots with respect to rotational position and would therefore affect boards sawn with different rotational positions to approximately equal extent.

All things considered, it seems to be profitable to use a CT scanner to rotate logs prior sawing for a sawmill producing strength graded spruce boards. This holds even when various practical issues and error sources are considered. There are, however, several aspects of sawing real logs at a sawmill that differs compared with sawing their virtual counterparts in a simulator. The best way to validate the profitability of rotating logs to their optimal positions is to perform actual tests at a sawmill. A drawback of this compared with a simulation study is that a real log only can be sawn into boards once, hence no rotational optimization in reference to horns down based on CT data can be obtained for individual logs. However, such practical tests can be performed in other ways, for example by sawing a group of logs in the horns down position while another group of logs are sawn in their value optimizing position based on CT data. The difference in value outcome between the two groups could then be compared. Without access to an operational industrial CT scanner in a sawmill, such a study would however be very time-consuming. Simulation
studies, such as described in the current paper, are therefore important in order to motivate more expensive studies.

Conclusions

The main conclusions of this article are that

- There is a possibility for Scandinavian sawmills producing strength graded spruce boards to increase their profitability by using a CT scanner to rotate logs prior sawing.

- If using a CT scanner to optimize log rotation with respect to the value of visually strength graded center boards, appearance graded side boards and chips, the average value increase for the logs in this case study was 11%.

- A normally distributed rotational error with expected value $\mu = 0^\circ$ and standard deviation $\sigma = 6^\circ$ reduced the average value increase to 5%.

- The average value increase for the strength graded center boards only was 11% for an ideal rotation and 6% with a rotational error present.

- The main reason for the value increase is that the number of boards in sorting classes T2 and T3 was increased, while the number of boards in class T1 was reduced.

4 Acknowledgements

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References


Effect of knot detection errors when using a computed tomography log scanner for sawing control

Authors: Lorenz Breinig, Anders Berglund, Anders Grönlund, Franka Brüchert, Udo Sauter

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Abstract

Roundwood scanners utilizing X-ray computed tomography (CT) provide the information required for individual log-sawing optimization. However, errors in the automated detection of quality-relevant internal wood features for sawing control may lead to improper log positioning at breakdown, impairing the realization of value recovery potential. It is thus of interest to have an estimation of the impact of feature detection errors on the performance of sawing optimization.

A sensitivity analysis was conducted to quantify the effect of errors in knot detection on a breakdown optimization by adjustment of log rotation. Therefore, sawing simulations were performed with the geometric descriptions of log shape and internal knots extracted from the CT scans of 57 Norway spruce \((Picea abies (L.) Karst.)\) logs. Three types of artificially set knot description errors were tested under different pricing and product scenarios, each in different magnitudes as systematic or random error.

Errors in knot diameter were found to have the greatest impact for both systematic and random errors. The effect of errors in dead knot border radial position was less pronounced but still substantial for higher error levels, while errors in knot rotational position could be neglected even for the highest magnitudes of error tested. The assumed price differentiation between product qualities had a major influence on the impact of the errors. It could be observed that with errors of higher magnitudes than those reported for present knot detection algorithms, an improvement in value recovery compared with outer-shape-based optimization still resulted in the simulated rotation optimization.

1 Introduction

Raw material costs amount to 65 to 75 percent of the total costs of a sawmill (Chiorescu and Grönlund, 2003), and thus there is great interest in utilizing the raw material in the most efficient way. Potential for further efficiency improvement is seen in optimizing the breakdown of each individual log.

Lundahl and Grönlund (2010) studied the potential to increase volume yield in Scandinavian sawmills by applying alternative log rotation
and lateral positioning using breakdown simulations in which only the outer shape of the logs was taken into account. The authors noted that sawing the logs horns down, i.e., with the largest crook vertically aligned in the first saw — a principle commonly used by Scandinavian sawmills in conjunction with curve sawing — on average yields relatively high volume recovery. However, they also found that the individual yield-maximizing rotation for a log most often differs from the horns down rotation. They reported an increase in average volume yield of 8.6 percent when applying the optimal rotation and lateral position to each log.

In a study similar to the one by Lundahl and Grönlund (2010), Berglund et al. (2013) investigated the potential to increase the value recovery in Scandinavian sawmills by applying an alternative log rotation rather than sawing logs horns down. Consideration was given only to knots and wane when determining the quality of the boards in this study. An increased average value recovery of 13 percent was found for the logs in this study using the log rotation for greatest profit return for each log. An introduced rotational error of the sawing machine reduced the increased average value yield to 6 percent.

Since full knowledge of internal log properties is required for utilizing the value potential of each individual log, there is a demand for internal log scanning (Schmoldt et al., 2000), and X-ray computed tomography (CT) has early been recognized as one of the most feasible technologies for this purpose (Taylor et al., 1984; Hodges et al., 1999). Thus, much research has been devoted to its application for the control of primary log conversion, and diverse approaches for automated feature extraction in CT images of various hard- and softwood species have been presented in the last three decades, e.g. (e.g. Funt and Bryant, 1987; Grundberg and Grönlund, 1992; Bhandarkar et al., 1999; Andreu and Alfred, 2003; Longuetaud, 2005). Most of them have included or even focused on knot detection since knots are the main internal wood feature that, except for logs with severe defects such as rot or cracks, determines the quality of the sawn timber.

Recently, Johansson et al. (2013) reported evaluation results for a knot detection algorithm that is based on the method by Grundberg (1999). This algorithm has been tested on pine and spruce logs, and the resulting knot data have been compared with reference data from manual measurements retrieved in the original CT images and on physical boards that
have been sawn from previously scanned logs in known orientation. It has been found that, in tests on Norway spruce (Picea abies (L.) Karst.) logs, the mean error for knot diameter measurement was about 0.6 mm for knots smaller than 10 mm, 3.1 mm for knots between 10 and 20 mm, and -4.1 mm for knots larger than 20 mm; standard deviations of the errors were 3.3, 5.3, and 8.2 mm, respectively. The detection of dead knot border position was not evaluated on spruce logs but showed a mean error of -4.0 mm with a standard deviation of 11.7 mm for Scots pine (Pinus sylvestris L.) logs. For both species, the errors in rotational position of the knots were small with mean errors below 0.5 degrees and standard deviation of the errors below 2.5 degrees.

While the accuracy of knot detection has been evaluated for most of the other algorithms developed as well, it is still not known to what extent the application of internal knot measurement for sawing control at the individual log level, i.e., log rotation and positioning, is affected by inaccuracy in terms of systematic or random errors of the detected knots.

Grundberg and Grönlund (1999) carried out a sensitivity analysis in the context of validating sawing simulation software and found that errors in both knot diameter and dead knot border position have an effect on simulated product value. This effect was more pronounced for knot diameter errors than for dead knot border position errors. The sensitivity of sawing simulations to knot measurement errors was thus assessed, but an estimation of the impact of these errors on breakdown optimization for single logs could not be deduced from those findings. In this context, the objective of the present study was to analyze the sensitivity of breakdown optimization, by adjusting log rotation to detected internal knottiness, to errors in the knot geometry description. As a result, an estimation of the required accuracy of knot measurement in CT scans can be provided.

The study has been conducted in conjunction with a research project with the objective of classifying wooden surfaces according to aesthetic perception of the visible features and incorporating this knowledge in sawn timber production procedures based on CT log scanning. The sample products used in this project are solid floorboards that have been sawn with custom sawing patterns. In this context, sawing patterns of that type are also tested here.
2 Materials and Methods

2.1 Material

The sample material used in this study was composed of 57 Norway spruce sawlogs that were collected from a stand on the western drop of the Black Forest mountain range in southwestern Germany. Their lengths varied between 3.9 and 4.2 m; 15 logs had top diameters in the range of about 45 to 58 cm, and the top diameters of the remaining 42 logs ranged from approximately 20 to 34 cm. The logs were graded according to European standard EN 1927-1 (Anonymous, 2008). Their grade distribution is given together with the grade limits for knots and log outer shape features in Table 1.

Table 1: Excerpt of grade limits for knots and outer shape features from European roundwood grading standard EN 1927-1 and grade distribution of the sample logs. Crook and taper limits are differentiated for log size classes based on mid-diameter under bark; all given limits are inclusive.

<table>
<thead>
<tr>
<th>Grade</th>
<th>Knot size (cm)</th>
<th>Crook (cm/m)</th>
<th>Taper (cm/m)</th>
<th>No. of logs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sound knots</td>
<td>Dead knots</td>
<td>20 – 34 cm</td>
<td>&gt; 35 cm</td>
</tr>
<tr>
<td>A</td>
<td>Not allowed</td>
<td>Not allowed</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>B</td>
<td>4</td>
<td>3</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td>C</td>
<td>8</td>
<td>6</td>
<td>2</td>
<td>2.5</td>
</tr>
<tr>
<td>D</td>
<td>No limit</td>
<td>No limit</td>
<td>3.5</td>
<td>4.5</td>
</tr>
</tbody>
</table>

2.2 CT scanning and feature extraction

All logs were CT scanned using the MiCROTEC CT.LOG scanner installed at the Forest Research Institute of Baden-Württemberg. The scanner was set to a resolution of 5 mm in the longitudinal direction and with a slice image size of 768 by 768 pixels (px), for a circular imaging area of 800 mm in diameter; resolution in the cross-section plane was approximately 1 mm²/px.
The CT images were processed for knot detection using software for wood feature extraction in images from a high-speed CT log scanner with the algorithms developed by Johansson et al. (2013). For every log, the software saved the outer shape and the sapwood-heartwood border described by 360 radii in reference to the detected pith position on every cross section as well as the geometry of each knot defined by nine parameters (Oja, 1999).

2.3 Sawing simulations

Sawing simulations were performed with the log breakdown simulation software Saw2003 (Nordmark, 2005). This software performs simulation of cant sawing with curve sawing in the second saw and is specifically adapted to grading the simulated boards according to the appearance grading rules in “Nordic Timber” (Swedish Sawmill Managers Association, 1994). The breakdown simulations are controlled by setting the properties of the simulated sawing machine (e.g., kerf width), the sawing patterns for the different log top diameter classes, the quality definitions (i.e., the implementation of the grading rules), and the prices for center and side-boards of different grades. When the knot geometry description of a log is loaded by the software, it is possible to add systematic or random errors to the knot diameter, the dead knot border position, and the rotational or longitudinal position of each knot. Random errors are taken from a normal distribution with the set error level defining the standard deviation. The results of the simulations were analyzed in two ways. First, the variation of apparent total value of the simulated sawn timber due to the imposed errors, when applying conventional log positioning, was assessed in order to estimate the magnitude of their impact. Second, the influence of the errors on the outcome of a breakdown optimization by adjustment of log rotation based on the knot information was examined.

Sawing patterns

Two types of sawing patterns were used in this study. While the first set consisted of standard cant sawing patterns for logs up to a top diameter limit of 449 mm with target board dimensions typical for the production of Nordic sawmills (Lundahl and Grönlund, 2010; Berglund et al., 2013),
the sawing patterns in the second set were adjusted to the production of sideboards and center boards of a single dimension, 32 by 130 mm nominal target width, which is an intermediate dimension of solid softwood floorboards. The sawing patterns in this set will be referred to as floorboard sawing patterns. Schematic drawings of the sawing patterns are shown in Figure 1.

Figure 1: Schematic drawings of the sawing patterns applied in the simulations. (a) An example of a standard pattern. (b and c) One- and three-cant floorboard patterns, respectively. The circles represent log top diameter, and the different gray values indicate sideboards from first and second saw and center boards, respectively; boards that are not located fully within the top diameter are drawn with dashed outlines.

The set of standard sawing patterns was applied only to the 42 smaller logs, the top diameters of the 15 large logs being beyond the upper limit for these sawing patterns, whereas the set of floorboard sawing patterns was also used on the full sample, including the larger logs (see Figure 2). The set of floorboard sawing patterns included patterns with one cant and one or two sideboards for logs with top diameters up to 427 mm as well as patterns with three cants and one or two sideboards for logs with a top diameter of 428 mm and above.
2. Materials and Methods

Table 2 gives an overview of the floorboard sawing patterns and their corresponding log top diameter classes. In the floorboard sawing patterns, only the sideboards from the first saw were defined as sideboards, whereas all boards from the second saw were defined as center boards since no distinction based on dimension or board orientation could be made here. For the standard sawing patterns, the allowed sideboard widths of the first and second saws were 75, 100, 115, 125, 127, 150, 175, 200, and 225 mm.
Table 2: Set of flooring sawing patterns used in the simulation. Second saw machine center is given for center cant only; for the side cants of a pattern, the respective number of boards is reduced by two.

<table>
<thead>
<tr>
<th>Sawing pattern</th>
<th>Log top diameter (mm)</th>
<th>Saw machine center (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Minimum</td>
<td>Maximum</td>
</tr>
<tr>
<td>32 × 130 × 3</td>
<td>140</td>
<td>175</td>
</tr>
<tr>
<td>32 × 130 × 4</td>
<td>176</td>
<td>211</td>
</tr>
<tr>
<td>32 × 130 × 5</td>
<td>212</td>
<td>247</td>
</tr>
<tr>
<td>32 × 130 × 6</td>
<td>248</td>
<td>283</td>
</tr>
<tr>
<td>32 × 130 × 7</td>
<td>284</td>
<td>319</td>
</tr>
<tr>
<td>32 × 130 × 8</td>
<td>320</td>
<td>355</td>
</tr>
<tr>
<td>32 × 130 × 9</td>
<td>356</td>
<td>391</td>
</tr>
<tr>
<td>32 × 130 × 10</td>
<td>392</td>
<td>427</td>
</tr>
<tr>
<td>32 × 130 × 11</td>
<td>428</td>
<td>463</td>
</tr>
<tr>
<td>32 × 130 × 12</td>
<td>464</td>
<td>499</td>
</tr>
<tr>
<td>32 × 130 × 13</td>
<td>500</td>
<td>535</td>
</tr>
<tr>
<td>32 × 130 × 14</td>
<td>536</td>
<td>571</td>
</tr>
<tr>
<td>32 × 130 × 15</td>
<td>572</td>
<td>607</td>
</tr>
</tbody>
</table>

Grading

For all simulations, the original quality definition implemented in Saw2003 was used, and thus grading was performed according to the specifications of “Nordic Timber”, restricted to the grade limits for dead and sound knot size and frequency as well as wane depth, width, and length, which are specified in Table 3. Internal features other than knots were not taken into account in the quality definitions because they were not represented in the log descriptions.
2. Materials and Methods

Table 3: “Nordic Timber” grade limits for knot size, knot frequency and wane applied in the simulations.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Board thickness (mm)</th>
<th>Board width (mm)</th>
<th>Grade</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Face</td>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>Sound knot size (mm)</td>
<td>16-25</td>
<td>75-115</td>
<td>20</td>
<td>35</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>125-150</td>
<td>25</td>
<td>40</td>
<td>55</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>175-225</td>
<td>30</td>
<td>45</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>5-9</td>
<td>32</td>
<td>38</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>125-150</td>
<td>25</td>
<td>40</td>
<td>55</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>175-225</td>
<td>30</td>
<td>45</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>3-5</td>
<td>44</td>
<td>50</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>125-150</td>
<td>30</td>
<td>45</td>
<td>60</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>175-225</td>
<td>35</td>
<td>50</td>
<td>70</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>6-9</td>
<td>63</td>
<td>75</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>125-150</td>
<td>40</td>
<td>55</td>
<td>70</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>175-225</td>
<td>45</td>
<td>60</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>Edge</td>
<td>16-19</td>
<td></td>
<td>15</td>
<td>a</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>22-25</td>
<td>20</td>
<td>a</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>32-38</td>
<td>25</td>
<td>30</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>44-50</td>
<td>30</td>
<td>40</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>63-75</td>
<td>35</td>
<td>50</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td>Dead knot size reduction factor (% of sound knot size)</td>
<td></td>
<td></td>
<td>70</td>
<td>70</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>No. of knots</td>
<td></td>
<td>Face</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Edge</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Wane length (% of board length)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Board thickness up to 25 mm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On both edges</td>
<td>20</td>
<td>30</td>
<td>40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On one edge</td>
<td>30</td>
<td>40</td>
<td>50</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Board thickness above 25 mm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On both edges</td>
<td>10</td>
<td>20</td>
<td>30</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>On one edge</td>
<td>20</td>
<td>30</td>
<td>40</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wane depth (% of board thickness) on each edge</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>15</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wane width on face (mm) on both edges</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>17</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Equal to board thickness.

*Total number of knots with maximum allowed size on the worst meter of the board. If individual knot sizes are below the limits for a grade, a higher number of knots is allowed, provided that the sum of their sizes does not exceed the allowed total knot size sum (number of knots multiplied with the maximum size) for the respective grade.
Pricing

Three different price lists were applied with each of the sawing pattern sets, representing a low, high, and intermediate (denoted as normal) price differentiation between board grades (see Table 4). While the price lists for the standard sawing patterns allowed board lengths from 1 800 to 5 400 mm in intervals of 300 mm, the price lists for the floorboard sawing patterns specified board lengths from 2 000 to 4 000 mm in intervals of 500 mm, thus reducing the number of trimming options to be evaluated by the trimming optimizer for the given logs by about 40 percent. This, together with the fixed sideboard dimensions instead of the sideboard width options of the standard sawing patterns, characterized the floorboard sawing patterns as considerably less variable than the standard sawing patterns.

Table 4: Price lists with different levels of price differentiation between board grades. Prices are relative with the price for center boards of grade B as reference.

<table>
<thead>
<tr>
<th>Board grade</th>
<th>Relative price (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Center boards</td>
<td></td>
</tr>
<tr>
<td>Grade A</td>
<td>108</td>
</tr>
<tr>
<td>Grade B</td>
<td>100</td>
</tr>
<tr>
<td>Grade C</td>
<td>81</td>
</tr>
<tr>
<td>Sideboards</td>
<td></td>
</tr>
<tr>
<td>Grade A</td>
<td>138</td>
</tr>
<tr>
<td>Grade B</td>
<td>88</td>
</tr>
<tr>
<td>Grade C</td>
<td>78</td>
</tr>
</tbody>
</table>

Error settings

Three types of errors were analyzed in this study: errors added to the knot diameter, to the radial position of the dead knot border, and to the rotational position of a knot (see Figure 3). For each error type,
both systematic and random errors were tested with different error levels specified for each of them (see Table 5). Absolute errors were specified for dead knot border and knot rotational position. Knot diameter error levels were defined as relative values based on the maximum diameter of each knot because inaccuracy in knot diameter measurement was assumed to be dependent on knot size.

For the specification of the error levels, evaluation results from the work by Johansson et al. (2013) were taken as orientation with the range of the error levels tested covering, and to some extent exceeding, the magnitude of errors reported there.

All errors were tested separately, i.e., there was no combination of different error types or systematic and random errors because the priority of this study was to identify the critical magnitudes of those error types having the largest effect on their own before examining the interactions of different errors.

Figure 3: Screenshot of the slice (log cross section) view in the Saw2003 software. Knot variables that were modified by the errors set are marked: knot diameter (Diam), dead knot border radial position (DKB), and knot rotational position (Rot).
Table 5: Error levels tested for the different types of systematic and random errors imposed on the knot description.

<table>
<thead>
<tr>
<th>Error type</th>
<th>Systematic errors</th>
<th>Random errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knot diameter (%)</td>
<td>-50, -25, -10, 10, 25, 50</td>
<td>10, 25, 50</td>
</tr>
<tr>
<td>Dead knot border position (mm)</td>
<td>-30, -20, -10, 10, 20, 30</td>
<td>10, 20, 40, 60</td>
</tr>
<tr>
<td>Rotational position (degrees)</td>
<td>-6, -4, -2, -1, 1, 2, 4, 6</td>
<td>4, 8</td>
</tr>
</tbody>
</table>

Simulation procedure

For every log, several simulation runs were executed. In each run, sawing of the log was simulated in 180 rotation angles. Curve sawing was enabled in the second saw, and lateral offset and skew were set to zero in both the first and second saws; therefore, logs and cants were always centered.

The simulation procedure can be divided into three steps:

1. Simulation runs with the original log models (i.e., without added knot errors)

2. Simulation runs with internal knottiness disregarded (i.e., only outer shape considered)

3. Simulation runs with the different knot error types imposed on the knots

In the first step, simulation runs without introduced knot errors for each combination of sawing pattern type and price list applied were conducted. The value-versus-rotation curves for each log obtained from these simulations were treated as truth and used as the basis for all calculations.

In order to assess the effect of errors on simulated total value recovery and on the value improvement through rotation optimization with respect to internal knottiness, a baseline for comparison was required for each log. Because the current practice in most high-production softwood sawmills is controlling the rotation of a log on the basis of its outer shape, this approach was simulated in the second step of the procedure. Knots were therefore not regarded in trimming and grading during the simulated
breakdown of each log, yielding a value-versus-rotation curve governed only by wane.

In the third step, sawing simulation runs were performed for all combinations of price differentiation, sawing pattern type, and specified levels of the tested error types. For each level of the random errors, the simulation run of each log was repeated 10 times. Because the simulations in 10 repetitions for the random error settings led to considerable computation time, the 15 large logs were not used in the random error simulation series with the floorboard sawing patterns (Figure 2).

The rotation angles yielding the greatest apparent value for each log were gathered from the simulation runs of the second step when knots were disregarded and set as reference. Then the true value (i.e., value when accounting for knots, obtained in the first step) resulting from the respective rotation angle was retrieved for each log and used as the previously mentioned baseline. The same procedure of retrieving the apparent value-maximizing rotation position and the corresponding true value of a log was also applied to the results of all simulation runs with different error settings performed in the third step. Exemplary value-versus-rotation curves for one log resulting from the simulation runs of the three steps described are presented in Figure 4, including indications of the true and error-influenced optimum rotation positions and corresponding true value recovery figures.

The optimization approach assumed an idealized case since the rotation angle yielding the global value maximum was always taken as the suggested optimum rotation position regardless of the shape of the value-versus-rotation curve. This means that errors in log rotation due to the sawing machines (that in a realistic case would make it necessary to choose only rotations that were sufficiently distant to minima of the value-versus-rotation curve) were not taken into account.
3 Results and Discussion

3.1 Effect of knot description errors on simulated total value

Simulated total value resulting from virtually processing the whole sample of 57 logs or the subsample of the 42 smaller logs, respectively, was retrieved for each level of the error types tested under the different settings. Each log was sawn in the individual optimum rotation angle determined by its outer shape. The relative differences in apparent total value recovery based on the case of unaltered knot description were calculated.
3. Results and Discussion

Effect of systematic errors

The most pronounced effect on simulated total value recovery could be found for errors in knot diameter. Reducing knot diameter by 50 percent resulted in an increase of apparent total value between 12 and 53 percent, depending on price differentiation and sawing pattern type, while increasing knot diameter to the same extent led to value decreases between 8 and 38 percent. Figure 5a shows simulated relative total value as a function of the tested levels of knot diameter error; these results are explicitly given in Table A1.

Errors in dead knot border position in general showed less effect. For the highest error levels tested, i.e., shifting dead knot border 30 mm inward or outward, changes in total value were between approximately -2 and -9 percent and between 3 and 17 percent, respectively. For this error type, a plot of total value against error level is presented in Figure 5b, with the underlying figures also listed in Table A1.

In contrast to the effect of these two types of knot description errors, the impact of a shift in rotational position of the knots was negligible, altering aggregated value by a maximum of about -0.6 percent. Thus, presenting these values has been omitted.

Comparing the simulation results of the full sample with those of the subsample of smaller logs, both sawn with floorboard patterns, it can be observed that for the subsample, the resulting value recovery generally shows a higher sensitivity to the knot description errors. While in most cases for the standard sawing patterns the value differences were between those observable when sawing either the small logs or the full sample with floorboard patterns, enlargement of knot diameter caused a stronger decrease of apparent value recovery for the standard sawing patterns.
Figure 5: Simulated relative total value versus the tested levels of (a) a systematic error in knot diameter and (b) a systematic error in dead knot border position. In the legend, the simulation scenarios represented by the graphs are specified with sawing pattern type applied, sample used, and price list applied.
Effect of random errors

When only random errors are imposed on the knot geometry descriptions, the effect on the resulting apparent value recovery is considerably less distinct, at a maximum of an 18 percent value decrease in the case of the highest level of the knot diameter error in conjunction with high price differentiation and standard sawing patterns (see Figure 6a or Table A2). It can be observed that in all cases tested with a random knot diameter error, the effect on total value seems to be greater for the standard sawing patterns than for the floorboard sawing patterns applied to the smaller logs.

Random errors in dead knot border position had only very limited impact on apparent total value, with no greater difference than about 2 percent occurring for the highest error level in combination with the standard sawing patterns and high price differentiation. While random errors in knot diameter within each scenario of price differences and sawing pattern solely simulated decrease in aggregated value, the effect of random dead knot border position errors was more indistinct, simulating positive changes in aggregated value in the majority of cases but mostly on a very small scale, as can be seen in Figure 6b and Table A2, respectively.

Just like in the case of systematic errors, random errors in knot rotational position least affected simulated total value recovery, causing an apparent reduction in aggregated value of only slightly more than 0.5 percent in the most distinct case, namely, the combination of high price differences and floorboard sawing patterns with the highest level of a random knot rotation error tested.

The tested levels of an error in dead knot border position seem to have an effect comparably as low as that of an error in knot rotational position in the random error case, while in the case of systematic errors, the impact of dead knot border position errors is considerably more pronounced.
Figure 6: Simulated relative total value versus the tested levels of (a) a random error in knot diameter and (b) a random error in dead knot border position. Note that only the subsample of small logs has been used in the random error simulations. In (B), the interval on the y axis spans only 2.5 percent. In the legend, the simulation scenarios represented by the graphs are specified with sawing pattern type and price list applied.
3. Results and Discussion

3.2 Effect of knot description errors on log rotation optimization

For each log, the relative difference in value recovery between sawing in true optimum rotation with respect to internal knottiness (not influenced by a knot error) and sawing in optimum rotation determined by outer shape alone, based on the latter value, was calculated. For each error level, the same calculation was also done using the true value recovery at the apparent optimum rotation angle of each log (Figure 4). Analogous to retrieving the simulated total value results, this was done for each combination of price list, sawing pattern type, and error type and level tested.

Effect of systematic errors

In Figure 7a, the mean value recovery differences over all logs are plotted against the tested levels of a systematic error in knot diameter (explicit numbers given in Table A3). As can be seen, depending on price differentiation and sawing pattern type, theoretical increases in average value recovery ranged between 4 and 20 percent when no knot errors were applied. When errors in knot diameter were imposed, the potential value recovery improvement was decreased to no more than about 13 percent for the combination of sawing the smaller logs with floorboard sawing patterns and enlarging knot diameter by 10 percent, and in the case of increasing knot diameter by 50 percent, even a slight loss of value recovery compared with outer-shape based optimization of 0.4 percent could be observed. The greatest loss of value recovery compared with outer-shape based optimization for an individual log was found to be 27 percent when knot diameter error was 50 percent and a standard sawing pattern was used under the precondition of high price differentiation.

In comparison to the systematic error in knot diameter, the tested levels of a systematic error in dead knot border position had in general less detrimental effect on the value recovery improvement obtained through adjusting log rotation with respect to internal knot structure. Even for the largest positive and negative error levels tested, the mean value recovery difference compared with conventional outer-shape based optimization was still always positive and not reduced by more than about two-thirds
of the relative value recovery improvement in the case of no error. Positive errors, i.e., an outward shift of dead knot border, showed a clearly more severe effect than negative errors on each absolute level as can be observed in Figure 7b and Table A4, respectively. For all tested levels of an error in dead knot border position, the greatest reductions in value recovery improvement for an individual log were just below 15 percent, occurring with the combination of standard sawing patterns and normal price differences as well as with floorboard sawing patterns in conjunction with high price differences, in both cases for the largest positive error.

As indicated by the results of simulated total value, the least effect could be observed for errors in rotational position of the knots. Even in the case of the largest effect — a shift of knot rotational position of ±6 degrees under the precondition of high price differentiation and applying floorboard sawing patterns to the smaller logs of the sample — the value improvement compared with conventional log rotation was not decreased by more than about 0.9 percent. When testing in combination with standard sawing patterns, the maximum levels of knot rotational position error did not cause a decrease of value improvement of more than about 0.1 and 0.2 percent, respectively. This was due to the fact that for all except three or four logs, identification of the value-maximizing rotation was not influenced by knot rotational position errors at all.
3. Results and Discussion

Figure 7: Mean value recovery difference between optimization taking into account internal knottiness and conventional outer-shape based optimization, plotted against the tested levels of (a) a systematic error in knot diameter and (b) a systematic dead knot border position error. In the legend, the simulation scenarios represented by the graphs are specified with sawing pattern type applied, sample used, and price list applied.
Effect of random errors

Modifying knot diameter had the most pronounced impact in the case of random errors just as it did in the case of systematic errors. For the tested error levels, decreases in value recovery improvement from slightly below 2 to 14 percent (Table A5) could be observed. The highest value loss when compared with outer-shape optimization for a single log occurred for the combination of an error level of 50 percent, a floorboard sawing pattern, and a price list with high price differentiation and amounted to 43 percent in the random error case, which was higher than the most severe value loss of 27 percent observed in the systematic error case. While the influence of sawing pattern type and price differentiation between board grades was generally comparable to the systematic error case, the results also indicate that the effect of a random error in knot diameter of a given level seems to be more similar to the positive than to the negative corresponding systematic error level. The results for all tested cases are presented in Figure 8a and listed in Table A5.

For the random errors in dead knot border position, the differences between the potential and the materialized value improvement compared with conventional log rotation control varied between around 1 percent and just above 8 percent (Table A6). The greatest value loss for an individual log was 24 percent when the value of the products from a floorboard sawing pattern was determined by the high difference price list and when the level of the random error was 40 or 60 mm, respectively. In contrast to the error in knot diameter, for the dead knot border position error, the effects seemed to resemble those of the negative rather than the positive levels of the systematic error for the observed instances of the two lower error levels tested. Even the highest level tested, defining a standard deviation of 60 mm for the shift in dead knot border position, had a smaller effect than an outward shift of 30 mm, as can be seen in Figure 8b and Table A6.
3. Results and Discussion

Figure 8: Mean value recovery difference between optimization taking into account internal knottiness and conventional outer-shape based optimization, plotted against the tested levels of (A) a random error in knot diameter and (B) a random error in dead knot border position. Note that only the subsample of small logs has been used in the random error simulations. In the legend, the simulation scenarios represented by the graphs are specified with sawing pattern type and price list applied.
4 Summarizing Discussion

The observed effects of systematic errors in the description of knot geometry on simulated total value recovery from the tested log samples were most pronounced for knot diameter with increases ranging from 2 to 53 percent and decreases from -2 to -38 percent. For dead knot border position, they were still considerable, with apparent value recovery increases in the range of 1 to 16 percent and reductions between -1 and -9 percent, whereas for knot azimuth, they were negligible. These simulation results are consistent with the findings of Grundberg and Grönlund (1999), who tested knot diameter and dead knot border position errors in their validation of the sawing simulation software and also observed a clearly larger effect for the former.

Regarding the response of simulated total value recovery to the random errors, it was noticeable that errors of the knot diameter in all cases caused a decrease in apparent total value (-0.5% to -18%), while errors of the dead knot border position led to indistinct — positive as well as negative — value changes at a much lower magnitude (below 2% in absolute values), reflecting the randomness of the error. This apparently deterministic effect of the random knot diameter error can be ascribed to its interaction with the knot rules in “Nordic Timber”, which set non-compensable limits for knot size, implicating that a single knot enlarged beyond the limit might decide on the grade of a board even if other knots are decreased in size by the random error so that the total knot area on the board face might stay constant or even decrease.

In general, the differences in effect on simulated total value recovery of the respective error types are reflected in the rotation optimization simulations, where the systematic or random errors in knot diameter had the largest impact as well. These errors led to reductions in realized value recovery potential between 26 and 103 percent based on the theoretical potential for the respective scenario. Systematic or random errors in dead knot border position caused corresponding decreases in realized value recovery potential from 9 to 66 percent. Here it could also be observed that increases in value recovery compared with solely outer-shape based optimization still resulted even for considerably high error levels, such as a systematic increase or decrease of knot diameter by 25 percent or a ran-
dom error causing variation of knot diameter with a standard deviation of 50 percent.

The specified price differentiation between lumber grades had a major influence on the outcome of the rotation optimization simulations, with higher price differences leading to a higher potential for value increase through optimization of log rotation with respect to internal knottiness. These observations on the small log sample used in the present study are in accordance with the findings of Berglund et al. (2013), who also noted a higher value improvement potential with higher price differences for the utilized sample of 1465 logs from the Swedish stem bank (Grönlund et al., 1995).

Comparing the value recovery improvement figures resulting from sawing the smaller logs with standard sawing patterns with those resulting from sawing the smaller logs or the full sample of logs with floorboard sawing patterns, it can be noted that for floorboard sawing patterns, the value improvement potential through knowledge of internal log features is apparently greater. One reason for this could be that in contrast to the volume-yield optimized standard sawing patterns, the custom floorboard sawing patterns are characterized by a considerably smaller number of dimension options available in the edging and trimming optimization (also entailing a volume yield significantly lower than that of the standard sawing patterns). A greater allowed flexibility in these controllable lumber properties thus can probably mitigate the effects of a suboptimal initial breakdown decision. The gain from knowledge of internal knottiness might therefore be larger in the case of sawn timber production with a lower number of alternative lumber dimensions.

The results of this study represent an idealized case because inaccuracy in adjusting log rotation due to the sawing machinery was not considered. As Berglund et al. (2013) observed, taking into account such an error with a standard deviation of 5 degrees can reduce the achievable value improvements considerably, in the reported case from about 13 percent to about 6 percent. Because the aim of the present study was to identify the basic effects of the individual knot error types and levels, this additional source of variation was not considered. According to Taylor et al. (2010), there seems to be a large variability in the average log rotation error and its standard deviation among saw lines currently operational.
The basic intention of the present study — providing an initial and general overview of the impact of knot detection inaccuracy — was also the reason for not testing the different systematic and random error types in combination. An exhaustive investigation in principle would require a factorial test design entailing considerable effort in computation and thus time with the hardware and software available. Performing such an analysis with respect to the present findings, however, is important for a more realistic assessment of the practical implications of knot detection inaccuracy and should be undertaken as a follow-up to the present study and should incorporate a log rotation error as well.

In this context, it would also be meaningful to additionally test the effect of an inaccurate determination of knot end as observed by Johansson et al. (2013) for the knot detection algorithm evaluated.

A limitation of the present study is that, in the simulated optimization approach, of the three parameters of adjusting log position relative to the saw lines in the first saw, i.e., log rotation, parallel offset, and skew, only the first one was tested. Indeed, the individual optimization of log rotation can be assumed to have the largest single influence on the improvement in value recovery (Lundahl and Grönlund, 2010). However, as the additional improvement in volume yield reported for an "extended optimization" that includes improved parallel offset adjustment in the first and second saw suggests, exploiting the full value recovery potential of each individual log might in many cases require applying a full log-positioning optimization, and thus the effect of knot detection inaccuracy should also be tested for such a strategy.

The Saw2003 sawing simulation software used in this study was built specifically for grading and optimizing boards according to the "Nordic Timber" rules. Therefore, testing the sensitivity of log rotation optimization to knot detection inaccuracy under the precondition of a different sorting standard applied was not readily possible. It can be assumed that in the case of appearance grading standards similar to "Nordic Timber", such as the European standard EN 1611-1 (Anonymous, 2002), the observed optimization potential and error effects would be on a comparable level. However, it would be of interest to know whether this also applied in the case of strength-grading standards with more specific sorting rules related to knots, such as those defined in the German standard DIN 4074-1 (Anonymous, 2012).
5 Conclusions

Among the three types of knot description errors tested in this study, both systematic as well as random errors in knot diameter clearly had the most severe impact on value improvement through individual log rotation optimization. Thus, this type of knot detection inaccuracy can be expected to have the greatest implications in an application case of knot detection by CT for log breakdown control.

Systematic or random errors in the determined radial position of the dead knot border can also be expected to have a marked effect, while systematically or randomly inaccurate measurement of knot rotational position within the tested magnitudes does not seem to have any relevant influence.

Except for the most severe levels of systematic or random errors in knot diameter, even a rotation optimization based on an error-affected value-versus-rotation curve can apparently yield a true gain in value recovery.

The value improvement potential through rotation optimization might in principle be greater for sawing patterns with lower freedom in the variability of sawn products dimensions. Apart from their limited generalizability due to the minor size of the log sample, the observations from this study also have to be treated as indicative only since they represent an idealized case of a perfectly accurate log rotation adjustment. Taking inaccuracy in log rotation due to the saw machinery into account could considerably change the outcome of the simulated optimization procedure.

References


Appendix

Table A1: Relative difference in simulated total value (when sawing each log in optimum rotation angle according to its outer shape) as a function of systematic error type and level. All values are in percent.

<table>
<thead>
<tr>
<th>Error type</th>
<th>Low price differences</th>
<th>Normal price differences</th>
<th>High price differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard</td>
<td>Floorboard</td>
<td>Standard</td>
</tr>
<tr>
<td>Knot diam. (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-50</td>
<td>17.16</td>
<td>18.26</td>
<td>12.38</td>
</tr>
<tr>
<td>-25</td>
<td>7.67</td>
<td>8.36</td>
<td>6.32</td>
</tr>
<tr>
<td>-10</td>
<td>3.02</td>
<td>2.35</td>
<td>2.08</td>
</tr>
<tr>
<td>10</td>
<td>-3.67</td>
<td>2.57</td>
<td>-2.04</td>
</tr>
<tr>
<td>Dead knot border position (mm)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-30</td>
<td>-2.94</td>
<td>-2.52</td>
<td>-2.16</td>
</tr>
<tr>
<td>-20</td>
<td>-1.76</td>
<td>-1.56</td>
<td>-1.39</td>
</tr>
<tr>
<td>-10</td>
<td>-1.12</td>
<td>-1.11</td>
<td>-0.81</td>
</tr>
<tr>
<td>10</td>
<td>1.24</td>
<td>1.59</td>
<td>0.92</td>
</tr>
<tr>
<td>20</td>
<td>1.88</td>
<td>3.34</td>
<td>1.91</td>
</tr>
<tr>
<td>30</td>
<td>3.51</td>
<td>4.97</td>
<td>2.78</td>
</tr>
</tbody>
</table>
Table A2: Relative difference in simulated total value (when sawing each log in optimum rotation angle according to its outer shape) as a function of random error type and level. For both sawing pattern types, only the subsample of the 42 smaller logs was tested.

<table>
<thead>
<tr>
<th>Error type</th>
<th>Low price differences</th>
<th>Normal price differences</th>
<th>High price differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard</td>
<td>Floorboard</td>
<td>Standard</td>
</tr>
<tr>
<td>Knot diameter (%):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>-1.02</td>
<td>-0.54</td>
<td>-2.15</td>
</tr>
<tr>
<td>25</td>
<td>-3.57</td>
<td>-1.19</td>
<td>-6.81</td>
</tr>
<tr>
<td>Dead knot border position (mm):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>0.04</td>
<td>0.11</td>
<td>-0.06</td>
</tr>
<tr>
<td>20</td>
<td>-0.05</td>
<td>0.06</td>
<td>-0.01</td>
</tr>
<tr>
<td>40</td>
<td>0.17</td>
<td>0.14</td>
<td>0.59</td>
</tr>
<tr>
<td>60</td>
<td>0.47</td>
<td>-0.11</td>
<td>1.22</td>
</tr>
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</table>
Table A3: Relative difference between value recovery resulting from sawing in (apparent) optimum rotation angle and value recovery from sawing in rotation angle determined by outer shape for the tested levels of a systematic error in knot diameter. Values are means (standard deviations) reported in percentages.

<table>
<thead>
<tr>
<th>Price differences</th>
<th>Knot diameter error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-50</td>
</tr>
<tr>
<td><strong>Low</strong></td>
<td></td>
</tr>
<tr>
<td>Standard</td>
<td>0.68</td>
</tr>
<tr>
<td>(3.78)</td>
<td>(4.32)</td>
</tr>
<tr>
<td>Floorboard (small logs)</td>
<td>0.25</td>
</tr>
<tr>
<td>(3.82)</td>
<td>(5.51)</td>
</tr>
<tr>
<td>Floorboard (all logs)</td>
<td>0.31</td>
</tr>
<tr>
<td>(3.35)</td>
<td>(4.82)</td>
</tr>
<tr>
<td><strong>Normal</strong></td>
<td>1.68</td>
</tr>
<tr>
<td>(5.71)</td>
<td>(8.14)</td>
</tr>
<tr>
<td>Floorboard (small logs)</td>
<td>0.46</td>
</tr>
<tr>
<td>(6.09)</td>
<td>(10.78)</td>
</tr>
<tr>
<td>Floorboard (all logs)</td>
<td>0.67</td>
</tr>
<tr>
<td>(5.39)</td>
<td>(9.42)</td>
</tr>
<tr>
<td><strong>High</strong></td>
<td>2.21</td>
</tr>
<tr>
<td>(6.75)</td>
<td>(11.29)</td>
</tr>
<tr>
<td>Floorboard (small logs)</td>
<td>1.17</td>
</tr>
<tr>
<td>(9.11)</td>
<td>(15.81)</td>
</tr>
<tr>
<td>Floorboard (all logs)</td>
<td>1.36</td>
</tr>
<tr>
<td>(8.00)</td>
<td>(13.81)</td>
</tr>
</tbody>
</table>
Table A4: Relative difference between value recovery resulting from sawing in (apparent) optimum rotation angle and value recovery from sawing in rotation angle determined by outer shape for the tested levels of a systematic error in dead knot border position. Values are means (standard deviations) reported in percentages.

<table>
<thead>
<tr>
<th>Price differences</th>
<th>Sawing patterns</th>
<th>Dead knot border position error (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>-30</td>
</tr>
<tr>
<td>Low</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard</td>
<td>3.55 (3.39)</td>
</tr>
<tr>
<td></td>
<td>Floorboard (small logs)</td>
<td>4.02 (4.70)</td>
</tr>
<tr>
<td></td>
<td>Floorboard (all logs)</td>
<td>3.44 (4.22)</td>
</tr>
<tr>
<td>Normal</td>
<td></td>
<td>7.12 (6.57)</td>
</tr>
<tr>
<td></td>
<td>Floorboard (small logs)</td>
<td>7.85 (8.93)</td>
</tr>
<tr>
<td></td>
<td>Floorboard (all logs)</td>
<td>10.11 (9.28)</td>
</tr>
<tr>
<td></td>
<td>Standard</td>
<td>12.14 (12.28)</td>
</tr>
</tbody>
</table>
Table A5: Relative difference between value recovery resulting from sawing in (apparent) optimum rotation angle and value recovery from sawing in rotation angle determined by outer shape for the tested levels of a random error in knot diameter. For both sawing pattern types, only the subsample of the $\frac{42}{4}$ smaller logs was tested. Values are means (standard deviations) reported in percentages.

<table>
<thead>
<tr>
<th>Knot diameter error (%)</th>
<th>Price differences</th>
<th>Sawing patterns</th>
<th>0</th>
<th>10</th>
<th>25</th>
<th>50</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>4.49 (3.57)</td>
<td>2.75 (3.87)</td>
<td>1.26 (4.31)</td>
<td>0.07 (4.69)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>5.66 (4.77)</td>
<td>3.90 (4.96)</td>
<td>2.45 (4.83)</td>
<td>0.95 (4.55)</td>
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</tr>
<tr>
<td>Normal</td>
<td>Standard</td>
<td>8.73 (7.00)</td>
<td>5.47 (7.46)</td>
<td>2.33 (7.59)</td>
<td>0.23 (8.11)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Floorboard</td>
<td>12.99 (9.44)</td>
<td>9.30 (9.79)</td>
<td>6.07 (9.69)</td>
<td>3.05 (9.77)</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Standard</td>
<td>12.30 (10.24)</td>
<td>7.79 (10.52)</td>
<td>3.64 (10.46)</td>
<td>1.26 (10.46)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Floorboard</td>
<td>19.72 (13.84)</td>
<td>14.52 (14.50)</td>
<td>10.08 (14.29)</td>
<td>5.72 (14.73)</td>
<td></td>
</tr>
</tbody>
</table>

Table A6: Relative difference between value recovery resulting from sawing in (apparent) optimum rotation angle and value recovery from sawing in rotation angle determined by outer shape for the tested levels of a random error in dead knot border position. For both sawing pattern types, only the subsample of the $\frac{42}{4}$ smaller logs was tested. Values are means (standard deviations) reported in percentages.

<table>
<thead>
<tr>
<th>Dead knot border position error (mm)</th>
<th>Price differences</th>
<th>Sawing patterns</th>
<th>0</th>
<th>10</th>
<th>20</th>
<th>40</th>
<th>60</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>4.49 (3.57)</td>
<td>3.76 (3.67)</td>
<td>3.37 (3.71)</td>
<td>2.84 (3.96)</td>
<td>2.66 (3.89)</td>
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<td></td>
<td></td>
<td>5.66 (4.77)</td>
<td>4.62 (4.81)</td>
<td>4.06 (4.73)</td>
<td>3.55 (5.07)</td>
<td>3.31 (4.89)</td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>Standard</td>
<td>8.73 (7.00)</td>
<td>7.33 (7.25)</td>
<td>6.51 (7.25)</td>
<td>5.91 (7.49)</td>
<td>5.25 (7.54)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Floorboard</td>
<td>12.99 (9.44)</td>
<td>10.91 (9.20)</td>
<td>9.89 (9.12)</td>
<td>8.00 (9.84)</td>
<td>7.35 (9.94)</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>Standard</td>
<td>12.30 (10.24)</td>
<td>10.68 (10.07)</td>
<td>9.75 (9.81)</td>
<td>8.57 (9.97)</td>
<td>7.81 (9.93)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Floorboard</td>
<td>19.72 (13.84)</td>
<td>17.02 (13.50)</td>
<td>15.07 (14.35)</td>
<td>12.58 (14.38)</td>
<td>11.56 (14.66)</td>
<td></td>
</tr>
</tbody>
</table>
Validating a crosscutting simulation program based on computed tomography scanning of logs

Authors:
Magnus Fredriksson, Anders Berglund, Olof Broman

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Abstract

Wood scanners and software for calculating crosscutting positions have been used in the wood industry for some years now. The scanners are used to detect biological and geometrical deviations on the sawn timber, which makes it possible to remove undesired defects using crosscut saws. Yield calculations for crosscutting have not been investigated to the same extent as sawing yield calculations for primary breakdown of logs, especially if the whole chain from log to end product is considered.

The objective of this study was to validate the result of a computer program developed for simulating crosscutting of boards. The crosscut simulations were performed with respect to knot characteristics on Scots pine (*Pinus sylvestris* L.) board surfaces. Validating a crosscutting simulation program would mean that it can be used to investigate how raw material and customization of quality rules affect the yield in a wood production chain from log to crosscut end product. The validation showed that crosscutting yield for boards could be predicted with a root mean square error of 13 percentage points, and the technique can be used to identify unsuitable logs for a certain product at an early stage of production.

1 Introduction

During the last three decades, sawmills in the Nordic countries have become more and more technically advanced. Measurement- and scanning equipment are used to control different processes and to measure how well various processes perform. The first category includes 3D-scanners in the saw line and scanning equipment at the edger, in the green sorting, trimming plant and further processing. The second category includes scanners for checking positioning errors in the saw, systems to measure green target sizes and systems for following up production disruptions.

This development has increased the use of computers in sawmill production. Automatic grading systems are one example where manual work, earlier made by a manual grader, has been replaced by systems based on computer programs. The data obtained from 3D-scanners, X-ray and CT-scanners has led to systems for sawing yield calculations, estimating the
sawing yield for different sawing patterns. Sawing yield calculations and how they can be optimized with respect to positioning and choice of raw material are important for sawmills in order to maximize profit. For this reason, yield calculations have been a part of numerous studies (Todoroki and Rönqvist, 1999; Rinnehofer et al., 2003; Pinto et al., 2005; Knapic et al., 2011; Berglund et al., 2013; Stängele et al., 2014).

Yield calculations for further processing have not been investigated to the same extent, especially if the whole chain from log to end product is considered. Lin et al. (1995) presents a model of an integrated sawmill and further processing unit, basing their study on 21 red oak (Quercus rubra L.) logs, and Usenius et al. (2012) presents the potential gains of a tool capable of linking forest properties to those of an end product.

Two examples of further processing are crosscutting and finger jointing. Crosscutting is normally used for two reasons, to remove unwanted features of a board and to adapt the board to a specified length (Grönlund, 1992). Crosscutting can be combined with finger jointing, where the short ends of the wooden pieces that were cut are milled to finger joints. The finger joints are then glued together into desired end products. The aim of a finger jointing process is to maximize yield and minimize waste, while maintaining an acceptable end product quality.

Wood scanners and computer programs for calculating crosscutting positions have been used for some years now. The scanners are used to detect biological and geometrical deviations on the sawn timber, which makes it possible to remove undesired defects using crosscut saws. By biological deviations, we mean any part of the wood that deviates in color or structure to that of the majority of the wood surface, which consists of straight wood fibres oriented parallel to each other. The positions of cuts are governed by an optimization program that maximizes the value of the end products produced out of each board. This optimization process means that price and quality rules for the different end products need to be considered, as well as the position of detected defects. Examples of biological features that can be undesirable for an end product are large knots, pitch pockets, rot and blue stain.

When primary sawing yield or crosscutting yield optimization is done in a production system, it is usually done at one production unit at a time, optimizing only that particular unit’s performance. This leads to suboptimization since the whole chain from log to a crosscut end product
is not considered. A system based thinking, where the whole chain is considered when optimizing, would be more efficient. This could be solved by using CT scanning of logs, together with sawing- and crosscutting simulation. CT scanning and sawing simulation is already widely used, so what is missing is a crosscutting simulation program capable of utilizing data from sawing simulation that in turn utilizes data from CT scanners. Developing and validating a crosscutting simulation program would mean that it can be used to investigate how raw material and customization of quality rules affect the yield in an entire production chain.

The objective of this study was to validate the result of a computer program developed for simulating crosscutting of boards. The crosscut simulations were performed with respect to knot characteristics on board surfaces, resulting from sawing simulation of CT scanned logs. The size and distribution of knots are the most important features for the general impression of a wooden surface. This is why the majority of grading rules are related to knots and why crosscut simulations in our study were focused on knots. A prerequisite for making this study possible was that log breakdown into sawn boards could be simulated as a pre-step. A second objective was consequently to validate the result of such a log breakdown simulation.

2 Materials and methods

2.1 Material

The study was based on 18 Scots pine (*Pinus sylvestris* L.) logs that were selected at the logyard of a sawmill in the north of Sweden, from two different sawing classes. They were measured by a RemaLog optical 3D scanner (RemaSawco, 2014), and log dimensions were recorded. The top diameters ranged from 156 to 214 mm, and the lengths from 3.4 to 4.9 m. The logs were taken from three different log types: butt logs, middle logs and top logs, six logs from each type, to study the effect of log type on yield in the crosscutting process. Of these six logs, three were taken from one sawing class and three from another, forming six different groups of logs. The log selection is described in Table 1.
Table 1: Log data. Both the nominal top diameter range of the sawing class and the actually measured top diameter range of the logs in this study are presented.

<table>
<thead>
<tr>
<th>Log type</th>
<th>Butt log</th>
<th>Middle log</th>
<th>Top log</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Sawing pattern</td>
<td>2 center boards</td>
<td>3 center boards</td>
<td>2 center boards</td>
</tr>
<tr>
<td></td>
<td>50 × 100</td>
<td>50 × 100</td>
<td>50 × 100</td>
</tr>
<tr>
<td>Sawing class top diameter range (mm)</td>
<td>156–167</td>
<td>194–210</td>
<td>156–167</td>
</tr>
<tr>
<td>Measured top diameter range of logs (mm)</td>
<td>161–168</td>
<td>206–214</td>
<td>160–165</td>
</tr>
</tbody>
</table>

2.2 Overview of study

The study was done as shown in Figure 1. One part consisted of a real industrial process, where logs were sawn into boards, and boards were crosscut for finger jointing. The corresponding simulations performed were sawing simulation and crosscutting simulation, based on CT data of the logs. Finally, a comparison was made between the results of the two processes.
2. Materials and methods

The logs were scanned with a medical CT scanner (SOMATOM AR.T, Siemens AG). The transportation and storage time from the log yard to the scanning site was three days. The CT scanning took seven days to complete, meaning that the logs were stored between three and ten days from log yard to scanning. During storage and transportation, the logs dried to some extent. However, the drying was not extensive and did not affect the results of knot detection and classification. The results from the scanning were $512 \times 512$ pixel image stacks of each log, with a voxel size of $0.68 \times 0.68 \times 5.34$ mm$^3$. A knot detection algorithm developed by Johansson et al. (2013) was used on the image stacks. This resulted in a parametrized description of the knots in the log, which was used for subsequent sawing simulation. The algorithm works on so called concentric...
surfaces, which are cylindrical surfaces on regular radial distances to the pith of the log. In the concentric surfaces, knots are detected and fitted to ellipse shapes. Ellipse shapes are then used for parametrization, which is based on the regression models presented in Table 2 (Johansson et al., 2013). Further information can also be found in Grönlund et al. (1995) and Andreu et al. (2003). The parametrized description includes the knots position, size and the position of the dead knot/sound knot border. The outer shape of the logs was also obtained from the CT image stacks. When scanning the logs, the rotational position of each log was marked with a felt tip pen on the butt end of the log, by drawing an arrow. The reason for this was to be able to simulate sawing of the logs in the same position as in the real sawmill.

Table 2: Knot parametrization models as described by Johansson et al. (2013). A–I are the 9 parameters used for describing knot position and size, and are different between different knots. \( r \) = radial distance to pith.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knot diameter (rad)</td>
<td>( \phi(r) = A + B r^{1/4} )</td>
</tr>
<tr>
<td>Lengthwise position (mm)</td>
<td>( z(r) = C + D \sqrt{r} + E r )</td>
</tr>
<tr>
<td>Angular position (rad)</td>
<td>( \omega(r) = F + G \ln(r) )</td>
</tr>
<tr>
<td>Knot end (mm)</td>
<td>( H )</td>
</tr>
<tr>
<td>Dead knot border (mm)</td>
<td>( I )</td>
</tr>
</tbody>
</table>

2.4 Sawing the logs

The logs were sawn at the sawmill together with other logs in the same sawing class. The sawmill had two sawing machines with circular saw-blades, sawing a cant in the first saw and splitting it in the second saw. The second saw employed curve sawing. In the first saw, images of the butt end of each log were recorded using a video camera during sawing. This made it possible to estimate the rotational position for each log that was sawn, which is shown in Figure 2. Logs were sawn as centered as possible, and the sawing patterns used are presented in Figure 3.

Only the center boards were used in this study. They were kiln dried to a moisture content of 12\%, and no trimming of the board ends was
2. Materials and methods

Figure 2: Example image of log being sawn. A drawn arrow indicating the rotational direction of CT scanning is visible in the butt end of the log.

Figure 3: The two sawing patterns used in this study, with nominal board dimensions. Each log was sawn into a cant that was rotated and split into two or three center boards. L = left board, M = middle board, and R = right board. Side boards were also sawn, but they were not used in this study and are therefore not shown in this figure.

carried out. Each board was manually graded by a professional grader, into three different quality grades, A, B and C. This was done according to the Nordic Timber Grading Rules (Swedish Sawmill Managers Association, 1994), where grade A has the strictest requirements. However only knots and wane were used for grading, to be able to compare the results to the sawing simulation which was made using knot- and outer shape information. The grading criteria for knots and wane according to the Nordic Timber Grading Rules are presented in Table 3. These criteria are for the board dimension used in this study, 50×100 mm. Figure 4 shows how knot sizes are defined depending on type of knot.
Table 3: Knot and wane restrictions according to the Nordic Timber Grading Rules, for grades A, B and C, and for the board dimension used in this study. Dead knot limits are 70% of green knot limits. For wane, ‘%’ refers to percentage of the board length or thickness. All criteria are given as maximum limits, so all features must fall below the limits for the board to pass a certain grade. The number of knots are multiplied by the size of knots to give a knot area, at the worst 1 m length of the board. (Swedish Sawmill Managers Association, 1994).

<table>
<thead>
<tr>
<th>Board feature</th>
<th>Grade A</th>
<th>Grade B</th>
<th>Grade C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of knots on faces</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Number of knots on edges</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Knot size on faces (mm)</td>
<td>30</td>
<td>45</td>
<td>60</td>
</tr>
<tr>
<td>Knot size on edges (mm)</td>
<td>30</td>
<td>40</td>
<td>50</td>
</tr>
<tr>
<td>Wane length, one edge (%)</td>
<td>20</td>
<td>30</td>
<td>40</td>
</tr>
<tr>
<td>Wane length, two edges (%)</td>
<td>10</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>Wane depth, per edge side (%)</td>
<td>10</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>Wane width (mm)</td>
<td>7</td>
<td>12</td>
<td>17</td>
</tr>
</tbody>
</table>

Figure 4: Definition of knot sizes according to the Nordic Timber Grading Rules (Swedish Sawmill Managers Association, 1994).
2.5 Sawing simulation

The result of the CT scanning (log outer shape, knot descriptions) were used for sawing simulation, by the simulation program Saw2003 developed by Nordmark (2005). The simulation program has been used extensively in earlier research (Chiorescu and Grönlund, 2000; Nordmark, 2005; Moberg and Nordmark, 2006; Lundahl and Grönlund, 2010). Saw2003 uses CT scanned logs as input data, and models a sawmill that employs cant sawing with two sawing machines, and curve sawing in the second saw.

To ensure that logs were sawn in similar positions in the sawing simulation as in reality, the logs were sawn several times in Saw2003, in different sawing positions close to the rotation indicated by the drawn arrow on the video images from the real sawing. The resulting boards were compared to images of the real boards, until a sawing position close to the real one was achieved. This comparison was done manually, matching the knots on the boards.

Grading of the boards resulting from sawing simulation was done according to the Nordic Timber Grading Rules (Swedish Sawmill Managers Association, 1994). The grading was based on knots and wane only, since other board features, such as pitch pockets or rot, were not represented in the log descriptions. Grading is done automatically in Saw2003. Board surfaces are created by calculating cutting planes through the log, that contains the parametrized knot model. Thus, board surfaces with shape and size of visible knots can be calculated and then used for grading.

2.6 Scanning and crosscutting the boards

The real boards were scanned and optimized for crosscutting using an industrial board scanner, WoodEye (Innovativ Vision, 2014). The scanner was equipped with four grey-scale line cameras, and the camera images were used for detection and classification of board features. These features were used for crosscutting decisions. The data stored for each feature was feature type, position in the length- and crosswise direction of the board, and size in the length- and crosswise direction of the board. The product made in the crosscutter was pieces for subsequent finger jointing, so it was a product with flexible length. Allowed lengths of crosscut pieces were 170–550 mm. Pieces 170–285 mm were valued differently from pieces 285–
550 mm, for the sake of optimization. If the value of 170–285 mm pieces are normalized to 100, the relative value of pieces 285–550 mm was 103. The reasoning behind this was to produce more of longer lengths, which are easier to handle in the production process. Crosscutting decisions were made on knots and wane only, to be able to compare the crosscutting decisions and yield to the simulation results. Knots were classified as dead or sound, depending on color. All board features were classified as either accepted or rejected, depending on a set of quality rules defined in Table 4. If both quality limits for length and width were exceeded, the feature was considered as a defect and was cut away. The rest of the wood was considered accepted, as long as there was a 15 mm knot-free zone at the end of each crosscut piece.

### 2.7 Crosscutting simulation

Using the boards that resulted from the sawing simulation, a crosscutting simulation program was written. The crosscutting optimization is based on the principles described in Rönnqvist and Åstrand (1998). The program classifies knots and wane as allowed or not allowed, using exactly the same grading rules as the WoodEye crosscutting optimizer, Table 4. This pre-processing divides the board into zones from where products can be cut out, or not. Using these results, the crosscut decisions are made, optimizing the value of the product mix made from each board. The value for each product is fixed and defined before-hand, as value per produced meter of material. In this case, the same product mix and relative values were used as in the WoodEye optimizer.

---

**Table 4**: Quality rules for crosscutting in this study. Length and width of features are defined using the board, i.e. feature length is size in the lengthwise direction of the board. If a feature is larger than the maximum length and width, it is considered unwanted and is cut away.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Maximum length (mm)</th>
<th>Maximum width (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sound knot</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Dead knot</td>
<td>Not allowed</td>
<td>Not allowed</td>
</tr>
<tr>
<td>Wane</td>
<td>5</td>
<td>2.5</td>
</tr>
</tbody>
</table>
3 Results

3.1 Validation of the sawing simulation

To have a functioning simulation model of the process of turning a log into a crosscut and finger jointed board, the log sawing process needs to be modelled correctly. To validate the sawing simulation program Saw2003 was therefore one of the objectives of this study. It was made by comparing the resulting board grades from Saw2003 to the grades of real boards, the latter grading being done manually by a professional grader. Since there was no information about which board was the left and the right in the sawing pattern, the boards were treated together in pairs, or in triplets for the larger sawing pattern. For instance, if both the manual grading and the simulated grading resulted in one A board and one C board, it was considered as two boards with the same grade regardless of which board was which. With these assumptions, 71% of the boards had the same grade. For none of the boards the difference was more than one grade, which can be observed in Table 5 showing the grade distribution.

Table 5: Comparing grades assigned to boards from sawing simulation based on CT scanning of logs, and boards sawn from the same logs that were manually graded. The sawing simulation grading results are read column wise and the manual grading results are read row wise.

<table>
<thead>
<tr>
<th>Manual grading</th>
<th>Sawing simulation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>10 2 0</td>
<td>12</td>
</tr>
<tr>
<td>B</td>
<td>2 17 6</td>
<td>25</td>
</tr>
<tr>
<td>C</td>
<td>0 3 5</td>
<td>8</td>
</tr>
<tr>
<td>Total</td>
<td>12 22 11</td>
<td>45</td>
</tr>
</tbody>
</table>

Total agreement: \( \frac{(10 + 17 + 5)}{45} = 71\% \)
3.2 Validation of the crosscutting simulation

The other objective was to validate the crosscutting simulation program. The crosscutting yield for each board was calculated, both for the results of the crosscutting simulation program and the industrial process. The crosscutting yield $Y_{cc}$ (%) was defined as

$$Y_{cc} = 100 \times \frac{L_{out}}{L_{in}}$$

where $L_{in} =$ length of input material (the board), and $L_{out} =$ total length of output material (crosscut pieces). The crosscutting yield for all boards is presented in Figure 5. The root mean square error (RMSE) of the crosscutting yield was 13 percentage points, between the simulation program and the industrial process.

![Figure 5: Crosscutting yield for all boards of the study, using the crosscut simulation program of this article compared to the WoodEye scanner and optimizer. An identity line is included as reference.](image)

Total yield for each log was also calculated for the results of the crosscutting simulation program and the industrial process. The total yield $Y_{tot}$ (%) was defined as
3. RESULTS

\[ Y_{\text{tot}} = 100 \times \frac{V_{\text{boards}}}{V_{\text{log}}} \]  

(2)

where \( V_{\text{boards}} \) = total dry volume of output material (crosscut pieces) from one log, and \( V_{\text{log}} \) = volume of the green log. The log volume was the volume measured by the 3D scanner at the sawmill.

Total yield for the 18 logs is shown in Figure 6, where logs are marked by log type. The RMSE of the total yield was 4 percentage points.

Figure 6: Total yield for the 18 logs of this study, using the crosscut simulation program of this article compared to the WoodEye simulation program. Squares = butt logs, triangles = middle logs, and circles = top logs.

The allowed length interval for crosscut pieces of 170–550 mm was divided into 20 mm-intervals. In each length interval, the number of crosscut pieces were counted, both for the simulation results and for the WoodEye optimizer. This created a distribution that is presented in Figure 7.
Discussion

In this paper it has been shown that a crosscutting simulation program utilizing data from CT scanning and sawing simulation of logs results in similar crosscutting results as a system used in the industry. The plot in Figure 5 shows that the crosscutting yield of a board for a certain production setup can be predicted well. The root mean square error of the simulation model compared to the industrial process was 13 percentage points, an error containing the entire process from log to crosscut board. It indicates that the CT scanning, knot parametrization and sawing simulation results in boards with realistic knot sizes and positions. The two outlier boards in the top left quarter of Figure 5 was examined in detail, and this examination showed that the WoodEye classified many knots on these boards as dead, whereas the knot parametrization algorithm, forming the input data for sawing simulation, classified them as sound. Since no dead knots were allowed in the quality rules used, this had a large impact on yield. It explains why the WoodEye yield is smaller than the yield obtained from crosscutting simulation in these two cases.
Furthermore, the length distribution of crosscut pieces in Figure 7 is rather similar between the WoodEye optimizer and the developed program. This length distribution depends on the knot structure of the input material, together with the optimization algorithm and the product values used in the optimization. For instance, in Figure 7 there is a large amount of pieces produced near the maximum length of 550 mm. This can be explained by the fact that longer pieces give less cuts and therefore a higher produced volume. The effect is that in very long segments of acceptable quality, 550 mm pieces will be chosen exclusively. Altogether this shows that the actual optimization, together with the detection of knots and sawing simulation, gives similar results when comparing the simulation to the industrial process.

The board grades resulting from sawing simulation was the same as the results of a manual grader for 71% of the boards. This can be compared to the agreement between two professional graders, that can be as low as 55–57% (Grundberg and Grönlund, 1997). This, together with the matching that was made between boards resulting from sawing simulation to images of the real boards, shows that Saw2003 results in sawn timber similar to that of a real sawing process. However this was done for the total outcome of a log, i.e. two or three boards together. Our study does not show how well the quality of individual boards can be predicted, just the outcome of sawing logs.

Other possible sources of error apart from the crosscutting simulation program itself are the CT scanning, that can give rise to images with noise and artefacts, the knot reconstruction algorithm, the sawing simulations, and the industrial scanner. The knot reconstruction algorithm, as described in Johansson et al. (2013), will not find all knots in a log. The hit rate is around 94% for Scots pine. Also, around 1% of knots found by the algorithm are false positives, i.e. a knot is found where there is none. The sawing simulation program Saw2003 has been validated through its predecessor vSM that was tested by Chiorescu and Grönlund (2000), and shows good conformity to a real sawmill. The test made in our paper showed that the conformity in terms of sawn timber quality between Saw2003 and a real quality grading was rather good, albeit not perfect. Finally, the industrial scanner is not perfect either, there are always errors present in the scanning of the boards and in the classification of board features. However, using the industrial scanner as reference meant that the devel-
oped crosscutting simulation program was compared to what it is meant to model, i.e. an industrial process.

The results should be interpreted while keeping in mind that the amount of logs used was limited. Also, the results were obtained using Scots pine logs. This means that it is not certain whether the method works in the same way for other species, that might have a different knot structure than Scots pine.

In research, the developed program can be used together with log databases to investigate how raw material, quality rules and crosscutter settings affect the end result in the form of crosscut products for various end uses. One interesting data set to study in this context, is the Swedish stem bank. It contains CT-data from about 600 Scots pine (*Pinus sylvestris*) logs (Grönlund et al., 1995) and about 800 Norway spruce (*Picea abies*) logs (Berggren et al., 2000). Also, industrial CT scanners are being made available (Giudicceandrea et al., 2011), something which will increase the amount of data that is available for simulation studies.

A practical use of this simulation program in the industry is possible if a sawmill has an installed CT scanner for scanning of logs. Simulation technique can then be used to predict how well suited a log is for further processing, thus controlling the flow of material. This would enable the sawmill to find other uses for the unsuitable logs, which would increase raw material efficiency. An indication that this would work is given in Figure 6, where the total yield of each log is predicted quite well by the crosscutting simulation program. The material of 18 logs is however too small to draw any definite conclusions from.

There are errors present when comparing the simulation results to the industrial process, however many of these errors will not affect the results when the program is used to do comparative simulation studies, testing different possible cases within the simulation environment itself. This approach will mitigate the effect of for instance log model errors, since all tested cases will be based on the same log models. For this reason it is highly recommended that any conclusions drawn from future simulation studies are done based on relative values when comparing cases, rather than absolute values.

Future work can include using this simulation program for various studies, such as how log characteristics influence end product properties, how
sawing and crosscutting can be controlled to ensure a high process efficiency, or the impact of quality rules on yield and end product properties.

5 Conclusions

It can be concluded that both the sawing simulation program and the crosscutting simulation program can be used to predict the outcome of real sawing and crosscutting processes. Sawing simulation results in a board quality that is the same as that of a professional grader for 71% of boards, and the crosscutting yield of individual boards can be predicted with a root mean square error of 13 percentage points using the crosscutting simulation program.

References


References


Comparing predictability of board strength between computed tomography, discrete X-ray, and 3D scanning of Norway spruce logs

Authors:
Erik Johansson, Anders Berglund, Johan Skog

Reformatted version of paper submitted to journal

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1. Introduction

In many Scandinavian sawmills, strength graded Norway spruce (Picea abies (L.) Karst.) boards are important products since they are used in wooden constructions. Boards are strength graded according to standards that define the strength classes (EN 338:2009, 2009) and standards specifying how the bending strength should be measured (EN 14081-1, 2011; EN 14081-2, 2010; EN 14081-3, 2012). Three important bending strength predictors of spruce boards are MOE, dry density and knot structure (Johansson et al., 1992; Hanhijärvi and Ranta-Maunus, 2008). MOE of sawn timber can be predicted using discrete X-ray scanning of logs (Oja et al., 2001). Using CT scanning of logs, knot structure can be detected and dry density can be estimated (Lindgren, 1991). Previous studies have shown that the bending strength of Norway spruce boards can be predicted by scanning logs from which the boards are sawn with discrete X-ray (Oja et al., 2001; Brännström et al., 2007; Hanhijärvi and Ranta-Maunus, 2008). However, the resolution of discrete X-ray scanning is
crude in the azimuthal direction compared to CT scanning, which results in relatively low resolution of the knot structure.

Lately, CT scanners that manage to scan logs at full production speed have been installed at sawmills (Giudiceandrea et al., 2011). Such scanners grant the information of where individual knots will be located in boards for a given position of the sawing pattern. Because the size and position of individual knots are important for the board strength, the hypothesis in this study is that the bending strength of boards can be estimated with higher precision using CT scanning of logs compared to using a combination of discrete X-ray and 3D scanning. If this hypothesis is true, a future industrial application is to optimize the log positioning with respect to expected board value, which is based on board strength.

In this paper, we will predict bending strength of Norway spruce boards using log data representing three different log scanning techniques: 3D scanning under bark, discrete X-ray scanning in two directions combined with 3D scanning, and CT scanning. The objective is to determine if board strength can be predicted with higher accuracy using CT than using discrete X-ray combined with 3D scanning.

2 Materials and methods

In this study, 59 Norway spruce logs that were CT scanned and sawn into boards were used. The rotational positions when sawing the logs have been documented and destructive tests of bending strength have been carried out on the center boards. Only center boards were tested, since in general, spruce side boards are not strength graded in Sweden. Using data from the CT images and the bending strength tests, multivariate models for predicting bending strength (modulus of rupture) were created. Each step will be explained in detail below.

2.1 Logs

The spruce logs originate from a dataset called the ESSB (Berggren et al., 2000). It consists of Norway spruce logs from Sweden, Finland and France, but in this study the logs were exclusively from Finland. A medical CT scanner (Siemens SOMATOM AR.T) was used to scan the logs and the
reconstructed images were stored as 256 × 256 pixel cross sections every 10 mm. Depending on log diameter, the resolution in each cross section varies from 1.4 to 1.8 mm/pixel. Knots are described by 10 parameters specifying size and position in the log as well as if knots are sound or dead. Log outer shape and heartwood shape are described in cylindrical coordinates with 360 radii values within each cross section with the pith position as the origin.

2.2 Boards and bending strength tests

The logs were cut using cant sawing (Figure 1) with curve sawing in the second saw and the rotational position of each log was documented. These are typical sawing methods for sawmills in the Scandinavian countries. Depending on log diameter, the sawing resulted in 2 or 4 center boards which were then dried to a moisture content of 12% and planed to dimension 45 × 95 mm, 45 × 120 mm, or 45 × 145 mm. During 13 years, these boards were stored in non-heated indoor climate in bundles.

Destructive bending strength tests were performed on all inner center boards (see Figure 1 for the definition of inner boards) according to a European standard (EN 408, 2003). The number of specimens and logs for each board dimension are presented in Table 1. On some boards, the identification tag was lost during the storage time and those boards were excluded when performing the tests. This issue is the reason why the number of boards used is less than twice the number of logs in this study. To ensure the quality of the data from the different dimensions, MOR was compared to MOE for each board dimension.

Table 1: Number of boards used for each board dimension and the number of logs which the boards originated from.

<table>
<thead>
<tr>
<th>Dimension (mm)</th>
<th>Number of boards</th>
<th>Number of logs</th>
</tr>
</thead>
<tbody>
<tr>
<td>45 × 95</td>
<td>41</td>
<td>21</td>
</tr>
<tr>
<td>45 × 120</td>
<td>46</td>
<td>25</td>
</tr>
<tr>
<td>45 × 145</td>
<td>26</td>
<td>13</td>
</tr>
</tbody>
</table>
Figure 1: Cant sawing. The first sawing machine cuts the log into side boards and a cant. The cant is then rotated by 90° and cut by the second sawing machine into side boards and center boards. The sawing pattern in the figure has four center boards, but only the inner, gray shaded, were used in the current study. In cases where only two center boards were obtained, both of them were used.

2.3 Variable extraction

To create prediction models for bending strength of boards, variables are needed that can explain the variability in MOR. This section presents an overview of the variables used for the four different prediction models in this study. These correspond to models using variables that can be extracted from logs by (1) a 3D scanner, (2) a 3D scanner combined with a discrete X-ray scanner, and (3) a CT scanner with knowledge of which rotational position the logs were cut. The fourth prediction model corresponds to a CT scanner, but without knowledge of the rotational position when sawing. Table 2 summarizes the number of variables used in each model and below follows detailed descriptions of the variables and how they were extracted.
2. Materials and methods

Table 2: Number of variables used in each model divided into different groups. CT* denotes the CT model where the rotational position of the logs when sawing was unknown.

<table>
<thead>
<tr>
<th>Model</th>
<th>Variable groups</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Outer shape</td>
<td>Discrete X-ray</td>
<td>CT</td>
<td></td>
</tr>
<tr>
<td>3D</td>
<td>65</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>65</td>
<td>189</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>CT</td>
<td>65</td>
<td>189</td>
<td>183</td>
<td></td>
</tr>
<tr>
<td>CT*</td>
<td>65</td>
<td>189</td>
<td>183</td>
<td></td>
</tr>
</tbody>
</table>

Outer shape

The outer shape of the logs was obtained from the outer shape data described in Section 2.1. The software Quality On-line (SP Wood Technology, 2014) was used to extract 65 variables describing the outer shape of each log. These outer shape variables describe the log in terms of e.g. length, crook, taper, ovality and bumpiness of both the whole log and divided into different parts of the log.

Discrete X-ray

Discrete X-ray variables were extracted from the CT images by simulating a two direction X-ray scanner. This simulation was conducted in MATLAB (MathWorks, 2014) and 189 variables were extracted describing the log based on discrete X-ray data. These X-ray variables describe some of the internal features of the log such as density, number of knot whorls, distance between knot whorls and heartwood content.

CT

The variables extracted exclusively from the CT data can be split into three groups:
1. 3D shape of the heartwood volume,
2. density variables, and
3. knot variables.
The shape of the heartwood volume can be extracted from CT images, and it was already available for each log in the ESSB. Using the information of the heartwood border, another 65 variables were extracted analogously to the outer shape variables using Quality On-line (SP Wood Technology, 2014).

An important bending strength predictor of boards is the dry density of the wood (Johansson et al., 1992; Hanhijärvi and Ranta-Maunus, 2008). The moisture content in clear heartwood for Norway spruce only varies slightly, typically in the range 34 – 40% (Esping, 1992). From this follows that changes in heartwood density measured by a CT scanner correspond to changes in dry density. Density variables were extracted by obtaining the average value of the clear heartwood pixels for each cross section of the CT image stack. This procedure resulted in a vector consisting of average pixel values every 10 mm of the log. The three variables extracted from this vector were average value, standard deviation, and the 20\textsuperscript{th} percentile. The proportion of heartwood in the logs was also included in this variable group.

The number of variables associated with knots is presented in Table 3, where they are sorted into groups. Many variables were extracted from the position in the log where the board was positioned. The rotational position was known for the logs, but the skew and lateral position of the logs were not documented when sawing. Therefore an approximation of the lateral position of the board cross sections was used in the CT images. This approximation was that for each CT slice, the corresponding board cross section was centered next to the pith as shown in Figure 2.
2. Materials and methods

Table 3: The number of knot variables used in the study divided into groups. The CS position column tells which part of the log cross section that was used, i.e. was the whole cross section used (global), was just the location of the board used (board), or was the location of the part of the board lying downwards in the bending strength tests used (board tension). The column lengthwise position specifies if only the knots in the middle 2.5 m were considered (middle) or if there was no such restriction (global).

<table>
<thead>
<tr>
<th>CS position</th>
<th>Lengthwise position</th>
<th>No. of variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>Global</td>
<td>19</td>
</tr>
<tr>
<td>Global</td>
<td>Mid</td>
<td>19</td>
</tr>
<tr>
<td>Board</td>
<td>Global</td>
<td>28</td>
</tr>
<tr>
<td>Board</td>
<td>Mid</td>
<td>10</td>
</tr>
<tr>
<td>Board tension</td>
<td>Global</td>
<td>28</td>
</tr>
<tr>
<td>Board tension</td>
<td>Mid</td>
<td>10</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>114</td>
</tr>
</tbody>
</table>

Figure 2: The position of the board cross section in a CT slice was approximated to be next to the pith and centered (the board width is denoted w). This approximation was only required when extracting knot variables from the CT images.

2.4 Multivariate models

We used the multivariate method PLS to predict the bending strength (MOR of the boards). PLS is a good method when dealing with a large number of variables in relation to the number of observations (Wold et al., 2001). It is also suitable when the predictor variables are correlated to each other and for noisy data. A PLS regression model can be analyzed by plots such as score plots, loadings, and VIP plots (Eriksson et al., 2006). These plots are important when interpreting a PLS model and makes the model easier to understand and validate.
Three multivariate PLS models were created for each board dimension using variables obtained by 3D scanning, 3D and discrete X-ray scanning, and CT scanning. Since both 3D variables and discrete X-ray variables can be obtained from CT images, all 3D and discrete X-ray variables were included in the CT model as described in Table 2. A fourth model was also created that was identical to the CT model, but where a random rotational position was used when extracting the rotation specific knot variables. The purpose of this fourth model was to investigate if knowledge of board position in logs contributed to bending strength predictability, i.e. to affirm the quality of the rotational dependent CT variables. Models were created for each board dimension separately since we were interested in predicting differences in bending strength among boards of the same dimension, rather than differences in bending strength between different board dimensions.

The software used was Simca 13.0.3 (Umetrics, 2014) and a manual variable reduction was performed in the software on each of the models with the aim to maximize the goodness of prediction ($Q^2$). The $Q^2$-value is based on cross-validation (Martens and Naes, 1989) which means that $n$ models are built each excluding a part, $(1/n)$, of the observations when creating a training set to build a model. Each model can then be tested on the observations that were excluded when building the model. These observations are called the test set. The value of $Q^2$ represents the proportion of variance in the test sets that is explained by the model. This means that $Q^2$ is a measure of the model's ability to predict new observations, i.e. observations that are not included when building a model.

Special care was taken in the variable reduction step so that enough work was performed for each model to achieve as high $Q^2$ value as possible. The main reason of maximizing the $Q^2$ value instead of $R^2$ or RMSE was to create prediction models that were good at predicting bending strength of new observations and not at predicting bending strength of this specific data set.

The exact procedure was to start by maximizing the $Q^2$ value for the model based on 3D variables, which resulted in a PLS model with a small number of variables. When maximizing the $Q^2$ value for the discrete X-ray model, the remaining 3D variables were added to all of the discrete X-ray variables. Again a PLS model was created by variable reduction leaving a small number of 3D and/or discrete X-ray variables. Last, these variables
were added to all the CT variables and a final variable reduction was carried out. With this procedure it was possible to evaluate the differences in predictability of bending strength between using 3D scanning, discrete X-ray combined with 3D scanning and CT scanning. For the model with CT variables extracted from a random rotational position, the variable reduction step was performed analogous to the ordinary CT model, i.e. producing a model with its own set of variables and coefficients.

Variable reduction was carried out by trying to remove variables one by one starting with the ones having the lowest VIP values. If the $Q^2$ value was increased the variable was removed, else the next variable in the VIP plot was considered. This procedure was repeated until no removal of variables would increase the $Q^2$ value.

3 Results

Scatter plots of observed MOR versus observed MOE are shown in Figure 3 for each board dimension. When performing linear regressions for 45 $\times$ 95, 45 $\times$ 120 and 45 $\times$ 145, the coefficients of determination ($R^2$) were 0.65, 0.69 and 0.24 respectively.

The results of the bending strength predictions using the four PLS models are shown in Table 4. A graphical view of the results is presented in Figure 4 to visualize the differences between the models. It is clear that $R^2$, $Q^2$, and RMSE were the best for the CT models and the worst for the 3D models for all three dimensions. The changes were larger between the 3D model and the discrete X-ray model compared to going from the discrete X-ray model to the CT model. The goodness of prediction for the two smallest dimensions was similar for all models, but for dimension 45 $\times$ 145 mm the models could not explain the variance to the same extent. Figures 5–7 show the predicted values of bending strength plotted versus the observed values.
Figure 3: Scatter plots of MOE versus MOR for each board dimension. A linear regression showed that the coefficient of determination was (a) 0.65 for dimension $45 \times 95$ mm, (b) 0.69 for dimension $45 \times 120$ mm and (c) 0.24 for dimension $45 \times 145$ mm.
3. Results

Table 4: The results of the $Q^2$ maximization procedure. CT* denotes the CT model where the rotational position of the logs when sawing was unknown.

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension (mm)</th>
<th>No. of PCs</th>
<th>$R^2$</th>
<th>$Q^2$</th>
<th>RMSE (MPa)</th>
<th>No. of variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D</td>
<td>45 × 95</td>
<td>1</td>
<td>0.69</td>
<td>0.63</td>
<td>6.1</td>
<td>14</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 × 95</td>
<td>2</td>
<td>0.82</td>
<td>0.78</td>
<td>4.8</td>
<td>17</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 95</td>
<td>2</td>
<td>0.86</td>
<td>0.83</td>
<td>4.2</td>
<td>19</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 95</td>
<td>2</td>
<td>0.82</td>
<td>0.79</td>
<td>4.7</td>
<td>21</td>
</tr>
<tr>
<td>3D</td>
<td>45 × 120</td>
<td>1</td>
<td>0.56</td>
<td>0.49</td>
<td>7.9</td>
<td>7</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 × 120</td>
<td>2</td>
<td>0.77</td>
<td>0.73</td>
<td>5.9</td>
<td>10</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 120</td>
<td>2</td>
<td>0.89</td>
<td>0.83</td>
<td>4.0</td>
<td>19</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 120</td>
<td>3</td>
<td>0.84</td>
<td>0.77</td>
<td>4.9</td>
<td>25</td>
</tr>
<tr>
<td>3D</td>
<td>45 × 145</td>
<td>1</td>
<td>0.53</td>
<td>0.48</td>
<td>5.9</td>
<td>3</td>
</tr>
<tr>
<td>Discrete X-ray &amp; 3D</td>
<td>45 × 145</td>
<td>1</td>
<td>0.62</td>
<td>0.57</td>
<td>5.3</td>
<td>17</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 145</td>
<td>1</td>
<td>0.73</td>
<td>0.66</td>
<td>4.5</td>
<td>16</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 145</td>
<td>1</td>
<td>0.64</td>
<td>0.59</td>
<td>5.1</td>
<td>20</td>
</tr>
</tbody>
</table>
Figure 4: (a) $R^2$, (b) $Q^2$, and (c) RMSE for each PLS model and board dimension. To clarify, X-ray denotes the model using both discrete X-ray and 3D variables, while CT* denotes the CT model where the rotational position of the logs when sawing was unknown. Lines are drawn to ease the interpretation.
Figure 5: Predicted bending strength of board dimension 45 × 95 mm plotted versus the observed values for (a) the 3D model, (b) discrete X-ray combined with 3D model, and (c) the CT model. The identity line is included in the scatter plots as reference.
Figure 6: Predicted bending strength of board dimension 45 × 120 mm plotted versus the observed values for (a) the 3D model, (b) discrete X-ray combined with 3D model, and (c) the CT model. The identity line is included in the scatter plots as reference.
Figure 7: Predicted bending strength of board dimension $45 \times 145$ mm plotted versus the observed values for (a) the 3D model, (b) discrete X-ray combined with 3D model, and (c) the CT model. The identity line is included in the scatter plots as reference.
In Table 5, the number of variables left after the variable reduction is presented. Of the discrete X-ray variables, no group of variables that were more important than others can be distinguished for the three board dimensions; the variables left after reduction varies much depending on dimension. Therefore it is hard to generalize which of the discrete X-ray variables that were removed when creating the CT models.

Table 5: Variables used in the variable reduced models sorted into groups. CT* denotes the CT model where the rotational position of the logs when sawing was unknown.

<table>
<thead>
<tr>
<th>Method</th>
<th>Dimension (mm)</th>
<th>CT</th>
<th>Discr. X-ray</th>
<th>CT*</th>
<th>CT knots</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D</td>
<td>45 × 95</td>
<td>14</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Discr. X-ray &amp; 3D</td>
<td>45 × 95</td>
<td>3</td>
<td>14</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 95</td>
<td>2</td>
<td>6</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 95</td>
<td>2</td>
<td>4</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>3D</td>
<td>45 × 120</td>
<td>7</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Discr. X-ray &amp; 3D</td>
<td>45 × 120</td>
<td>0</td>
<td>10</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 120</td>
<td>0</td>
<td>7</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 120</td>
<td>0</td>
<td>7</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>3D</td>
<td>45 × 145</td>
<td>3</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Discr. X-ray &amp; 3D</td>
<td>45 × 145</td>
<td>3</td>
<td>14</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>CT</td>
<td>45 × 145</td>
<td>2</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CT*</td>
<td>45 × 145</td>
<td>2</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Seen over all board dimensions for the CT models with known rotational position, 73% of all CT knot variables left after reduction were calculated using the knot volume at the position of the boards. The corresponding number before variable reduction was 58%. For the CT models with random rotational position, 54% of the knot variables left after the reduction were of this type. Knot variables associated with the actual board were thus more important when applying the correct rotational position than when applying the random.
4 Discussion

For board dimensions $45 \times 95$ mm and $45 \times 120$ mm, the relations between observed MOR and observed MOE in the current study agree well to literature, which presents $R^2$ values in the range $0.55$–$0.72$ (Johansson et al., 1992; Hanhijärvi and Ranta-Maunus, 2008). The corresponding $R^2$ value for dimension $45 \times 145$ mm was low in our study ($0.24$), which could be explained by relatively high amounts of splits in the boards of that dimension.

An issue to discuss is the high goodness of prediction achieved in this study compared to what have been achieved in a previous study. For the model with discrete X-ray and 3D variables, the $Q^2$ values were between $0.57$ and $0.78$ in the current study compared to $0.44$ in Brännström et al. (2007). Part of the explanation is that we complemented the discrete X-ray variables with 3D variables. Another part is that our measurements were carried out in a laboratory environment in contrast to a log sorting line where more noise is expected. We also had much fewer observations per board dimension which increases the risk of over-fitting the models. These three parts combined make it inadvisable to directly compare the results from the current study to that of Brännström et al. (2007). However, this does not stop us from comparing the results from different models within this study to each other.

In the current study the PLS models were cross-validated, which decreases the risk of over-fitting. A more rigorous way of validate the models is to use an external test set with observations not used when creating the models. This could unfortunately not be done due to the low number of boards for each dimension, thus some over-fitting might still be present. Therefore it is important to put emphasis on the relative differences in $R^2$, $Q^2$ and RMSE values between models rather than the absolute ones. We believe that by following this guideline our study gives an understanding of whether CT scanning of logs may predict the bending strength of boards better than discrete X-ray scanning combined with 3D-scanning.

The previous lines of reasoning lead to the first conclusion: CT scanning of logs seems to predict the bending strength of boards with higher accuracy than discrete X-ray scanning combined with 3D scanning. Figure 3.8 shows this distinctly for all three board dimensions; at least when the rotational position of the logs is known when sawing them. One can argue
that the cheer amount of additional variables going from the discrete X-ray to the CT model in combination with few boards per dimension could introduce this improvement by pure chance; add sufficiently many random variables and there will be one that improves the model strength. To meet such an argument, the quality of the CT variables must be validated, which is carried out by analyzing the CT models with random rotational position.

The second conclusion is that it is the quality of the CT variables which yield the improvement in predictability between the discrete X-ray and the CT models. The information in the knot variables using the correct rotational position were likely the ones that contributes the most to the increase in predictability when going from the discrete X-ray model to the CT model. This since the CT models with random rotation were just slightly better than the discrete X-ray models and distinctly worse than the CT models with known rotational position. An additional fact that supports this statement is that the knot variables that are based on knot volume in the boards were over-represented in the CT models with known rotational position compared to the models with random rotational position. This fact indicates that knowing the rotational positioning gives important information about the bending strength of the sawn timber.

Although this study showed that CT scanning of logs improves the predictability of board bending strength compared to scanning using a combination of discrete X-ray and 3D scanning, some questions remain unanswered. The most obvious is what the best possible values of $R^2$, $Q^2$, and RMSE are when using CT scanning for bending strength prediction. The answer depends on errors in positioning of the sawing machines and the material used, but to know an upper limit of these statistics one could CT scan a high number of boards of a single dimension. Such a method would eliminate error sources in positioning and with more observations the results would be even more trustworthy.

In the current study, the parallel and diagonal positioning of the logs was not known and instead assumed that the sawing pattern was centered with respect to the pith. Despite this relatively rough estimate of sawing pattern position the developed models gave an increase of predictability compared to the models that did not take into account the rotational position. The results of this study show that CT scanning of logs predicts bending strength of boards with higher accuracy compared to discrete
X-ray combined with 3D scanning even when there are uncertainties in sawing pattern position.

**Acknowledgements**

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**References**


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

Authors:
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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 magnitude 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 necessarily mean that saw mismatch is present on the other side face.

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 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 was that the measurement system would be simple and cost effective and 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 green sorting line of a sawmill where the boards are moving in transversal direction on an industrial conveyor (Figure 3). 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 $\alpha$ that the laser makes with the surface normal, a saw mismatch results in a laser line that
is separated (Figure 4). The separation, $s$, is proportional to the saw mismatch and can be measured by fitting two linear regression lines to the coordinates of the two groups of separated laser line pixels. The coordinates of the laser line pixels are segmented by a threshold followed by a calculation of the laser line centre. 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 Norway spruce (*Picea abies* (L.) Karst.) boards of thickness and width 38 by 125 mm respectively 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.

The reliability and repeatability of the measurement system was evaluated by measuring all boards in the sample five times with 1 cm intervals along their length on each side face. This was carried out by moving the boards lengthwise on a conveyor passing by the laser triangulation unit (Figure 4). 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.
2. Materials and methods

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 5a. Define the vector $X_i$ as containing the saw mismatch measurements of a side face from one of the five measurement runs

$$X_i = (x_1, x_2, \ldots, x_N), \quad i = 1, 2, 3, 4, 5$$

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

\[
\text{medfilt}(A, w),
\]  

(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 \( X_i \) (Figure 5b) is calculated as

\[
M_i = \text{medfilt}(X_i, 51).
\]  

(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

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

(4)

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

\[
\hat{S}_b = \max(\hat{S}_p, \hat{S}_s),
\]  

(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.
2. Materials and methods

Figure 5: Detected saw mismatch of a side face before and after applying a median filter with a window size of 51 values (≈ 50 cm).

2.3 Number of cameras and positioning

For the final placement of the measurement system in the green sorting line of a sawmill a question is how many cameras that are needed. Since the cameras will be installed at a transversal industrial conveyor they can only be placed at selected positions along the board length. To simulate the setup for measuring saw mismatch in selected positions the unfiltered measurements of saw mismatch along the length of the boards in the sample was used. The demand was to detect whether the maximal saw mismatch of a board exceeds 0.5 mm and 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 6. Since there are positions at which these are more likely detected, the following cases of pairwise positioned cameras were investigated (Figure 7).

1. Two cameras, one on each side face, with the Field Of View (FOV) centred at a distance of 50 cm from the top end (\( d_1 \)).

2. Four cameras, two on each side face, with the FOV centred at a distance of 50 and 150 cm from the top end respectively (\( d_1, d_2 \)).
3. Six cameras, three on each side face, with the FOV centred at a distance of 50, 150, and 200 cm from the top end respectively \( (d_1, d_2, d_3) \).

4. Eight cameras, four on each side face, with the FOV centred at a distance of 50, 150, 200, and 400 cm from the top end respectively \( (d_1, d_2, d_3, d_4) \).

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

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

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 6: The sample distribution of the lengthwise position of the estimate of maximal saw mismatch on pith side, \( \hat{S}_p \), and sapwood side, \( \hat{S}_s \).
3. Results and discussion

3.1 Reliability and repeatability of measurement

The result shown in Figure 8 indicates that the sample mean of the saw mismatch measured by laser triangulation corresponds with the sample mean measured manually with the depth gage. There are some deviations 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 9. 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
Figure 8: Scatter plot of sample means of five repeated measurements of saw mismatch using depth gage and laser triangulation respectively. The straight line is the identity line \( y = x \) drawn as reference. Boards 7 and 8 are absent due to missing data.

Figure 9: Sample standard deviations of five repeated measurements of saw mismatch using depth gage and laser triangulation respectively. Boards 7 and 8 are absent due to missing data.

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 ac-
curately as the saw mismatch since one of the linear regression lines will be fitted to the coordinates of a smaller number of laser pixels. This is an area of improvement for the saw mismatch detection algorithm in its current implementation.

Worth considering is also the variability of the moisture content in the wood. Laser light scattering along the grain direction in wood, as in this case, increases with higher moisture content (Simonaho et al., 2003). Since the measurement system will be placed in the green sorting line the moisture content will be high. Typically the moisture content for heartwood and sapwood in green Scots pine \textit{(Pinus sylvestris} \textit{L.)} and Norway spruce, the main species processed by Scandinavian sawmills, varies between 30–150\% (Esping, 1992).

### 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, $\hat{S}_s$, was shown in Figure 6. The lengthwise position of $\hat{S}_p$ and $\hat{S}_s$ is mainly close to one of the board ends or in a position closer to the centre of the boards.

Figure 10 shows a scatter plot of the lengthwise position of $\hat{S}_p$ and $\hat{S}_s$ respectively. The correspondence 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 is also an indication 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 correspondence 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.

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 on the conveyor. 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 11. 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 11. 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 result corresponds to the sample distribution of all measurements of saw mismatch along the length of the boards (Figure 12), which shows that a large number of measurements of saw mismatch exceeds 0.5 mm. Additionally, in a sawmill a large number of boards will be measured in a short period of time so a small number of cameras should be enough to detect a trend in the sawing process.
3. Results and discussion

Figure 11: 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, $\hat{S}_b$. 
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%.

<table>
<thead>
<tr>
<th>Number of cameras</th>
<th>Number of detected boards</th>
<th>Rate of detection (%)</th>
</tr>
</thead>
<tbody>
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<td>2</td>
<td>15</td>
<td>75</td>
</tr>
<tr>
<td>4</td>
<td>15</td>
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<tr>
<td>8</td>
<td>19</td>
<td>95</td>
</tr>
</tbody>
</table>

Figure 12: 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 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 before a final measurement system can be installed 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 either close to one of the board ends or in a position closer to the board centre. Also the correspondence 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 correspondence 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 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 sample distribution of saw mismatch magnitude in this specific case. In general, the equipment must be adjusted with respect to the saw mismatch magnitude and desired tolerance limit.
Acknowledgments

This work was financially supported by Wood Centre North, a research program jointly funded by industrial stakeholders, the European Union (ERDF) and the country administrative boards of Norrbotten and Västerbotten.

References


An industrial test of measuring saw mismatch by laser triangulation

Authors:
Anders Berglund, Anders Grönlund

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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 evaluated 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 ($Q^2 = 0.135$) 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.

1 Introduction

In order to maximize the profit return for a sawmill the sawing yield is important since 65–75% of the total costs are related to the raw material (Chiorescu and Grönlund, 2003). One way to increase the sawing yield is by reducing the saw kerf width (Steele et al., 1992; Wasielewski et al., 2012). Combining this with an adapted shrinking allowance and a lower
sawing allowance can increase the 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 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?
2. Materials and methods

2.1 Setup

A laser triangulation unit was installed in the green sorting line of a sawmill where the boards are moving in transversal direction on an industrial conveyor (Figure 2). The unit consisted of a GigE UI-5240CP-M-GL camera and a Lasiris SNF 660 nm laser that was mounted above the conveyor. 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.

The laser was positioned above the conveyor so that it measured saw mismatch 50 cm from the board end board in the lengthwise direction (Figure 3). Because of the angle $\alpha$ that the laser makes with the surface normal, a saw mismatch results in a laser line that is separated. The separation, $d$, is proportional to the saw mismatch and can be measured in the captured images.

Figure 1: Saw mismatch seen from the board end.
Figure 2: The laser triangulation unit as it was installed in the green sorting line of a sawmill. The arrow indicates the direction of transversal board movement on an industrial conveyor.

Figure 3: The laser line was 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.
2. Materials and methods

During the time period of the measurements, the different sawing classes that was processed and the sawing patterns applied can be seen in Table A1. The feed speed used is presented in Table A2.

2.3 Data analysis

To analyse this large number of observations 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 of each other. 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,

$$X = (x_1, x_2, \ldots, x_N).$$  \hspace{1cm} (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,
\[ W_j = (x_{i-S}, x_{i-S-1}, \ldots x_i) \quad \forall i \in \{S, S+1, \ldots, N\} \]
\[ \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{2} \]

The vector \( W_j \) was defined as the values within the sliding window that were larger than \( y \) mm,
\[ W_j = (x \in W_j | x > y \text{ mm}) \quad \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{3} \]

The elements of the first response variable, \( Y_1 \), were calculated as
\[ Y_1(j) = \frac{\text{length}(W_j)}{S} \quad \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{4} \]
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
\[ Y_2(j) = \bar{W}_j \quad \forall j \in \{1, 2, \ldots, (N-S)\}. \tag{5} \]
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\textsuperscript{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, \( Q^2 \), 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.

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, $Q^2$, of the PLS model using one or two principal components is shown in Table 1. The best goodness of prediction ($Q^2 = 0.135$) 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 $Q^2$ 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 $Q^2 = 0.135$ 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 need 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 can be achieved by 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.
Table 1: Goodness of prediction, $Q^2$, for the three response variables $Y_1, Y_2$ and $Y_3$ using different threshold values and different window sizes.

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<thead>
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(a) $Y_1$

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</table>

(c) $Y_3$
Figure 5: The significant ($\alpha = 0.05$), centred and scaled regression coefficients of the PLS using two principal components.
4. Conclusions

This work showed that the robustness when measuring saw mismatch during sawmill operation using laser triangulation was satisfactory. The response variable for saw mismatch in a PLS-model that resulted in the largest goodness of prediction ($Q^2 = 0.135$) was defined 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 the saw blade characteristics into account as well and to design an experiment where the predicting variables are varied systematically.

Acknowledgements

This work was financially supported by Wood Centre North, a research program jointly funded by industrial stakeholders, the European Union (ERDF) and the country administrative boards of Norrbotten and Västerbotten.
References


Appendix

Table A1: 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.

<table>
<thead>
<tr>
<th>SC</th>
<th>Sawing pattern(mm)</th>
<th>Lower limit (mm)</th>
<th>Upper limit (mm)</th>
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</tr>
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Table A2: The used feed speed for different cant heights.

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Customer adapted grading of Scots pine sawn timber using a multivariate method

Authors:
Anders Berglund, Olof Broman, Johan Oja, Anders Grönlund

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1. Introduction

Manual grading of sawn timber has been the traditional way of grading boards with respect to customer preferences in sawmills. In a sawmill, a manual grader typically has 2–3 seconds to make a decision regarding the board grade. During this time, the grader needs to consider visual defects on all sides of the board. The board should also be value optimized, meaning that the grader should know the price of all the grades in order to maximize the board value by trimming the board and removing undesired defects. It is not difficult to understand why this is a tiresome and
monotonous work, when thousands of boards are produced in a sawmill every hour.

Manual grading is subjective in the way that two different manual graders are not consistent. Grönlund (1995) showed that only 57% out of 2045 boards were given the same grade by two different graders, both using the Nordic timber grading rules which are practised in the Nordic countries (Swedish Sawmill Managers Association, 1994). This subjectivity is sometimes desired by the customer, the grading rules are in fact an attempt to describe the product that is demanded by the customer.

To improve efficiency and repeatability, rule-based automatic grading (RBAG) systems have been used in Nordic sawmills for nearly three decades. RBAG systems scan individual boards from four directions, performs image processing and image analysis and assigns each board a grade, based on user specified grade requirements. Nowadays RBAG systems can be found in many parts of the process, for example in the green sorting, final grading and in the secondary processing. The RBAG systems are configurable and can grade sawn timber in many different ways. The limiting number of grades that can be used are related to logistics and technology, rather than to the RBAG systems themselves. One reason for formulating the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994), was to be able to implement grading in RBAG systems. In practice these grading rules are not strictly used, either for manual or RBAG. Each sawmill typically have their own sets of grading rules, adapted for different raw material, board dimensions, markets and customers. The measurement errors of the board scanning equipment also need to be considered when configuring grading rule settings. If defects are underestimated in the scanning, this needs to be accounted for when configuring the grading rules in order to have a satisfied customer.

Customization of grading rules becomes more and more important in order to deliver the sawn timber that the customer desires (European confederation of woodworking industries, 2004). Configuring a RBAG system takes time and there are many parameters that can be changed for each grade, which is why changes are rarely made (Lycken and Oja, 2006; Lycken, 2006). Configuring grading rule settings becomes a challenge for sawmills using RBAG systems. It is easier to configure and customize grades by visually inspecting boards together with a customer, compared with customizing grading rule settings according to customer preferences.
This is why grading rules quickly become complicated and difficult to relate to the actual preferences of a customer.

A common belief in the sawmill industry is that a customer tends to tolerate a few defects that are slightly larger than allowed, if the rest of the board is better than the average board of that grade. Also the opposite is common, a customer may find a board unsatisfying because the general impression of the board is not representative for the given grade, even though all defects are within allowed limits.

This describes the difficulty with grading rules since discrete levels of allowed defect size and defect frequency need to be set. The consequence is that there are boards that a customer would accept, but they are downgraded to a lower grade only because a few grading rules are exceeded. There are also boards that a user does not accept, even though all grading rules are fulfilled. This points out the need of a holistic-subjective automatic grading (HSAG) where the idea is to combine the advantages of manual and RBAG.

There have been attempts using neural networks, self-organizing maps (SOMs) and fuzzy logic to automatically detect and classify board defects, as well as to grade boards for appearance (Labeda, 1995; Kauppinen, 1999; Kline et al., 2003; Niskanen, 2003; Silvén et al., 2003). This has proven to be difficult, as neural networks used for HSAG have not yet been introduced in commercial systems on a large scale. One reason is the complicated procedure of changing and formulating new grading rules, where the system has to be calibrated using numerous good examples of each new grade or defect type (Kline et al., 2003).

A different approach to accomplish HSAG is to use multivariate models, which has been proposed in earlier work by Lycken and Oja (2006). Information of defect properties obtained when scanning individual boards in a RBAG system can instead be used in multivariate models, forming a HSAG system. This is illustrated by Figure 1, which shows the process of the current RBAG systems. The last rule-based grading step could be replaced by a multivariate model and instead resulting in a HSAG system. Lycken and Oja (2006) recommended using PLS (Geladi and Kowalski, 1986; Wold et al., 2001) for HSAG, because with PLS some of the problems experienced with neural networks can be handled.

PLS models are, just as neural networks, calibrated by training the models on a training set of boards that have been manually graded ac-
According to customer preferences. However, a PLS prediction model gives a transparency impossible to reach with neural networks (Esbensen, 2002). This makes the calibration of a PLS model easier to understand and validate. A PLS model is also robust to noise and can, despite measurement errors, still highlight the important systematic effects (Eriksson et al., 2006). A measurement error in one or a few single defects or defect types does not have as large impact in a PLS model as it has in a RBAG.

Lycken and Oja (2006) showed that the consistency between their PLS models and manual grading, according to the Nordic timber grading rules, was 80–85% depending on board dimension. This is considered fairly good when comparing with manual grading. If accurate PLS models are obtained for predicting board grade, Lycken and Oja (2006) concluded that it would be easier to adapt the grading according to customer needs and thereby affecting the quality and value yield.

This article describes the continuation of the work by Lycken and Oja (2006). The objective is to develop a method that replaces the calibration of grading rule settings by HSAG using PLS. The objective is also to investigate if this approach can improve sawmill profitability and at the same time have a satisfied customer.
2. Materials and methods

2.1 Grading rules

This paper is focused on appearance grading of boards, which in the Nordic countries is based on the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994). These grading rules describe four board grades, namely A, B, C and D, where grade A is considered as the best grade and grade D the worst. Consequently, market prices for grade A are higher than prices for grade B, etc.

In the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994), consideration is given to most wood features on a board’s surfaces. The size and distribution of knots are however most important for the general appearance of a board and why the majority of grading rules are related to knots. This is the reason why this study was focused on knots for the development of HSAG models for prediction of board grade.

Grade D was not considered when developing HSAG models and the reason was that grade D does not have the same characteristic knottiness as grades A, B and C. When a board gets grade D it is because of one or several extreme wood features, i.e. it is not the same problem to separate grade D using RBAG systems as it is to separate grades A, B, and C which are more closely related.

2.2 Test material

The material used was 323 randomly selected Scots pine (Pinus sylvestris L.) boards from a sawmill in northern Sweden. The board dimension was $38 \times 150$ mm and board lengths varied between 3.4 and 5.6 m. The logs were sawn into four centre pieces from each log $(38/50/50/38) \times 150$ mm using cant sawing, where the boards used in this study were the outer center boards.

In this study, an expert in customer preferences for the North African market served as an example of an important customer. That is, a customer that regularly purchases significant volumes of sawn timber. The expert visually inspected and graded the 323 boards into grades A, B, and
C. The expert was instructed to only consider knots and was not allowed to trim the board in any way to enhance its grade.

Each board was also scanned by one example of a RBAG system, a *Finscan Boardmaster* (Finscan, 2014). The RBAG was performed in the final grading where the individual boards are scanned on all sides during cross transport. Knots and other wood features were detected in the obtained images and board grading was performed according to grading rule settings. The grading rule settings were based on the Nordic timber grading rules, but the settings were customized with respect to the current sawmill’s experience of customer preferences for the North African market. As before, only knots and no other features were taken into account when grading and no trimming was allowed. The RBAG was performed with respect to knot distribution on the entire board.

### 2.3 Prediction models

A total number of 58 variables related to knots on the scanned board surfaces were extracted using knot descriptive data, obtained from the RBAG system (Table 1). Each board was divided into one, three and five equally large sections (Figure 2) and variables were extracted for each section. The reason to use board regions was that knot characteristics in some board sections may be more important than others for a customer. The variables were extracted for the pith and sapwood side sections separately, but altogether for the edge sections. This resulted in $58 \times (1 + 3 + 5) \times 3 = 1566$ variables in total for each board. The variables were used to train prediction models for the three grades A, B and C according to customer preferences of the North African market.

Partial least squares (PLS) is a good method when dealing with a large number of variables (1566), in relation to the number of observations (323 boards) (Wold et al., 2001). It is also suitable when the predictor variables are correlated to each other and when there can be noise in the data. A PLS regression model can be analyzed by plots such as score plots, loadings, and VIP plots (Eriksson et al., 2006). These plots are important when interpreting a PLS model and makes the model easier to understand and validate. A holistic grading, using PLS models, can be complemented with grading rules for specific defects, such as wane, pitch pockets or blue stain as desired. Another strength with PLS models, which was mentioned
2. Materials and methods

Table 1: The 58 variables (marked x) related to knots that were extracted for each of the four board surfaces. Knot size was measured according to guidelines in the Nordic timber grading rules (Swedish Sawmill Managers Association, 1994).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Knot type</th>
<th>Sound &amp; dead</th>
<th>Sound</th>
<th>Dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total no. of knots</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Average knot size (mm)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>St.dev. knot size (mm)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Maximum knot size (mm)</td>
<td></td>
<td></td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Ratio of knots ≤ 9 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 10 - 19 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 20 - 29 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 30 - 39 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 40 - 60 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 60 - 80 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; ≥ 80 mm (%)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>No. of knots ≤ 9 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 10 - 19 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 20 - 29 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 30 - 39 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 40 - 60 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; 60 - 80 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>&quot; ≥ 80 mm (No./m)</td>
<td></td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

in the introduction, is that PLS regression models make it easier to control and change settings in a HSAG grading system and thereby affecting the quality and value yield. PLS regression has also been used in previous work, when grading logs as well as boards (Oja et al., 2004; Lycken and Oja, 2006).

The 1566 variables extracted from the RBAG system were used as predictor variables (X-variables) in a PLS. Dummy variables of board grade were used as response variables (Y-variables), in accordance with the expert of customer preferences for the North African market.
Figure 2: Variables were extracted for one, three and five equally large sections along the board.

Two PLS models, both consisting of three principal components, were used for the prediction of board grade. The first model, PLS model I, separates boards of grade C from grades A and B. The second model, PLS model II, separates boards of grade A from grades B and C.

In detail, PLS model I was trained using two classes and hence represented by two dummy response Y-variables, one for each class. Class I was here defined as boards graded by the expert as grade C and Class II was defined as boards of grade A or B. PLS model II was also trained using two classes. Class I was then defined as boards graded by the expert as grade A, while Class II was defined as boards of grade B or C. A description of the classes for the two models are summarized in Table 2. A prediction model separating grade B from grades A and C was not used. The reason was that prediction of grade B is more difficult with grade B boards somewhere in between grade A and C boards, with respect to knot characteristics. Also, using two models is sufficient in order to separate boards into three grades.

Table 2: Predefined classes for PLS model I and II. Grades A, B and C are grades for sawn timber customized according to preferences of a customer in North Africa.

<table>
<thead>
<tr>
<th></th>
<th>Class I</th>
<th>Class II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model I</td>
<td>C</td>
<td>A, B</td>
</tr>
<tr>
<td>Model II</td>
<td>A</td>
<td>B, C</td>
</tr>
</tbody>
</table>
Furthermore, using the two PLS models to predict the grade of boards gives a probability value for each board to be grade A and C, respectively. A high probability value (close to 1) means that, according to the PLS model, the probability is high that the board fits that grade. In the same way, a low probability value (close to 0) indicates that the board does not belong to that grade. In the model it is possible to skew the distribution to a better fit by using an adjustable threshold limit for the separation of the board grades. If, for example, a low threshold limit is used for grade C, the probability is high that each board is a grade C board. All boards are then graded as C which means that all grade C boards are graded correctly and thus found. At the same time, a lot of non-C boards are erroneously graded as C (false positive). If a high threshold limit is used for grade C, no board is graded as C and all grade C boards are missed (false negatives). On the other hand no non-C boards are erroneously graded as C. When adjusting the threshold limits for the grades, it is important to consider how many false positives and false negatives that are acceptable. It is possible to find all boards of a specific grade, with a risk of also obtaining some false positive boards that do not belong to that grade. It is also possible to find only boards belonging to a specific grade, but with the risk of missing some boards of that grade. So, by choosing the value of the threshold limit, it is possible to choose a level of risk and to choose an acceptable number of false positives and false negatives. If not skewing the distribution, a natural choice of threshold limit would be 0.5.

The two models were used to predict board grade according to the following decision tree (also illustrated in Figure 3).

1. Does the PLS model I estimate for Class I, $\hat{y}_i$, for $i = 1 \ldots 323$, exceed a specified threshold limit i.e. $\hat{y}_i > L_C, L_C \in [0, 1]$ then the board is grade C, otherwise continue.

2. Does the PLS model II estimate for Class I, $\hat{y}_i$, exceed a specified threshold limit i.e. $\hat{y}_i > L_A, L_A \in [0, 1]$ then the board is grade A, otherwise continue.

3. If the board is neither grade A nor grade C, then it is grade B.

From a sawmill as well as customer perspective, grading a board of true grade C as grade A or B is worse than grading a board of true grade A as
grade B or C. This is the reason prediction of grade C is performed first in the decision tree. Boards that are difficult to assess are more likely graded as grade C than grade A or B in this way. This can also be controlled by adjusting the threshold limits for board grade separation, $L_A$ and $L_C$.

For both PLS models (PLS model I, PLS model II), the goodness of fit is given by the calculated coefficient of determination ($R^2$) and the goodness of prediction by the $Q^2$-value. The $Q^2$-value is based on cross-validation (Martens and Naes, 1989). Cross-validation means that $n$ models are built, each excluding a part, $(1/n)$, of the observations when creating a training set to build a model. Each model can then be tested on the observations that were excluded when building the model. These observations are called the test set. The value of $Q^2$ represents the proportion of variance in $y$-values in the test sets that is explained by the model. This means that $Q^2$ is a measure of the model’s ability to predict new observations, that is observations that are not included when building a model.

To analyze and verify the grading performance of the two created PLS models, prediction of board grade was performed for all 323 boards according to the procedure described in Figure 3. This was carried out using two different settings of $L_C$ and $L_A$, but using the same two PLS models (PLS model I, PLS model II). The first setting (HSAG I), using $L_C = 0.78$.
and $L_A = 0.28$ and the second setting (HSAG II), using $L_C = 0.41$ and $L_A = 0.34$. HSAG I consequently grading more boards as grade A and B compared with HSAG II, since $L_C$ is larger and $L_A$ smaller for HSAG I compared with HSAG II.

2.4 Follow-up grading

All 323 boards were assigned a board grade by three different strategies, according to a RBAG system and according to HSAG I and HSAG II. To simulate an inspection by a customer and to compare the different strategies for grading in practice, the expert in customer preferences for the North African market visually inspected the boards again. The boards were sorted into nine equally large groups, representing the three different grading strategies (RBAG, HSAG I, HSAG II) and the three different grades (A, B, C).

To ensure objectivity, the sorting of the 323 boards was performed according to the following procedure:

1. One board, graded by the RBAG as grade A, was randomly selected for group 1.
2. One board, graded by HSAG I as grade A, was randomly selected for group 2.
3. One board, graded by HSAG II as grade A, was randomly selected for group 3.
4. One board, graded by the RBAG as grade B, was randomly selected for group 4.
5. One board, graded by HSAG I as grade B, was randomly selected for group 5.
6. One board, graded by HSAG II as grade B, was randomly selected for group 6.
7. One board, graded by the RBAG as grade C, was randomly selected for group 7.
8. One board, graded by HSAG I as grade C, was randomly selected for group 8.

9. One board, graded by HSAG II as grade C, was randomly selected for group 9.

As long as all of the steps 1–9 were possible to fulfil (nine boards existed), the boards were added to each respective group and the procedure was repeated. Once one or several of the steps 1–9 were not fulfilled (one or several boards did not exist), the procedure was cancelled and no more boards were added.

The sorting procedure resulted in nine groups with 31 randomly selected boards in each group, 279 boards in total.

The expert’s task was to visually inspect the boards, grade by grade. The instruction to the expert was that the nine groups represented grades A, B and C, where the grading was performed by three different strategies that all were adapted to preferences of customers from North Africa. To ensure objectivity, five boards from each group were inspected in sequence before considering five boards from the next group and so on, until all boards of a grade had been inspected. Only knots were considered and no trimming was allowed when inspecting each board.

The experts opinion of the grading of each board was documented according to the following options:

1. The board is graded correctly
2. The board is of a lower grade
3. The board is of a higher grade
4. The board grade is a borderline case of being of a lower grade
5. The board grade is a borderline case of being of a higher grade

One of the options 1–3 had to be marked for each board while option 4–5 could be marked as complementary information.
3. Results

3.1 Rule-based automatic grading

A comparison between the grading of the 323 boards by the RBAG system compared with the grading by the expert for the North African market is presented in Table 3. The share of boards that the RBAG system graded correctly according to the expert was 63%. Out of the 323 boards, the expert graded 24% of the boards as grade A, 44% as grade B and 32% as grade C. The corresponding numbers for RBAG were 24% for grade A, 31% for grade B and 45% for grade C. Apparently the expert considered more of the boards as of grade B compared with the RBAG system, while they were equal in share of grade A.

Table 3: The number and percentage of the 323 boards in each grade by automatic grading column-wise and by the customer expert row-wise. For the different grades according to the automatic grading, the consistency with the customer expert was also calculated.

<table>
<thead>
<tr>
<th>Grade</th>
<th>RBAG</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A (16%)</td>
<td>B (6%)</td>
</tr>
<tr>
<td>Customer expert</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>51</td>
<td>19</td>
</tr>
<tr>
<td>B</td>
<td>22(7%)</td>
<td>68(21%)</td>
</tr>
<tr>
<td>C</td>
<td>5(2%)</td>
<td>14(4%)</td>
</tr>
<tr>
<td>Total</td>
<td>78(24%)</td>
<td>101(31%)</td>
</tr>
</tbody>
</table>

Correct grade total: \( \frac{(51+68+83)}{323} = 63\% \)
Correct or underestimated grade total: \( \frac{(51+68+83+19+8+53)}{323} = 87\% \)
Correct grade A: \( \frac{51}{78} = 65\% \)
Correct or underestimated grade B: \( \frac{68+19}{101} = 86\% \)

3.2 Holistic-subjective automatic grading

For PLS model I, separating boards of grade C from grade A and B, the \( R^2 \) value was 0.70 and the \( Q^2 \) value was 0.43. This means that 70% of the variance in board grade is explained by the model and 43% can be predicted according to cross-validation. The \( R^2 \) value for PLS model II was 0.66 and the \( Q^2 \) value 0.49. Looking at Figure 4, the separation
between grade A (squares) and grade C (triangles) is clear. There are mixed zones between grades A and B (circles) and between grades B and C.

![Figure 4: Score plot showing the different grades, according to the customer expert, and their formation in the coordinate system of the two first principal components, \( t[1], t[2] \). Squares = grade A, circles = grade B and triangles = grade C. Included is also a tolerance ellipse based on Hotelling’s T2 (Hotelling, 1931).]

The share of boards that was graded correctly according to the expert was 76% for HSAG I (Table 4). The grade distribution for HSAG I shows that 32% of the 323 boards were graded as grade A, 51% as grade B and 17% as grade C. For HSAG II the share of boards that had the correct grade according to the expert was 87% (Table 5). The grade distribution for HSAG II shows that 28% were predicted as grade A, 41% as grade B and 31% as grade C.
3. Results

Table 4: The number and percentage of the 323 boards in each grade by HSAG I column-wise and by the customer expert row-wise. The threshold limits used for separating board grades were $L_C = 0.78$ and $L_A = 0.28$. For the different grades according to HSAG I, the consistency with the customer expert was also calculated.

<table>
<thead>
<tr>
<th>Grade</th>
<th>HSAG I</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Customer expert</td>
<td>73(23%)</td>
<td>5(2%)</td>
</tr>
<tr>
<td>B</td>
<td>26(8%)</td>
<td>117(36%)</td>
</tr>
<tr>
<td>C</td>
<td>4(1%)</td>
<td>42(13%)</td>
</tr>
<tr>
<td>Total</td>
<td>103(32%)</td>
<td>164(51%)</td>
</tr>
</tbody>
</table>

Correct grade total: \((73+117+56)/323 = 76\%\)
Correct or underestimated grade total: \((73+117+56+5+0+0)/323 = 78\%\)
Correct grade A: \(73/103 = 71\%\)
Correct or underestimated grade B: \((117+5)/164 = 74\%\)

Table 5: The number and percentage of the 323 boards in each grade according to HSAG II column-wise and by the customer expert row-wise. The threshold limits used for separating board grades were $L_C = 0.41$ and $L_A = 0.34$. For the different grades according to HSAG II, the consistency with the customer expert was also calculated.

<table>
<thead>
<tr>
<th>Grade</th>
<th>HSAG II</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Customer expert</td>
<td>71(22%)</td>
<td>6(2%)</td>
</tr>
<tr>
<td>B</td>
<td>16(5%)</td>
<td>118(37%)</td>
</tr>
<tr>
<td>C</td>
<td>2(1%)</td>
<td>9(3%)</td>
</tr>
<tr>
<td>Total</td>
<td>89(28%)</td>
<td>133(41%)</td>
</tr>
</tbody>
</table>

Correct grade total: \((71+118+91)/323 = 87\%\)
Correct or underestimated grade total: \((71+118+91+6+1+9)/323 = 92\%\)
Correct grade A: \(71/89 = 80\%\)
Correct or underestimated grade B: \((118+6)/133 = 93\%\)

3.3 Follow-up grading

According to the expert, 88% of the boards graded by RBAG had the correct grade (Table 6). As for HSAG I, the share of correctly graded boards was 94% according to the expert (Table 7). The boards graded according to HSAG II had the highest share of correct grade according to the expert, 98% (Table 8).
Table 6: The result of a customer expert inspection of three equally large groups of randomly selected boards representing grades A, B and C according to a RBAG grading system.

<table>
<thead>
<tr>
<th>Grade</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>25(81%)</td>
<td>30(97%)</td>
<td>27(87%)</td>
<td>82(88%)</td>
</tr>
<tr>
<td>Lower</td>
<td>6(19%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>6(6%)</td>
</tr>
<tr>
<td>Higher</td>
<td>0(0%)</td>
<td>1(3%)</td>
<td>4(13%)</td>
<td>5(5%)</td>
</tr>
<tr>
<td>Total</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td>93</td>
</tr>
<tr>
<td>Borderline lower</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
</tr>
<tr>
<td>Borderline higher</td>
<td>0(0%)</td>
<td>1(3%)</td>
<td>9(29%)</td>
<td>10(11%)</td>
</tr>
</tbody>
</table>

Table 7: The result of a customer expert inspection of three equally large groups of randomly selected boards representing grades A, B and C according to HSAG I, using $L_C = 0.78$ and $L_A = 0.28$.

<table>
<thead>
<tr>
<th>Grade</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>29(94%)</td>
<td>27(87%)</td>
<td>31(100%)</td>
<td>87(94%)</td>
</tr>
<tr>
<td>Lower</td>
<td>2(6%)</td>
<td>4(13%)</td>
<td>0(0%)</td>
<td>6(6%)</td>
</tr>
<tr>
<td>Higher</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
</tr>
<tr>
<td>Total</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td>95</td>
</tr>
<tr>
<td>Borderline lower</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
</tr>
<tr>
<td>Borderline higher</td>
<td>0(0%)</td>
<td>9(29%)</td>
<td>0(0%)</td>
<td>9(10%)</td>
</tr>
</tbody>
</table>

Table 8: The result of a customer expert inspection of three equally large groups of randomly selected boards representing grades A, B and C according to HSAG II, using $L_C = 0.41$ and $L_A = 0.34$.

<table>
<thead>
<tr>
<th>Grade</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td>29(94%)</td>
<td>31(100%)</td>
<td>31(100%)</td>
<td>91(98%)</td>
</tr>
<tr>
<td>Lower</td>
<td>2(6%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>2(2%)</td>
</tr>
<tr>
<td>Higher</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>0(0%)</td>
</tr>
<tr>
<td>Total</td>
<td>31</td>
<td>31</td>
<td>31</td>
<td>93</td>
</tr>
<tr>
<td>Borderline lower</td>
<td>0(0%)</td>
<td>0(0%)</td>
<td>1(3%)</td>
<td>2(2%)</td>
</tr>
<tr>
<td>Borderline higher</td>
<td>0(0%)</td>
<td>1(3%)</td>
<td>3(10%)</td>
<td>4(4%)</td>
</tr>
</tbody>
</table>
4 Discussion

When comparing HSAG I in Table 4 and RBAG in Table 3, it is clear that the total share of correctly graded boards is higher for HSAG I compared with RBAG. The total share of correctly graded boards was 76% for HSAG I, while it was 63% for RBAG. HSAG I also had a larger share of higher grade boards 32%, 51%, 17% for grades A, B, C, respectively, compared with 24%, 31%, 45% for RBAG. The share of grade A has been increased by 8 percentage points and the share of grade B has increased by 20 percentage points using HSAG I compared with RBAG.

When evaluating the customer satisfaction, a good measure is the share of boards that are graded correctly or where the grade has been underestimated. For a customer, a correct grade is the expected while an underestimated grade would mean that the customer purchases boards of a perceived higher grade to a lower price. The share of boards with a correct or underestimated grade according to the expert was 78% for HSAG I, while it was 87% for RBAG. These results indicate that the customer would be more satisfied with RBAG compared with HSAG I. The threshold limits used for separating board grades in HSAG I increased the share of higher board grades too much, at the expense of customer satisfaction. This is also supported by the follow-up grading that was performed. For HSAG I, 4% of the boards were a borderline case of being a higher grade while 10% were a borderline case for a lower grade according to the expert (Table 7). This can be compared with RBAG where 11% of the boards were a borderline case of being a higher grade while 0% were a borderline case for a lower grade according to the expert (Table 6).

If comparing the grading by HSAG II in Table 5 with RBAG in Table 3, the total share of correctly graded boards according to the expert is also higher for HSAG II compared with RBAG. The total share of correctly graded boards was 87% for HSAG II, while it was 63% for RBAG. HSAG II also had a larger share of higher grade boards 28%, 41%, 31% for grades A, B, C, respectively, compared with 24%, 31%, 45% for RBAG. The share of grade A has been increased by 4 percentage points and the share of grade B has increased by 10 percentage points using HSAG II compared with RBAG.

Furthermore, when evaluating the customer satisfaction and looking at the share of boards with a correct or underestimated grade according
to the expert the results look better for HSAG II. The share of boards with correct or underestimated grade was 92% for HSAG II, while it was 87% for RBAG. This indicates that board grading according to HSAG II would result in a satisfied customer. The follow-up grading of HSAG II also shows a more reasonable balance between borderline cases, now 4% of the boards were a borderline case for a higher grade and 2% were a borderline case for a lower grade according to the expert (Table 8).

To summarize, the results obtained show that it is possible to increase the share of higher board grades while still meeting the demands of the customer using a HSAG system that is based on PLS models. Choosing threshold limits for board grade separation in a HSAG system is a trade off between increased sawmill revenues and customer satisfaction. How much that the share of higher grades can be increased to improve sawmill profitability depends also on the current market situation. In times of high market demand, customers’ quality requirements tend to be more tolerant compared to when market demand is low.

As an example of economical benefits with HSAG, let’s consider a sawmill that produces 400 000 m³ of sawn timber a year and that the current prices are 198 €, 170 € and 142 € for grades A, B and C respectively. Assume that this sawmill has an important customer purchasing 100 000 m³ sawn timber a year, thus 25% of the sawmill’s annual production. For the 323 boards, the RBAG system had a grade distribution of 24%, 31%, 45% for grade A, B and C respectively (Table 3). For HSAG I the same grade distribution was 32%, 51%, 17% (Table 4) and for HSAG II it was 28%, 41%, 31% (Table 5). Assume that each of the three grading strategies RBAG, HSAG I, HSAG II was used for grading the 100 000 m³ of sawn timber for the important customer and that the grade distributions were the same as for the 323 boards in this study. If grading according to HSAG I, the sawmill would increase their revenues by 1 008 000 € annually compared with RBAG. This corresponds to a 6% annual increase of revenues compared with RBAG. If grading according to HSAG II, the sawmill would increase their revenues by 504 000 € compared with RBAG. This corresponds to a 3% annual increase of revenues compared with RBAG. This rough calculation example shows the economical benefits with introducing HSAG in a sawmill.

Lycken (2006) showed that RBAG systems can replace manual graders for grading according to the Nordic timber grading rules (Swedish Sawmill
Managers Association, 1994). Lycken and Oja (2006) and Lycken (2006) states that the problem with RBAG systems is the difficult work of defining new grades or changing the ones in use. With HSAG based on PLS models it is easier to control and change settings according to customer needs. For a RBAG system, numerous grading rules need to be changed and fine-tuned. In the example considered in this paper, only two values in the HSAG approach need to be tuned once data of customer preferences has been collected and PLS models created. Those are the threshold limits ($L_A$, $L_C$), for separating grade A respectively grade C. By properly adjusting these values, it is possible to control customer satisfaction and sawmill profitability.

To calibrate PLS models, as with any other statistical method, a reliable and representative data set is essential (Eriksson et al., 2000). In this study, this depends on how well the expert can describe customer preferences of the North African market. Also, the number of boards of each grade that are needed in order to have a representative data set is essential. For this work, 323 boards were used as training set where 78 boards were of grade A, 143 of grade B and 102 of grade C according to the expert. Our experience is that this has been satisfactory, even though we would have preferred more boards of grade A in the training set. Lycken and Oja (2006) suggested that using 100 boards of each grade would be necessary to calibrate a model, which seems reasonable. There is no upper limit for how many boards of each grade to use in a training set, the limiting factor is that the work load to perform such a manual grading must be feasible.

For a final application in a sawmill, the number of variables used in the PLS models can probably be reduced. In this paper we used about 1500 variables in each model. Most likely, all of these variables are not necessary to obtain satisfying results. This study shows that board grading using PLS is possible, but future work is to study the 1500 variables more to see which variables that can be excluded from the PLS models. Also, the trimming decision need to be considered and in some way handled by the PLS models.

With this type of HSAG implemented in a sawmill, it will be possible to use a larger board material. This will make it easier to evaluate HSAG for other markets and board dimensions, which is also left for future work. Lycken and Oja (2006) found that board dimension was important when
calibrating PLS models for predicting board grade. The knot structure of a board depends on the board size and where in the tree the log comes from (Houllier et al., 1995; Jäppinen, 2000; Nordmark, 2005). Also, in this work the PLS models were tested on the same boards that were used to create the models. The models should be tested on a new, larger board material that has not been used to create the models to see how this affects the result.

5 Conclusions

In this paper, an alternative way of grading boards with respect to knot distribution and appearance on board surfaces was used. Instead of a typical rule-based automatic grading (RBAG), a holistic-subjective automatic grading (HSAG) based on multivariate models was used to predict board grade. The multivariate models were generated using about 1500 variables related to knot size and knot distribution on the board surfaces.

The result show that the HSAG system was more correct, with respect to customer preferences, than the RBAG system. HSAG based on multivariate models for 323 Scots pine boards resulted in 76–87% of the boards graded correctly, while the corresponding number was 63% for a RBAG system. This means that when using multivariate models to predict board grade, the share of boards of higher grade can be increased, while still adapting to customer preferences.

An increased share of grade A boards between 4–8 percentage points was found when using multivariate models to predict board grade and compared with the RBAG grading. For grade B, the corresponding increase was between 10–20 percentage points. The variability in the increased share of higher board grades obtained in this study depends on the choice of threshold limits for board grade separation. Assume this increased share of higher grade could be directly applied to a sawmill, having an important customer that purchases 100 000 m$^3$ of sawn timber annually. This would result in increased revenues of between 3–6% a year, depending on chosen threshold limits and compared with a RBAG. For a sawmill to decide threshold limits for board grade separation will be a trade off between increased sawmill revenues and customer satisfaction.
Future work is to evaluate multivariate models for predicting board grade on a larger board material in a sawmill. A reduction of the number of variables used in the multivariate models and a way to handle the trimming decision when using the multivariate models should also be considered.

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References


