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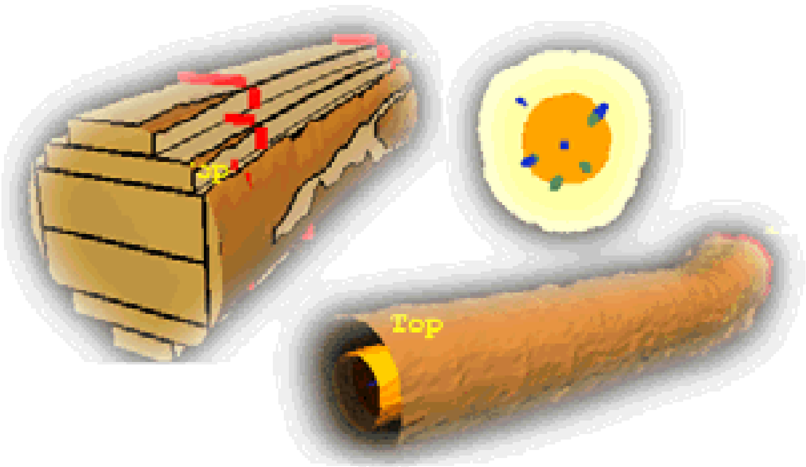
DOCTORAL THESIS

Value Recovery and Production Control in the Forestry-Wood Chain using Simulation Technique



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LULEÅ UNIVERSITY OF TECHNOLOGY

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Value Recovery and Production Control in the Forestry–Wood Chain using Simulation Technique

by

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ABSTRACT

This thesis deals with value recovery and production control in the forestry–wood chain for improved competitiveness of sawmills through higher profit and better adaptation to product requirements of the customers. The subject was approached using simulation technique with a database of virtual logs and a sawing simulator capable of processing the logs in the database.

CT images of young Scots pine (*Pinus sylvestris*) sawlogs were processed with artificial neural networks (ANN) for identifying knots in sapwood where the contrast in the images is low. ANN classifications were deemed a feasible method where traditional image analysis methods failed. Further processing of the classified image allowed for parametric descriptions of the logs in a format compatible with the previously established Swedish Pine Stem Bank (SPSB).

Static models of stem shape and interior knot structure were used to create stems that were also compatible with the SPSB. Processing the stems with the sawing simulator demonstrated the possibility of predicting timber grade recovery and volume yield from stands based on site, stand and tree characteristics. It was also shown that timber values in logs can be predicted using variables derived from 3-dimensional (3D) scanning of stems' external geometry as well as from 3D scanning in combination with X-ray log scanning. The improvement achieved with the combined scanning was rather low compared to using 3D scanning alone.

Results of a study of bucking methods, log sorting methods and production control showed that the more detailed information the bucking and log sorting decisions are based on, the higher the value recovery. Furthermore, the more processing stations involved in production control, the better are the demand targets met.

In a study aiming at increased share of target board lengths, different bucking alternatives were evaluated. It was concluded that optimizing forest operations, value recovery and production as separate entities will not produce optimal results. A case study of a sawmill where the length of the timber was of high interest showed that increasing the share of target lengths of small dimensions can only be done at a relatively high cost in terms of volume yield loss. It was also shown that log classes should be defined with varying diameter limits for different log lengths at the conventional diameter-based log sorting. In order to meet the desired length distribution of the timber, it is necessary to alter the log length distribution, and this can be done with adaptive control heuristics that dynamically updates control log prices during bucking.

It is concluded that there is an unexploited value potential in the forestry–wood chain which can be reached using modern measurement techniques and that a better characterization of the wood raw material will facilitate an improved customer-order orientation.

Keywords: ANN, bucking, CT, cross-cutting, image analysis, knots, log geometry, log scanning, log sorting, models, order oriented, outer shape, production control, sawing, simulation, Scots pine

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Finally, I would like to thank my parents for their love, and for making me believe that impossible tasks only need some extra time and effort to accomplish. My warmest gratitude goes to *Jessica* and our children *Evelina* and *Rasmus* for giving life meaning

Piteå, June 2005

Urban Nordmark

LIST OF PAPERS

This doctoral thesis is based on the work reported in the following seven papers, referred to by roman numerals. Published articles have been reproduced in this thesis with kind permission of *Scandinavian Journal of Forest Research* and *Forest Products Journal*:

I. Nordmark, U. 2002. Knot identification from CT images of young Pinus sylvestris sawlogs using artificial neural networks. *Scand. J. For. Res. 17: 72–78.*

II. Nordmark, U. 2003. Models of knots and log geometry of young *Pinus sylvestris* sawlogs extracted from computed tomographic images. *Scand. J. For. Res. 18: 168–175.*

III. Moberg, L. & Nordmark, U. 2005. Predicting lumber volume and grade recovery for Scots pine stems using tree models and sawmill conversion simulation. *Submitted to Forest Prod. J.*

IV. Nordmark, U. & Oja, J. 2004. Prediction of board values in Pinus sylvestris sawlogs using x-ray scanning and optical three-dimensional scanning of stems. *Scand. J. For. Res. 19: 473–480.*

V. Nordmark, U. 2005. Value recovery and production control in bucking, log sorting and log breakdown. *Forest Prod. J. 55(6): (73–79).*

VI. Nordmark, U. & Chiorescu, S. 2001. Satisfying consumer demand – A comprehensive view on the sawmill economy using simulation techniques. Proceedings of the 7th international conference on sawing technology. pp 3–10. Szymani, R. (Ed.). November 7–9, 2001, Seattle, USA.

VII. Nordmark, U., Eklund, M. & Nygren, M. 2005. Targeting the length of lumber – a case study of a small dimension softwood sawmill. *Submitted to Forest Prod. J.*

Specification of the author's (Nordmark, U.) contribution to above listed papers with several authors:

III Paper III was produced in collaboration with Dr. Lennart Moberg at SkogForsk, Uppsala. Lennart did the modelling and while the author carried out sawing simulations and analysis of results.

IV The author carried out most of the research while Dr. Johan Oja at Luleå University of Technology provided bumpiness data and X-ray log scanner data and assisted in the PLS analysis.

VI Paper VI was produced in collaboration with Dr. Sorin Chiorescu at Luleå University of Technology. The author provided the virtual sawlogs and did most of the analysis. Sorin carried out sawing simulations and assisted in analysis.

VII Most of the work was carried out by the author. Magnus Eklund and Mats Nygren, SETRA, Piteå, assisted in planning and data acquisition.

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Papers

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1. INTRODUCTION

1.1. Background

The sawmill industry is competing in a global market. There is competition between companies as well as between wood and other materials. Strategies used to face the competition are increased efficiency and better adaptation to requirements put by the markets. As the wood raw material represents approximately two thirds of a sawmill's total costs, the level of efficiency in utilizing the wood will obviously have a large impact on the economic results. Meeting market requirements means producing timber with dimensions and qualities that satisfy the needs and expectations of the customers. When shifting from a bulk-oriented strategy towards a customer-oriented strategy, it is clear that characterisation of wood early in the forestry–wood chain and communicating requirements between different processing units are key elements for producing the right products efficiently. Developments of computers have facilitated simulations as a technique used to study complex systems at low cost and with good control. Computer simulations are widely used, accepted and recognized as a valuable tool for R&D. The large variation of wood properties that are mostly hidden within the trees and logs along with the complex chain of activities involved in converting trees to timber makes simulations suitable for studies within the forestry–wood chain. The previously established Swedish Pine Stem Bank (SPSB) is a database of 198 mature Scots pine (*Pinus sylvestris*) stems (Grönlund et al. 1995). The SPSB holds parametric descriptions of the 3-dimensional outer shape and interior knot structure of stems, which together with sawing simulation software can be used to study activities within the forestry–wood chain and monitor the outcome in terms of products produced. A sawing simulator program (Saw2003) able to read and process the stems in the SPSB has been developed. Features of the software are given in detail in appendices A–D.

Thinning in younger stands is estimated to have a large potential of increased harvest in Sweden. Combined with a change of demand towards smaller dimensions of wood products, there has been interest in augmenting the stem bank with younger Scots pine stems. The SPSB was built using computer tomography (CT) of the stems. From the CT images, external geometry and internal knot structure could be extracted. Young stems appear differently in CT images, and as a consequence, other methods are needed for extraction of internal knot structure (Papers I and II).

Knot properties are of great importance for many solid wood products. The quality grade and value of a product are largely determined by the size, type and distribution of its knots, and economic gains may be achieved by picking the right raw material and by processing it more intelligently based on knowledge of the interior knot structure of trees and logs (Steele et al. 1993; Todoroki 2001). Grade classification of solid wood products serves as a label of suitability for different end uses; e.g., construction, appearance or window framing. Not knowing the grade distribution of boards until after the sawing process is a great hindrance to fully applying a customer-oriented production strategy. Indirect estimates of knot properties and stem shape of standing trees through prediction models may be useful for tactical decisions and thus should be evaluated (Paper III). Online measurements of log shape during log sorting at sawmills have proven useful for prediction of board grades (Grace 1994; Jäppinen & Beauregard 2000; Lundgren 2000; Oja 2003). However, at the log-sorting stage, the potential of the raw material to fulfil requirements has already been reduced by the decisions taken when the trees were bucked (cross-cut) to logs, hence the desirability of the application of predictions of the boards' properties in the bucking operation (Paper IV).

When the needs of timber specified by thickness, width, length and grade are to be communicated through the chain from sawmill to forest operations, a difficult but important step is the conversion and link of timber dimensions to log dimensions. Today, log sorting at sawmills is primarily controlled by log diameter, and bucking is controlled by log price lists with individual prices on different combinations of log diameter and log length. Modern measurement techniques such as three-dimensional (3D) scanning practiced at sawmills and CT scanning used in research allow for an interesting alternative to the communication problem. With data acquired with any of these devices in combination with sawing simulations, the outcome of timber from individual logs can be predicted, thus easing the need to couple timber dimensions to log dimensions. More detailed characterisation of logs and stems may also allow for higher value recovery. Thus the influence on value recovery and production control of different degrees of characterisation of the raw material has been studied (Paper V). When specific products are targeted in production and different alternatives are evaluated, optimizing each activity individually may lead to results that are not globally optimal to the chain of operations. To obtain good economic results, the chain must be seen in its entirety (Usenius 1996). In Paper VI the production economy of a sawmill is evaluated for different bucking alternatives aimed at increasing the share of certain lengths of timber. In order to produce products with the desired lengths, it is also necessary to have a deep understanding of the relation between log dimensions and final board lengths. Once the model is established, it is possible to optimize the process by economic means using Linear Programming (LP) (Hillier & Lieberman 1995) (Paper VII).

1.2. Measuring knot parameters in CT images of young Scots pine sawlogs

The X-ray based CT scanner measures the transmission of an X-ray beam through an object. The transmitting X-ray source and the detector array on the opposite side of the object are rotated and thus measure the transmission in many direction of a cross-section of the object. From this data the linear attenuation coefficient of each small volume element within the cross-section is calculated with the aid of filtering methods such as Fast Fourier Transform (FFT). The coefficients are further scaled to CT numbers, which gives the coefficients in relation to the linear attenuation coefficient in water. The CT numbers thus obtained can then be mapped to a digital grey-scale image providing visual information that can be interpreted directly by the viewer or further processed using image processing and analysis. Such an image provides an approximate representation of the density variations within the cross-section, as the linear attenuation coefficients are highly density dependent (Lindgren 1991). Images yielded when scanning a specimen, e.g., a log, at many positions can be grouped together into an image stack that provides a full three-dimensional representation of the density variations within the specimen. From this image stack, new cross-section planes can be calculated in any direction. In order to automatically segment and extract properties from the images other than the density of small volume elements, extensive use of image processing is necessary. Much research effort has been dedicated to feature extraction from CT images of softwoods (McMillin et al. 1984; Funt & Bryant 1987; Grundberg & Grönlund 1992) as well as hardwoods (Zhu 1991; Bhandarkar et al. 1999).

When processing CT images of newly cut fresh logs, it becomes obvious that the contrast between the features of interest should be high and that the variations within each feature class should be low for successful segmentation and classification. Within softwoods the contrast between the denser knots and the lighter surrounding wood is high when the knots are situated in the heartwood, while it is very low when the knots are situated in sapwood, as high water content adds to the density of sapwood and the density sums up to the same level as the knots. Unfortunately, young Scots pine sawlogs have only a small proportion of heartwood, or are totally lacking in heartwood. Furthermore, with wood being a biological material, the variations in density and appearance are large. The difficulties of detecting knots in the sapwood have also been recognized by Andreu & Rinnhofer (2003) for Norway spruce (*Picea abies*) and by Flood et al. (2003) for Scots pine. While traditional image processing such as filtering and thresholding failed to segment knots in young Scots pine sawlogs, the knots were clearly detectable by visual examination of the images on a computer screen. This annoying fact led to the conclusion that the human brain has image processing capabilities worth trying to mimic, and attention was drawn to the field of Artificial Neural Networks (ANN). Feed-forward backpropagation ANN

(Hassoun 1995) has been used by Li et al. (1996), and Schmoldt et al. (2000) has demonstrated the feasibility of using ANN for segmentation and labelling of features in several hardwood species, while Hagman & Grundberg (1995) used ANN for classification of knot type in CT images of Scots pine.

1.3. Sawing simulations

With the large inherent variation in wood, every individual stem and sawlog is unique. Furthermore, the processing of a log into boards, chips and sawdust is an irreversible process; thus each log can only be processed once. This implies that research within a system involving the processing of logs into timber is hard to realize with actual studies in the field or laboratory for several reasons: 1) the variation of the input raw material cannot be controlled; 2) variations in processing cannot be controlled; hence 3) dimensioning the studies for statistical analysis will be too costly. The solution is to use simulation tools. The combination of a database of virtual logs and a sawmill simulator able to read and process the logs makes comparisons of the outcome of sawing possible on identical raw material and at low cost. Furthermore, sawing simulation software able to predict the outcome of real logs may be used as an online application within the sawing process for automatic decision making and process control.

Early sawing simulators treated the logs as truncated cones with circular cross-sections (Cummins & Culbertson 1972; Richards 1973; Johansson 1978). Later sawing simulators handle more realistic log geometries (Singmin 1980; Lewis 1986; Occena et al. 1988; Funk et al. 1993), while the most recent also include the inner features of sawlogs (Todoroki 1996; Björklund & Julin 1998; Chiorescu & Grönlund 1999; Usenius 1999; Bhandarkar et al. 2002). Yield attributes estimated with sawing simulations may also provide input to bucking optimizations. The combined sawing and bucking models presented by Faaland & Briggs (1984), Reinders & Hendricks (1989) and Maness & Adams (1991) used simplified log models, while the tool presented by Björklund & Julin (1998) handles more realistic log geometries. Usenius (2001) presents a system of simulation modules with a sawing simulator as a central part that together are used for an integrated approach to optimization of the conversion of trees to timber. The simulator Saw2003 presented here operates on true shape virtual logs and is capable of integrating bucking decisions based on yield attributes. Appendices A–D provide further information on the interface, capabilities and internals of the software. The appendices were included as an aid to deeper understanding of how the results of the studies were obtained and for the purpose of gathering the author's work in one place (this thesis).

1.4. Predicting grade and value recovery in logs

At a strategic level, the grade distribution of different stands is valuable information for wood procurement, i.e., which stands will match the sawmill's targeted market segment the best and vice versa. At a tactical level, the grade distribution of different stands is valuable information for scheduling the harvesting either in order to avoid fluctuations in grade distribution or in order to fulfil orders. At the operational level, when the stem is being bucked into logs, the spatial grade distribution within a stem is together with the stem's geometry valuable information in order to obtain high value recovery and to produce the desired products. Furthermore, the grade distribution of a specific log is valuable information connecting grade to the dimensions of the board when a sawing pattern is assigned to the log at the log sorting station, thus giving the final product.

Researches aiming at modelling quality features such as interior knot structure of trees and logs or predicting the grade of sawn products follow alternative approaches. One alternative is to use growth models together with models of taper, live crown and branching (Houllier et al. 1995; Briggs 1996; Barbour et al. 1997; Ikonen et al. 2003). These models recursively predict the development of trees over a long period, arriving at stem shape and internal knot structure at the time of harvest. The second approach models the static state of stem shape and interior knot structure directly from site, stand and tree characteristics (Høibø et al. 1996; Moberg 2000). While the recursive approach is biologically appealing, there are statistical implications, as errors in one model might be magnified over time or carried over to other integrated models (Houllier et al. 1995). Moreover, the models depend on historical data, which can be difficult to assess. The static state models have the advantage that they can be based on preharvest measurements. The static models developed for Scots pine and Norway spruce by Moberg (2005) and Moberg et al. (2005), if integrated with sawing simulations, provide a system for strategic and tactical planning within a customer-oriented forestry–wood chain in Sweden. However, before such a system is applied, its ability to predict timber volume and grade recovery should be verified.

A third alternative for modelling quality features is to directly predict grade from 3-dimensional scanning of logs' external geometric properties (Jäppinen & Beauregard 2000; Lundgren 2000) or from information on whorls' properties revealed with X-ray scanning (Grundberg & Grönlund 1998; Oja et al. 2003) or from a combination of both methods (Oja et al. 2004). These models do not predict the interior knot structure, but the grade, which is a consequence of knot structure. Currently, several sawmills are using such grade predictions for online control of the log sorting operation. However, at the log sorting stage, the potential of the raw material to fulfil requirements has already been reduced by the decisions taken when the trees were cut to logs. The combination of grade prediction with yield prediction obtained from simulated sawing with the log's 3D profile as input makes it possible to calculate the outcome of a log and hence its correct value. If stems are scanned and the values of logs not yet cut from the stems can be calculated, then the bucking operation, as well, can be based on product requirements and orders rather than today's log-price-list–based bucking. Thus, grade predictions of stem segments are desirable for a customer-oriented production at the operational stage of bucking.

1.5. Controlling the production of boards

The conversion of forest resources to solid wood products is a chain of closely related activities. Decisions taken at one stage will have consequences for the following ones. At an early stage, the bucking operation occurs. At this stage, where the stem is cut into sawlogs, the dimensions of a particular log (i.e., length and small-end diameter) place upper limits on the length, width and thickness of the timber that can be sawn from it. While shorter and smaller timber dimensions can be sawn from the same log, production economy will suffer as the volume yield becomes low. This means that undersized logs, as well as oversized logs, are undesirable, and it emphasizes the importance of high measurement accuracy (Chiorescu & Grönlund 2001). The second step in the conversion chain determining the dimensions of the timber is when breakdown patterns are assigned to the logs, either in a log sorting station for batch processing or in line with the breakdown machinery. Accurate descriptions of the logs' cross-sections are important for making the right sorting decisions (Skatter et al. 1998). After primary breakdown the sideboards are edged, setting their widths, and eventually all boards are trimmed to their final length. Optimizing each activity individually is not likely to produce results that are globally optimal to the forestry–wood chain. Furthermore, in order to control the production of boards targeting current orders or plans, the ability to communicate the needs to all processing stations is favourable.

Traditionally, a log price list with individual prices on different combinations of log diameter and log length works as the interface through which the sawmill communicates its need for the supply of specific log dimensions. The generation of such a log price list is not straightforward. The need for timber must be translated into log dimensions, and this requires good knowledge of the outcome of timber from different log dimensions. Values reflecting both timber values and desired quantities must be assigned to different log dimensions, and the characteristics of the stems to be bucked must be known. The optimal bucking pattern of a stem is the pattern yielding the highest summed value of the logs cut from the stem. Dynamic programming (DP) (Dreyfus & Law 1977) is an optimization technique widely used in bucking applications for finding the optimal bucking pattern of individual stems (Pnevmaticos & Mann 1977). However, static log prices assume open market conditions, i.e., no constraints on the volume produced in different log classes. So as to meet order book constraints from a set of stems, i.e., a stand, different approaches have been investigated. Kivinen & Uusitalo (2002) used DP at the lower stem bucking level and a fuzzy logic algorithm to adjust the relative log prices at an upper stand level in an effort to maximize the apportionment degree—a measure of how well the target log distribution was met. Laroze (1999) used a taboo search algorithm at the lower level to generate efficient bucking patterns and an LP model at the upper level to combine different bucking patterns subject to demand constraints. Pickens et al. (1997) used DP at the lower level and LP at the upper level, maximizing net value under log length demand restrictions. Kivinen & Uusitalo (2002) concluded that the calibration of a price list prior to bucking a stand is very sensitive to the precision of the prior information and that the same or even better results can be obtained by continuously adjusting the log prices after each cut stem when the objective is to meet order book demands.

A more direct approach to the communication problem is to use a log breakdown simulator. Faaland & Briggs (1984), Reinders & Hendriks (1989) and Maness and Adams (1991) integrated a log-sawing algorithm that evaluates the value of the boards sawn from the logs into the bucking model. 3D scanning of logs common at the log sorting station yields a detailed description of the logs' external geometries that can be used as input to sawing simulation software for predictions of timber yield. And if complete stems are 3D scanned, the bucking operation can be adaptively controlled by product demand and timber product prices, easing communication and possibly leading to even better value recovery and production control. Thus the potential of such systems should be assessed and related to today's practice and ultimately related to the full potential of the wood raw material as provided by a full knowledge of the stem's outer shape and interior knot structure.

2. OBJECTIVES

The hypothesis set at the beginning of the work was that there is an unexploited value potential in the forestry–wood chain which can be reached using modern measurement techniques and that a better characterization of the wood raw material will facilitate an improved customer-order orientation. Thus the overall objective of the work presented in this thesis has been to explore the potential of a higher value recovery and improved production control within the forestry–wood chain, aiming at higher profits and better customer orientation. The connections between the different papers are shown in Fig. 1.

- The objective of Paper I was to investigate the prospects of segmenting knots in CT images of young Scots pine sawlogs with the aid of ANN.
- The objectives of Paper II were to present a method for building parametrical descriptions of young Scots pine sawlogs and to evaluate the accuracy of the extracted descriptions by comparing real boards with simulated ones based on the descriptions.
- The objectives of Paper III were to investigate whether stems modelled from site, stand and tree characteristics can be applied together with sawing simulations for prediction of grade recovery and to compare results with empirical data from the SPSB.
- The objective of Paper IV was to assess the accuracy of predicting board values in stem segments using X-ray scanning and optical 3-dimensional scanning of stems.
- The objective of Paper V was to investigate how value recovery and production control are affected by the measurement techniques used in bucking, log sorting and sawing.
- The objective of Paper VI was to investigate the outcome of products, productivity, value and economy for different bucking strategies using simulation techniques.
- The objectives of Paper VII were to develop a model able to explain the relationships between log dimensions and sawmill yield, with emphasis on the lengths, and to optimize the processing of logs for higher value recovery and better market adaptation.

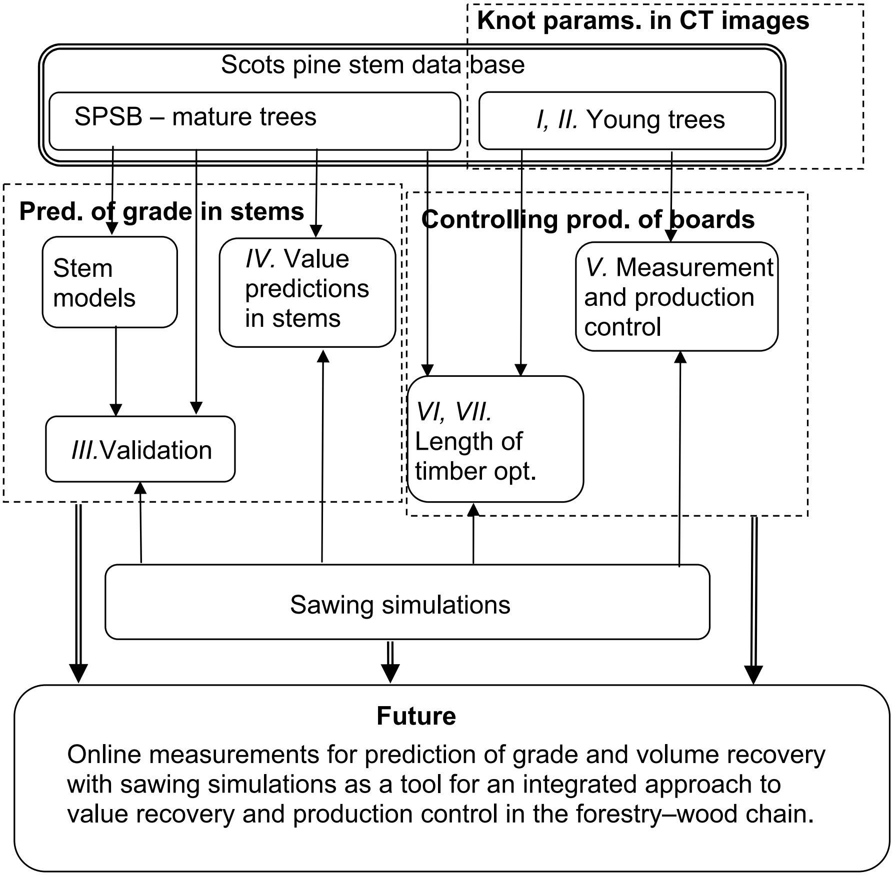

Fig. 1. *Schema of how the papers in the thesis connect to each other and how they may contribute to a future application.*

3. LIMITATIONS

The studies presented were based on simulations using a limited set of virtual sawlogs. No industrial measurements were performed. Properties of stems, logs and boards considered were limited to geometry and knots. In practice there are several other important properties to consider, such as heartwood, compression wood, spiral grain, rot, etc. Furthermore, all studies are based on Scots pine. Other species may have different properties and end uses and thus yield different results and conclusions.

4. MATERIALS AND METHODS

4.1. Measuring knot parameters in CT images of young Scots pine sawlogs

Papers I and II involve the use of an artificial neural network for identifying knots in CT images. An image analysis framework was built using MS Visual C++. The computer program integrates the use of a feed-forward backpropagation neural network with routines for processing digital images. The use of an ANN is a two stage process, where the first stage is to train the network on a known set of features. In the second stage, the trained ANN is used as a predictor. The concept of training the ANN in Paper I is summarised in Fig. 2. The feed-forward backpropagation neural network consists of several processing elements (nodes) organized in layers connected to each other. The number of layers and nodes in each layer defines the network's topology. Here, the notation 50:15:1 means a topology with 50 input nodes, one hidden layer with 15 nodes and 1 output node. As there is no way of telling in advance which topology will perform well, different configurations had to be tested. Additionally, the network does not give a statistical estimate of the prediction rate. Hence, cross-validation was used to assess the network's general prediction ability for a chosen topology. The performance of the ANN was measured as a prediction rate defined as the proportion of pixels correctly classified as either clear wood or knot.

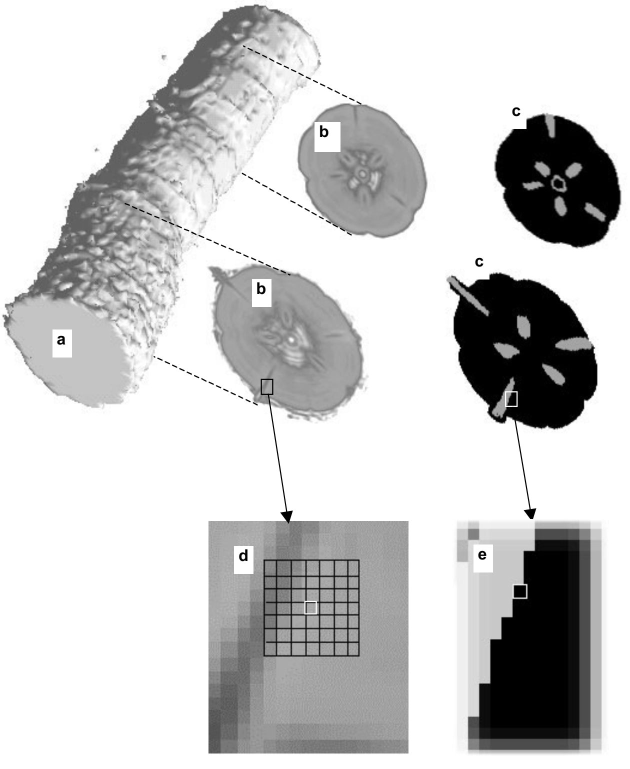

Fig. 2. *Schematic description of the ANN method. From a log scanned with CT (a), digital images of transverse sections containing whorls were chosen (b). Grey-scale values of a squared window with the targeted pixel in the centre are fed to the ANN as input (d). During the training stage the desired output (e) is given by manually classified duplicates (c). Iterating through the images, the prediction error is minimised and the trained ANN can be used as a pixelwise classifier.*

In Paper II, a complete algorithm for extracting parametrical descriptions from CT images of young Pinus sylvestris sawlogs is presented. The descriptions are in concordance with the format of the previously established Swedish Stem Bank. The knot structure is given by a set of mathematical models with distance in pixels from pith *(r_p)* as the only independent variable. The knot's diameter ($\varnothing_p$) is given in Radians by Eq.1, tangential position (Ω_p) is given in degrees by Eq.2 and height position (Z_p) is given in mm by Eq 3. Each knot has its own coefficients in the models, making it possible to compute the position of the knot axis in three dimensions and its size at different positions along its axis. The individual coefficients were obtained from regression of the knot's development from the pith outwards as given in the images classified by an ANN. The complete algorithm was accomplished within the ANN image analysis framework that was developed.

$$\varnothing_P = A + B(r_P)^{1/4} \qquad (1)$$

$$\Omega_p = C + D\ln(r_p) \qquad (2)$$

$$Z = G + H\sqrt{r_p} \qquad (3)$$

A set of 89 logs originating from 48 trees was sampled from 8 young, not previously thinned stands in the north of Sweden. The logs were scanned in a medical CT scanner (Siemens SOMATOM AR. T.). Once parametrical descriptions of the logs were made, the ability to correctly simulate the yield of a sawing operation had to be validated. Five logs originating from three trees were through-and-through sawn. Two logs yielded two boards each and three logs yielded four boards each. On the sapwood side of the outermost pair of boards, the size and position of the knots were measured. The knot size was measured in both longitudinal and tangential direction. The longitudinal position was measured with the butt end as a reference, and the tangential position was measured with the left edge as a reference. Corresponding boards were reconstructed by simulated sawing of the parametrically described logs.

4.2. Sawing simulations

In this thesis, two different sawing simulation tools were used. A sawing simulation program named virtual SawMill (vSM) (Chiorescu & Grönlund 1999) was used in Paper VI. The vSM is a graphic simulator which reads logs from the SPSB and is able to calculate the boards resulting from sawing, edging and trimming operations with these logs as input. Machinery settings, grading criteria and price lists can be adapted to resemble real sawmills, and the software can be controlled and its functionality extended with a built in scripting ability. With the upcoming tasks of this thesis in mind, a decision was taken to build another sawmill simulation program—Saw2003. Reasons behind the decision were: 1) vSM operates on the Macintosh platform which is rarely used in the sawmill industry or at the university (Saw2003 was designed to operate on the PC/Microsoft Windows platform); 2) new functionality allowing for reconstruction of stems from the logs and rebucking into new lengths along with production control algorithms had to be included in the software; 3) the ability to easily change the source code and extend the functionality was desirable; and 4) this allowed full control and understanding of calculations and simplifications underlying the simulations. A first version named Saw2k was used in Paper II where logs were through-and-through sawn in order to evaluate the knot models derived for young Scots pine sawlogs. The software then was re-engineered, keeping the best code parts while rewriting other parts, into the second version named Saw2003, Apps. A–D.

Saw2003 was used in Papers III, IV, V and VII. It is a Windows™-based program developed in C++ with a graphical interface partly based on OpenGL, allowing the user to view and interact with logs and boards in three dimensions (Fig. 3). The software is capable of reading logs from the SPSB database and optionally assembles logs into stems for bucking into other lengths. The sawmill modelled uses cant sawing, in which the first sawing machine cuts the log into a cant and side boards, while the second sawing machine cuts the cant into centre boards and side boards. Side boards are edged and trimmed, while trimming is the only operation on centre boards. Both edging and trimming are value-optimizing operations based on timber prices and grade. Grading is based on wane criteria and knot properties following the structure of the Nordic Timber Grading Rules (Anon. 1994). Throughout the processes complete 3D information of log and boards is retained. The simulator also exposes a great deal of its functionality to a built-in scripting module where Visual Basic scripts (vbScript) can be executed. A complete list of scriptable properties, functions and methods native to Saw2003 is given in App. D. Through scripts, simulations can be automated, and reports of the sawing process and properties of logs and boards can be tailored.

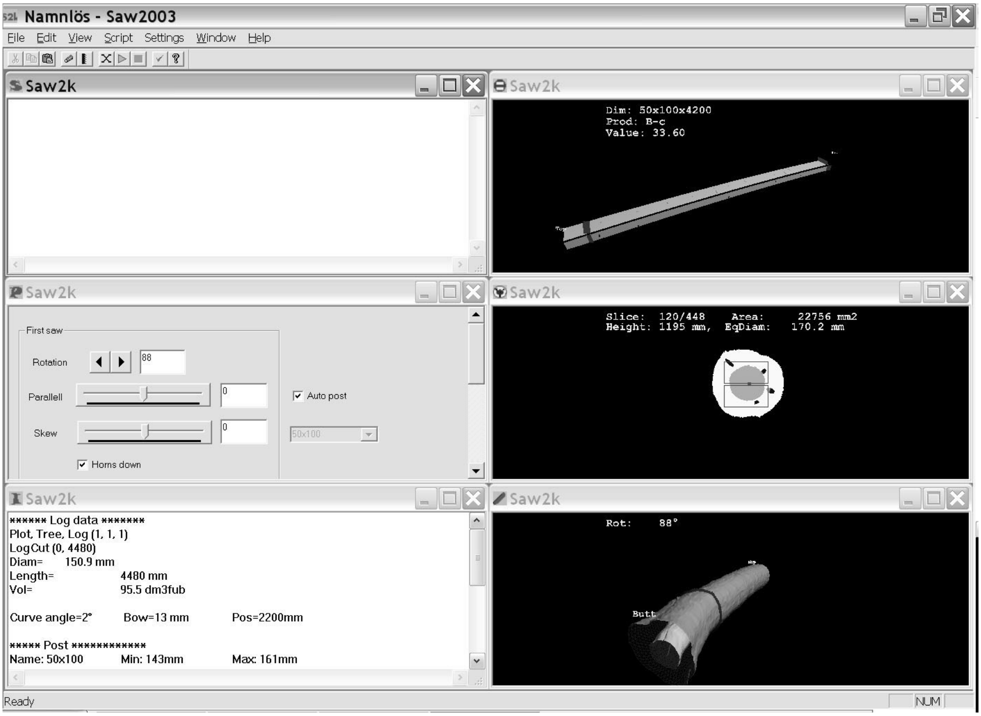

Fig. 3. *Interface of the sawing simulation software Saw2003.*

In Paper III, Saw2003 was used to compare grade recovery of stems modelled from stand and tree characteristics connected to the SPSB, with grade recovery from the virtual logs in the SPSB. In Paper IV the software was used to derive the average board values from logs that were to be predicted by the PLS regression models. In Paper VI the software was used for simulating different scenarios in bucking, log sorting and production control while monitoring the effect on value yield, volume yield and order fulfilment. In Paper VII, Saw2003 was used to calculate the contribution on log level, for combinations of log small-end diameter, log length and sawing pattern, to be further used for log sorting optimizations using LP.

4.3. Predicting grade and value recovery in logs

The SPSB data material was used by Moberg (2005) and Moberg et al. (2005) as a basis for developing static models of stem taper and internal knot properties with site, stand and tree characteristics as independent variables. These models directly predict stem shape and knot properties without the recursive use of growth models, and in Paper III the models were used to create a second set of virtual logs, giving a model-based representation of the SPSB. In total, 604 twin pairs of sawlogs containing compatible data from both model simulations and empirical measurements from the SPSB were used for validating the simulated logs.

In Paper IV an even more direct approach is taken when average board values of stem sections are predicted without the use of site and stand characteristics. Such an average board value can be considered a prediction of grades weighted by their price. In the study, measurements by a 3D log scanner and a 2-axis X-ray log scanner were simulated on the stems in the SPSB. The outer shape profiles originating from the 3D log scanner were processed into a variable describing the bumpiness of the stems at 1 cm increments in longitudinal positions. Secondary variables were then derived, giving the distribution in bumpiness classes. The distribution along with standard measures such as tapers, diameters and position of log within stem were used to predict the average board value of stem sections that were candidate sawlogs in one regression model (M:3D). From the density profiles issued by the simulated X-ray log scanner (Grundberg & Grönlund 1997), secondary variables describing properties of the whorls within the stem were derived. The X-ray log scanner variables were used in a regression model (M:3D-X) together with bumpiness data. The regression method used was Partial Least Squares regression (PLS) (Geladi & Kowalski 1986; Lindgren 1994). Conventional Multiple Linear Regression (MLR) is based on the assumption that the predictor variables are independent and without errors and that the residuals of the predicted variable are randomly distributed. When predicting average board values, the predictors are definitely collinear, there is likely to be noise in the data and there are probably important factors not measured. PLS handles these problems well.

4.4. Controlling the production of boards

In Paper VI, the Scots pine logs in the Swedish Pine Stem Bank (SPSB) were re-assembled into the original stems and then rebucked according to three different strategies, in addition to the original one, and new versions of the stem bank were formed. The targeted timber had the dimensions 50 x 100, 50 x 125 and 50 x 150 mm, with lengths of either 240 cm or 480 cm. With a trimming allowance of 10 cm and an extra 5 cm due to the harvester's measurement inaccuracy, the targeted log lengths were fixed at either 255 cm or 495 cm, or a combination of both lengths. The virtual SawMill was used to assess the outcome of boards in processing the four versions of the stem bank. In the log breakdown simulation, only the gross values were accounted for. In order to include the influence on sawmill productivity of the log lengths resulting from the different bucking strategies, the product flow was simulated with a program named Extend™. Buffers and interruptions were modelled, as well as diverging and merging of flows along with processing times of different operations (Hermansson & Johansson 2000). The results, dependent on the average log length, were received as the flow of products (pieces/h). By putting the results from the sawmill simulations together with the results from the flow simulation, the contribution per hour could be calculated and used as a relevant measure of the alternatives.

In Paper V, the sawmill simulator Saw2003 was used with the added capability of value optimizing the bucking pattern and with integrated production control algorithms. The simulations were done on the set of young Scots pine stems described in Paper II. In the simulations, bucking was either performed conventionally with a log price list giving individual prices on different combinations of log small-end diameter and log length, or else bucking was performed with a timber price list in combination with sawing simulations. Log sorting was based on either a small-end diameter look-up table or on sawing simulations. When sawing simulations in bucking and log sorting were used to predict values of logs, the alternative yielding the highest value was chosen. In addition, combinations of production control were employed in bucking, log sorting and log breakdown, with the target set to produce a given volume share of four specific products. The production control algorithm continuously adjusts prices of the products in order to meet targets. When the desired share of a particular product is lower than the target share, and the share is decreasing, the product price is raised. If the target share is higher than desired, and the share is increasing, the price is lowered. Whenever the share is moving towards the target the price remains the same. In total, 28 simulations were carried out. The results monitored were value and volume recovery and how well the targeted volume share of the four products was met. Results were further evaluated using PLS.

In Paper VII the stems within the SPSB and the additional set of young Scots pine stems were used for simulating and optimizing a real sawmill. Segments of the stems with varying lengths and at different positions within the stems were used to create a large number of logs representing all combinations of log length and small-end diameter (SED). The simulator was set up to model the studied sawmill with respect to machinery, product prices, processing costs and positioning error of the logs within the first saw. Each log was sawn with several sawing patterns and the results were postprocessed to account for measurement error in the log sorting station. The compiled results were then used in an LP model able to maximize the profit out of the sawmill's log supply with constraints on the products produced and available logs. The log distribution was found to restrict the ability to produce the desired volumes of boards in specific lengths. Hence, the log length distribution should be altered. Bucking simulations were used on a virtual stand, compiled from forest inventorying data, to find a set of log prices that would produce the desired log length distribution when used to control the harvester's bucking operation.

5. RESULTS & DISCUSSION

5.1. Measuring knot parameters in CT images of young Scots pine sawlogs

Paper I showed that ANNs are feasible for knot identification in CT images of young Scots pine logs. It was concluded that the number and position of knots would be quite accurate in a parametric description based on images classified with an ANN (Fig. 4). It was also shown that the prediction rate in general increased with increased window size as well as with increased size of the hidden layer. The textural orientation given by the growth rings and knots provided further information, making it possible to increase the efficiency of the network by aligning the input feature window to the tangent given by the radii from the pith to the centre of the window. A summary of the prediction rates achieved with the topologies evaluated is given in Table 1. The computational time increases with the larger window and larger hidden layer. Thus, the topology chosen in an application must be a compromise between prediction accuracy and speed.

Table 1. *Summary of prediction rates achieved with the topologies evaluated on the training set*

Window size	Method	No. of hidden layers	Nodes in hidden layer	Average prediction rate (%)	SD
7 x 7	Std	1	15	97.01	0.75
7 x 7	Std	1	21	97.34	0.66
9 x 9	Std	1	40	97.61	0.65
5 x 5	Tang.	1	5	97.06	0.85
5 x 5	Tang.	1	9	97.29	0.82
5 x 5	Tang.	1	12	97.40	0.71
5 x 5	Tang.	1	15	97.45	0.81
5 x 5	Tang.	1	21	97.34	0.76
7 x 7	Tang.	1	5	97.04	0.87
7 x 7	Tang.	1	9	97.48	0.69
7 x 7	Tang.	1	12	97.52	0.72
7 x 7	Tang.	1	15	97.76	0.56
7 x 7	Tang.	2	15:5	97.75	0.56
7 x 7	Tang.	1	21	97.82	0.53
9 x 9	Tang.	1	5	96.50	1.08
9 x 9	Tang.	1	9	97.62	0.65
9 x 9	Tang.	1	12	97.73	0.65
9 x 9	Tang.	1	15	97.79	0.57
9 x 9	Tang.	1	40	98.21	0.54

The differences in prediction rate between different topologies seem small but as the knots only cover approximately 10% of the disc area even small improvements in prediction rate are valuable.

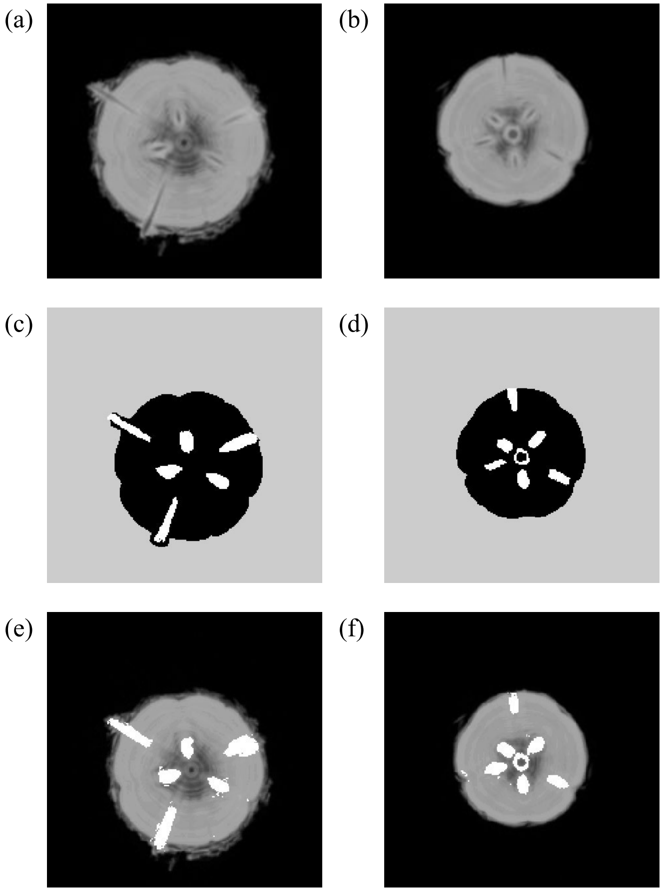

Fig. 4. *Examples of two discs classified by an ANN with a 7 × 7 input window, 15 nodes in hidden layer and one output. Original images (a) and (b), manually classified images (c) and (d), images classified by the ANN (e) and (f).*

Paper II presents a complete algorithm for extracting log geometry and knot structure. The algorithm is based on image classification with an ANN in combination with image processing and analysis. A comparison between real boards and simulated boards verified that the number of knots showed high correlation ($R^2 = 0.9$) between real and simulated boards (Fig. 5). The differences in tangential and longitudinal position were 0.3 ± 3.6 mm and 1.6 ± 4.2 mm respectively, and differences in tangential and longitudinal diameter were 0.6 ± 4.0 mm and -0.6 ± 3.9 mm respectively. Knot diameters were more accurately predicted on boards distant from the pith than on boards close to pith. The relatively large random errors on knot diameter imply that grading simulated boards with the explicit Nordic Timber Grading rules (Anon. 1994) will not produce reliable results on the single-board level when compared to real boards sawn from the original logs. Grundberg & Grönlund (1999) have shown that for large groups of logs, the random error in knot diameter has a limited influence on value recovery and volume yield. Hence, the virtual logs are a realistic approximation of real logs and can be used for modelling the knot structure of trees and for simulating the yield of different strategies in forestry and sawmilling. As the simulated boards otherwise compared well with real boards, it was also concluded that the sawmill simulation software is reliable; visual evidence is given in Fig. 6.

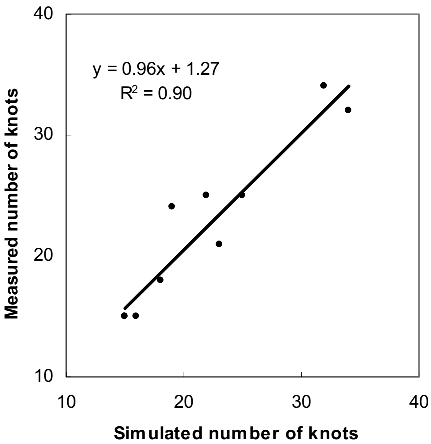

Fig. 5. *Number of knots measured on real boards as a function of predicted number of knots based on simulated sawing of the same logs.*

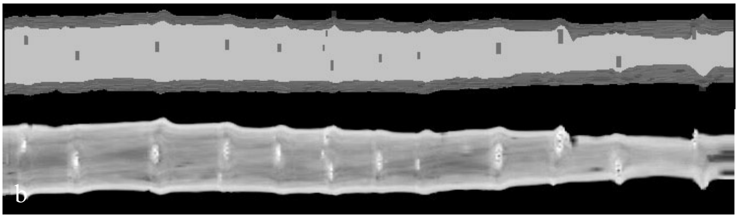

Fig. 6. *Board reconstructed from simulated sawing based on parametrical description of a log (a) and corresponding section of the CT image stack (b). N.B. Horizontal and vertical scaling are not equal.*

The results from Papers I and II show that the segmentation of knots in CT images is not perfect. There are several other alternatives in setting up the input feature vector that have not been investigated; thus, the prediction rate may be further improved. In the training stage of the ANN, the keys were given by manually classified CT images, and this is probably a source of variation. Though it is easy to see a knot in the image, it is not easy to determine the border to the surrounding wood. The fact that the knots were fitted in a mathematical model must also be considered. Biological material with great natural variation, as is the case with knots, does not always fit models perfectly.

5.2. Predicting grade and value recovery in logs

The comparison in Paper III between model stems and the stems in the SPSB showed that it was possible to predict the timber grade recovery on the basis of stand and tree measurements (Fig. 7). When comparing results of tree models against empirical data for 604 logs, the volume recovery of side boards was overestimated with the modelling approach, but the volume recovery of centre boards and the grade recovery showed good agreement (Table 2). The overestimation of sideboards is likely attributable to overly round and straight model stems, whereas real stems are crooked in many directions and the cross-sections are irregular in shape. For both methods, the recovery of the strictest grade decreased slightly with increasing tree size class, but increased with increasing timber dimension. The results of this study illustrate how the Saw2003 system can be applied to estimate the timber volume and grade recovery of standing Scots pine trees. This could be useful in planning applications to support decisions early in the solid wood supply chain regarding industrial potential of a standing timber resource for assessing stumpage rate, allocation of sawlogs to different specialized mills or evaluation of future conversion strategies for a specific mill.

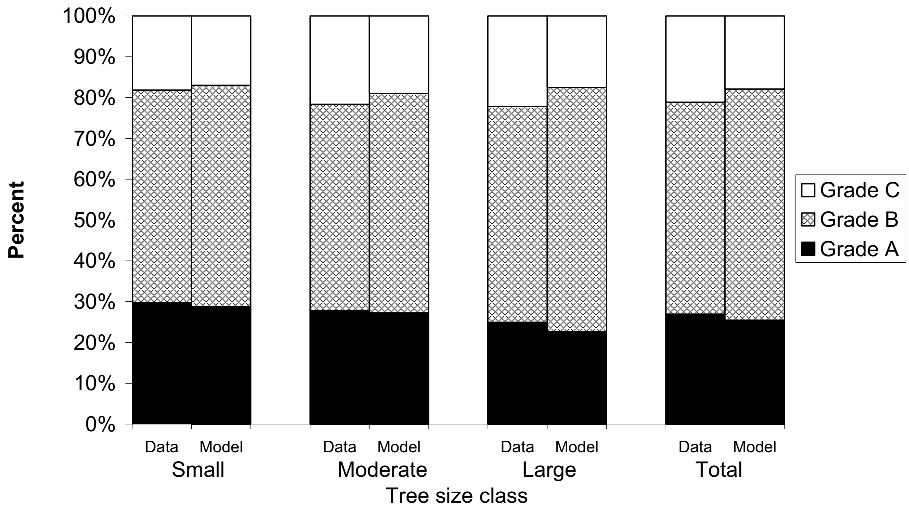

Fig. 7. *Timber grade distribution by tree size class using tree model and empirical measurement data respectively.*

Table 2. *Total sawlog volume, timber volume, volume recovery rate, total timber value and relative product value using tree models and empirical measurements respectively.*

	Log volume (m^3)	Centre board volume (m^3)	Side board volume (m^3)	Volume yield (%)	Board value ($)	Value recovery ($\$ \cdot m^{-3}$)
Model simulation	104.0	40.2	18.0	56.0	12,500	214.57
Empirical data	106.5	39.8	14.8	51.3	11,600	212.57

Results of Paper IV showed that average board values could be well predicted from measurements on stems. With variables derived from a 3D measuring device (model M:3D), R^2 was 0.68. Adding X-ray log scanner measurements to the regression model improved R^2 to 0.72. In summary, with model M:3D, high values were achieved with large diameter, smooth (no bumps) butt logs with large butt end taper from tall trees. With model M:3D-X, low to moderate values on X-ray-measured knot properties in the log and in the lower part of the stem also indicate high value. Fig. 8 shows predictions of average board values with model M:3D-X on an independent test set.

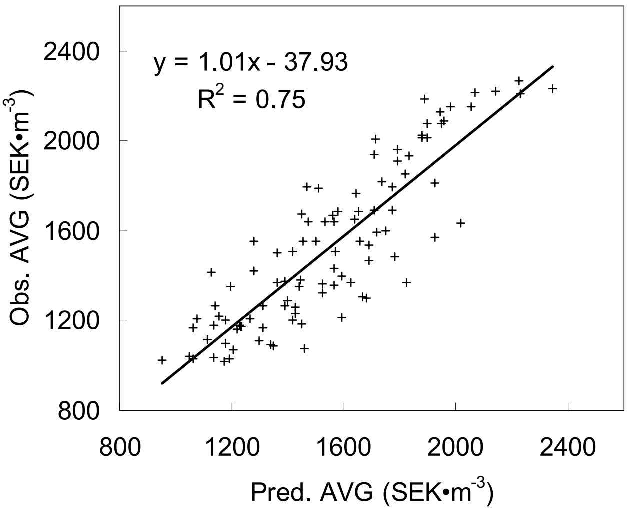

Fig. 8. *Predicted and observed average board value (AVG) for the independent test set of 100 logs using model M:3D-X.*

In the study there was a rather small improvement in prediction accuracy achieved by adding X-ray log scanner data. Oja et al. (2004) reported an improvement in classification accuracy when classifying logs by centre board grade from 57% when using only 3D scanning to 66% when using both 3D and X-ray scanning of logs without knowledge about stem properties. Conclusions drawn from these results are: 1) the return on investing in and adding an X-ray log scanner to an already existing 3D scanner is questionable in bucking applications; and 2) the log's position in the stem and properties in relation to the stem explain some of the variation in knot properties that also are revealed with X-ray log scanning. An example of the application of model M:3D on three stems is provided in Fig. 9, and the example is extended to prediction of log values in Fig. 10. In both examples a 4-m-long log was assumed, but values can be predicted on logs with any lengths between 3.0 and 5.6 m. Such log values derived from sawing simulations and board value predictions can be used as the objective function to maximize in bucking optimizations.

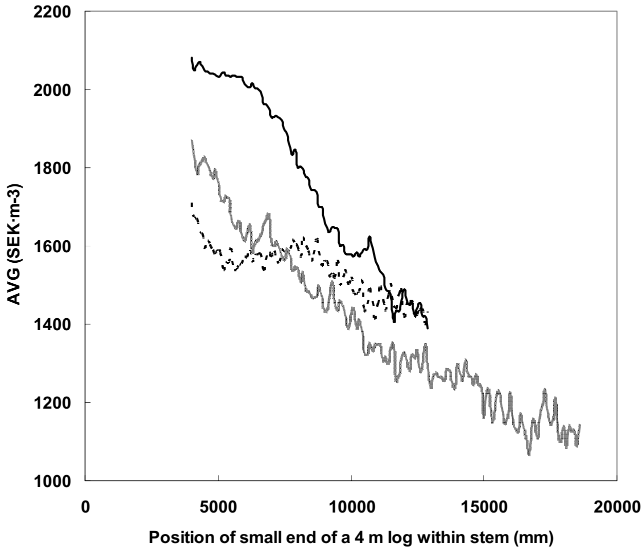

Fig. 9. *Average board value (AVG) predicted with model M:3D on a 4-m log at different positions within stem. Example with three stems.*

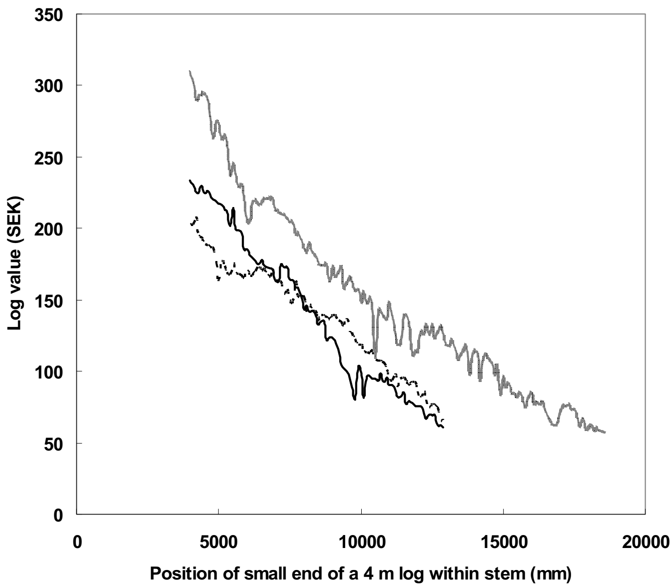

Fig. 10. *Gross value of a 4-m log at different positions within stem estimated by combining predictions of board values with model M:3D and volume yield predicted with the saw mill simulator software Saw2003 and adding the value of byproducts, example with three stems.*

5.3. Controlling the production of boards

Results of the study of bucking methods, log sorting methods and production control in Paper V show that a high value recovery is accompanied by high volume yield. The results also show that the more detailed information the bucking and log sorting decisions are based on, the higher the value recovery. Furthermore, the more processing stations involved in production control, the better the demand targets are met. The results are summarised in the PLS scatter plot of Fig. 11. In the study, the apportionment degree was negatively correlated with value recovery. This could be interpreted as indicating that the pricing of the boards did not reflect their true value in terms of saleability.

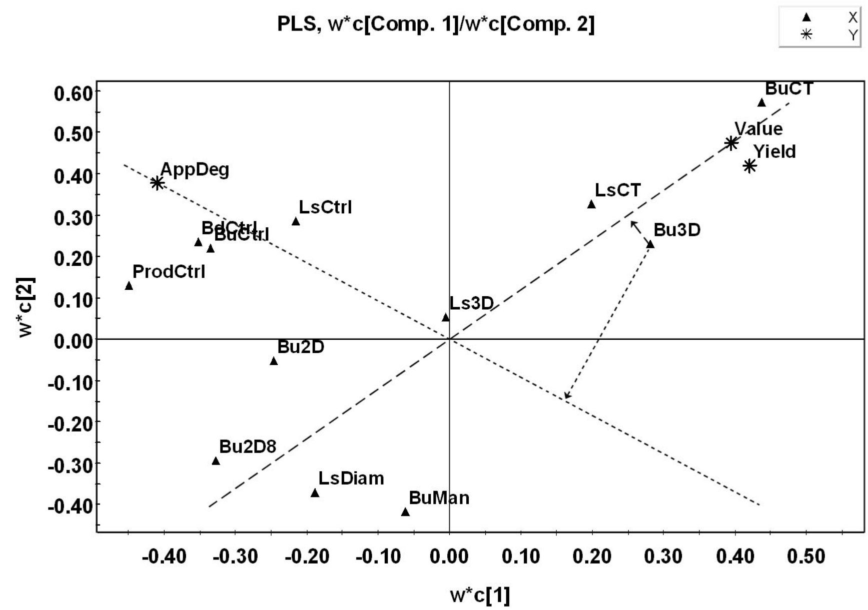

Figure 11. *PLS scatter plot. Y-variables are the modelled responses. AppDeg = apportionment degree; Value = gross value of the products; Yield = volume yield. X-variables are binary, indicating the presence of a treatment in the simulations. ProdCtrl = production control; BuCtrl = production control in bucking; LsCtrl = production control in log sorting; BdCtrl = production control in log breakdown; Bu2D8 = bucking based on diameters with errors and a log price list; Bu2D = bucking based on diameters and a log price list; Bu3D = bucking based on the stems' full 3D profiles; BuCT = bucking based on the stems' full 3-D profiles and interior knot structure; LsDiam = log sorting based on the logs' small-end diameters; Ls3D = log sorting based on the logs' full 3D profiles; LsCT = log sorting based on the logs' full 3D profiles and interior knot structure. Variables close to each other are positively correlated. Projecting the x-variables to the line drawn from a y-variable through origin gives the prediction coefficients of the scaled and centred x-variables (e.g., Bu3D) for that y (e.g., Value, AppDeg), i.e., the relative importance of the predictors. In the example, Bu3D is positively correlated to value but negatively correlated to the apportionment degree.*

The absolute values assessed for different treatments depend on the constitution of the raw material as well as prices used. Thus, the relative values are better measures when comparing the results. The possible gain in value recovery when introducing 3D-based bucking and log sorting amounts to 6.4% compared to today's practice with 2D-based bucking and diameter-based log sorting. If a precise description of internal knot properties is added to information underlying the bucking and log sorting decisions, the value can be increased by 8.8% from today's situation. CT scanning may be a future possibility to provide such information. The objective function used here was the gross value of the produce. In order to maximize profit, the cost side of the process must be included in the prices given the boards. Ultimately, all activities in the process should be assigned cost or revenue functions to allow the prices to be updated dynamically as orders, stockpile and production change. From today's situation, the first step would be to base log sorting on simulated sawing of logs described by their shape as measured with a 3D measuring device, and with product prices as input. A prerequisite for the implementation of such a strategy is the existence of a 3D measuring device at the sawmill where the software is to be installed. The next step would be to extend the process to bucking based on 3D shape. Technically speaking, all the required components are available, but in practical terms, it would take some effort to convert from the cut-to-length system to a tree-length system.

In Paper VI, the results showed that the volume of desired product dimensions could be substantially increased by alternative bucking strategies. The results of the simulated sawing gave the highest value from the alternative with 255 cm long logs. This alternative would have been chosen if the objective was to maximize the value out of a given wood supply. More high quality boards, along with a high yield of products with a bonus on the price, outbalanced the low use of raw material originating from a large portion of residual top logs shorter than minimum length. A likely cause of the high quality is that the probability of a board containing sections with low quality increases with increased length. Since the grade of a board is determined by its worst section, longer boards will get a lower grade. The same alternative (255) had the highest productivity on a piece per hour basis. This is a bad criterion for selection of strategy. A better measure of productivity is volume per hour.

Based on volume per hour, one would have chosen the 495 + 255 alternative. However, only when the value is combined with the production rate, forming a measure of contribution per hour, does one have the appropriate criteria for evaluating different strategies and picking the most profitable one. In this study, the best alternative was the reference alternative (Fig. 12). It was concluded that a holistic approach, as taken here, would be necessary for good decision-making within the supply chain. By using simulation techniques, it is possible to foresee the outcome of different operations along the production line and thus avoid expensive surprises. Optimizing forest operations, value recovery and production as separate entities will not produce optimal results.

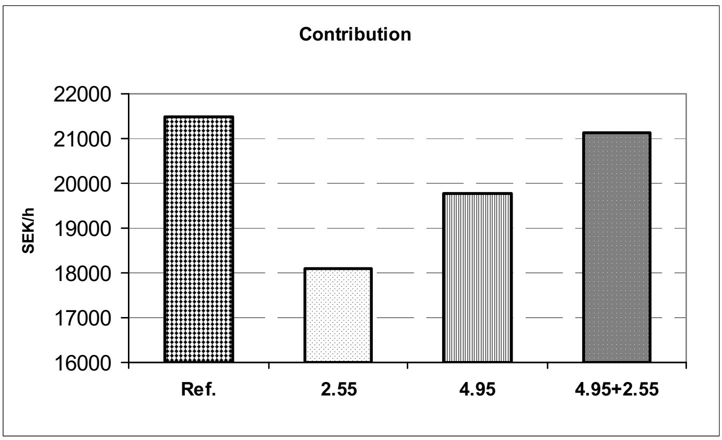

Fig. 12. *Contribution per hour calculated by combining product flow with product value in four bucking alternatives.*

In Paper VII, a real sawmill was simulated. In the model, realistic log geometries were used and imperfections in log positioning at the first saw and measurement errors in log sorting were accounted for. The model that assesses product yield in different log classes gave reasonable explanation of why the lengths of the boards do not match the lengths of the logs and why this is more pronounced with smaller dimensions of timber. In Fig. 13 it is shown that for a small dimension such as 38 x 100 mm, the sorting limits depicted by maximum volume yield will produce a large proportion of boards with lengths shorter than the target length 4200 mm when sawing 4300 mm long logs. Increasing the share of target lengths of small dimensions can only be done at a relatively high cost in terms of volume yield loss. For larger dimension timber, a significantly larger proportion of target lengths can be produced without yield losses. The model reveals one more interesting finding. Small-end diameter sorting limits should vary with log length. Short logs should have larger diameters than long logs. At the studied sawmill, as well as at many others, log sorting is based on small-end diameter alone.

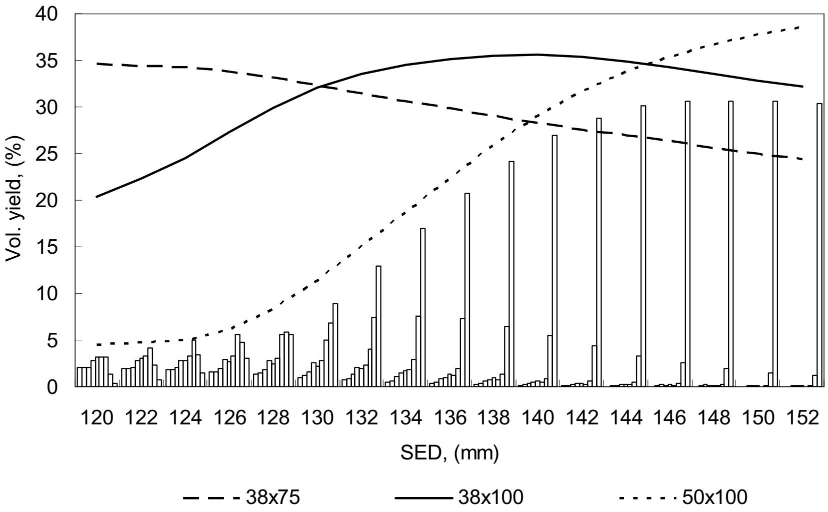

Fig. 13. *Predicted volume yield length distribution of 38- x 100-mm boards yielded from 4300-mm-long logs with varying small-end diameter. Yield is expressed as proportion of log volume. In each presented 2-mm-wide log class, the leftmost bar represents boards 1800 mm long, and succeeding bars show boards with a 300-mm length increment up to the rightmost bar representing 4200-mm-long boards. Lines show total volume yield for three competing dimensions.*

Optimizing the log sorting of the sawmill's current log distribution indicates a possible increase of 2.4% in contribution. In order to meet the desired length distribution of the timber, it is necessary to alter the log length distribution. Simulations of bucking the virtual stand showed that a desired log length distribution could be produced by changing the log prices controlling the bucking. However, results also indicate that there is no set of fixed log prices that yield the desired log length distribution. To meet targets, log prices must be dynamically changed by an adaptive control algorithm during production. Applying value-optimized log sorting on the altered log distribution gave an increase in contribution of 6.1%. Furthermore, the desired length distribution of the timber could be fulfilled.

6. CONCLUSIONS

The most important conclusions drawn from the papers presented are:

- Virtual stems in combination with simulations of bucking, log sorting and sawing are powerful tools for research within the forestry–wood chain.
- Artificial neural networks are suitable for knot identification in CT images with low contrast, but do not yield perfect results.
- Grade and volume recovery can be predicted from models of stem shape and internal knot structure based on site, stand and tree characteristics in combination with sawing simulation. However, the prediction of side boards needs to be improved.
- 3D measurements of stems and logs can provide data for accurate predictions of board grade expressed as average board values.
- There is an unexploited value potential in the forestry–wood chain. The full potential can only be reached with a precise description of stem shape and internal knot structure prior to the bucking operation and with a processing into logs and boards that is free from errors.
- A large portion of the value potential can be reached if stem shape and log shape as measured with a 3D scanner are used together with sawing simulations for decisions in bucking and log sorting.
- It is almost equally important to employ production control in bucking, log sorting and sawing in order to meet target shares of products produced.
- Targeting specific lengths of small dimension timber is difficult, and they can only be produced at the cost of volume yield losses.
- Log classes should be defined with varying diameter limits for different log lengths at the conventional diameter-based log sorting.

The overall conclusion from this work is that the 3D scanner used online on stems and logs provides data for grade predictions and stem shape that when used together with sawmill simulations will allow for higher value recovery and improved production control.

7. FUTURE WORK

Results and conclusions drawn from the papers within this thesis are all based on simulations. Hence, the most promising alternatives presented should be validated in practice. This could be done by gradually introducing the concepts while carefully monitoring the outcome. 3D scanning of stems for the purpose of bucking decisions seems to be a promising method for improved value recovery and production control. However, the harsh environment at the processing heads of harvesters makes it less likely that such measuring capabilities will be realized in the near future. On the other hand, 3D scanning of stems at sawmills implies that the current short-wood system practiced in Sweden might better be abandoned. These questions need to be analyzed and tackled.

This thesis has focused on dimensions and knot properties of the timber. Undoubtedly there are other properties of the wood that should be accounted for in operational decision making—properties such as heartwood, spiral grain, compression wood, strength, etc. In order to include these properties in bucking decisions and log sorting decisions, further research is required.

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Paper I

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Knot Identification from CT Images of Young *Pinus sylvestris* Sawlogs Using Artificial Neural Networks

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The value of solid wood products is to a large extent determined by the sizes, types and distribution of the knots in the products. Hence there is a great interest in describing the internal knot structure of individual logs. The Swedish Stem Bank has been extensively used for modelling the interior knot structure of Scots pine (*Pinus sylvestris* L.) and for simulating the outcome of sawing operations. The stem bank holds parametric descriptions, extracted from computer tomography (CT) imagery, of mature trees. To enlarge the stem bank with trees from younger stands, a better method for extracting the knot properties from the CT images is needed. In this study, artificial neural networks were used for segmenting and classifying knots in transverse CT images of a 30-year-old Scots pine. The cross-validated prediction rate of correctly classified pixels was 95.9% $\pm$ 1.2%. Classified knots were distinctly separated. Misclassifications were mainly located in the border areas between knots and clear wood. *Key words: ANN, computed tomography, image analysis, knots, Scots pine.*

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INTRODUCTION

Knot properties are of great importance to many solid wood products. The quality of the product, as well as its value, is to a large extent determined by the sizes, types and distribution of its knots. Economical gains may be achieved by picking the right raw material and by processing it more intelligently based on knowledge of the interior knot structure of trees and logs (Steele et al. 1993, Grönlund 1995, Todoroki 2001). Thus, there is a great interest in describing the knot structure.

Traditional means of measuring knot properties (Koehler 1936, Liljeblad et al. 1988) involve a lot of work and are destructive. The medical computer tomography (CT) scanner is suitable for automated nondestructive measurement of knot properties (Grundberg 1999) and has been used in establishing the Swedish Stem Bank (Grönlund et al. 1995), a database of 200 Scots pine stems. Besides a detailed description of the stems' origin, stand characteristics and timber grading, the interior knot structure is available in a parametrical form. The data base has been used in forest research for developing knot structure models (Björklund 1997, Moberg 1999) and in the wood technology sector for simulation of sawmill operations (Björklund & Julin 1998) and simulation of a log scanner (Grundberg & Grönlund 1997). The stems originate from mature stands with an age ranging from 70 to 153 years. Scanning the stems in a CT scanner revealed the knot structure in the Swedish stem bank. A semiautomatic algorithm was used on the CT images to obtain the parametric description of the knot structure. As a basis for the algorithm, the high contrast between the dense knots and the lighter heartwood was used (Grundberg 1994).

Thinning in younger stands accounts for a large portion of the increase in the estimated potential harvest in Sweden. Combined with a change of demand towards smaller dimensions of wood products, the importance of young trees as a raw material is increasing. For this reason, there is an interest in augmenting the stem bank with young Scots pine logs. Initial attempts to apply the same method to images from young trees with little or no heartwood gave erroneous results. Several other algorithms for feature extraction from CT images of hardwood logs have been developed by other researchers (Funt & Bryant 1987, Bhandarkar et al. 1999) using traditional image analysis techniques such as analysis of shape and texture in combination with thresholding and filtering. Work by Li et al. (1996) and Schmoldt et al. (2000) has demonstrated the feasibility of using artificial neural nets (ANN) for the segmentation and labelling of features in several hardwood species.

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ANNs are used in the engineering disciplines of pattern recognition, modelling and prediction (Huang 1997, Schmoldt et al. 2000). The network represents a complex set of interdependencies which may incorporate any degree of nonlinearity, allowing very general functions to be modelled (Michie et al. 1994). ANNs are capable of combining segmentation and classification in a single step (Schmoldt et al. 2000) when classifying images, while traditional methods usually involve a sequence of operations.

The objective of this study was to investigate the feasibility of ANNs for segmenting knots in CT images of Scots pine logs from young stands.

MATERIALS AND METHODS

Samples

The study was carried out on images from a butt log of a 30-year-old Scots pine (*Pinus sylvestris* L.) scanned with computer tomography (CT) (Fig. 1). The log was 492 cm long and the diameter was 14 cm at the top. Digital images sized 256×256 pixels and with an 8-bit grey scale showing the density variations in transverse sections of the logs were produced, one image per 1 cm in the longitudinal direction. The scale of the images was 350 mm per 256 pixels, or approximately 1.37 mm/pixel. 13 images containing whorls with varying types of knots and at different heights in the log were arbitrarily chosen. The knots were manually marked out on duplicates of the chosen images with the aid of software developed for the purpose. The background and bark were also marked out by a threshold operation defining the wood as the region of interest. The classified duplicates served as keys when training the artificial neural network.

Artificial neural network

In this study an artificial neural network (ANN) was used for pixelwise classification of the CT images. Each pixel was classified as either belonging to a knot or belonging to clear wood. The use of ANNs is a two stage process where the first stage is to train the network on a known set of features. In the second stage the trained ANN is used as a predictor. Here, the ANN was given input from the original images and trained to predict the desired output given by the manually classified duplicates. The ANN used was a feed-forward back-propagation neural network (Hassoun 1995) consisting of one input layer, one or two hidden layers and one output layer (Fig. 2). Each layer has one or more nodes that act as processing elements. The number of layers and nodes in each

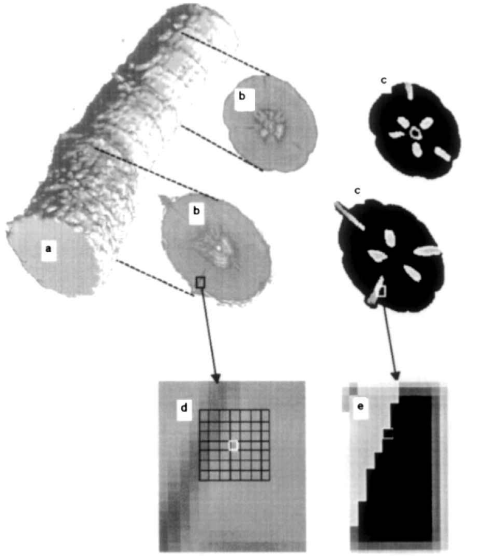

Fig. 1. Schematic description of method. From a log scanned with computed tomography (a), digital images of transverse sections containing whorls are chosen (b). Greyscale values of a squared window with the targeted pixel in the centre are fed to the artificial neural network (ANN) as input (d). During the training stage the desired output (e) is given by manually classified duplicates (c). Iterating through the images, the prediction error is minimized and the trained ANN can be used as a pixel-wise classifier.

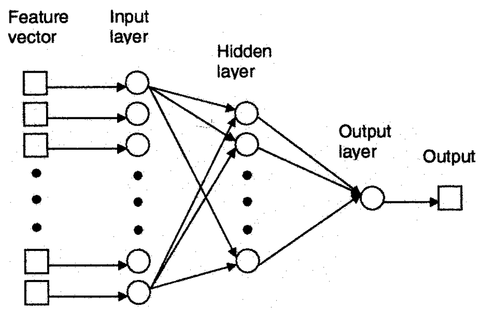

Fig. 2. General layout of a three-layer artificial neural network (ANN). The feature vector is standardized and fed directly to the input layer. Each node in the hidden layer receives a weighted input from the input layer. The output of a node is then calculated by a transfer function applied to the sum of inputs of that node. This is repeated in the output layer, giving the final output.

layer defines the network's topology. The layers are fully connected, meaning that every node in the input layer will send its computed output to every node in the first hidden layer, which in turn will send its output to every node in the next layer, and so on until the output layer is reached. Each connection between nodes in different layers has a weight term. The input of a node is the sum of its weighted inputs plus a bias term. The output of the node is then computed by a transfer function; here a logistic transfer function was used.

When training the network, a feature vector is presented to the input layer and fed forward through the network. The difference between the computed output and the desired output forms the error term. The differential of the error to every weight is calculated and used for updating the weights. The weights are updated by adding a fraction of the calculated error gradient; the fraction is often referred to as the learning rate. It usually takes several iterations to minimize the error using the gradient-descent search algorithm described above. When multidimensional systems are modelled, there is a risk that the network will get stuck in a local optimum. The risk can be reduced by adding momentum to make the weight changes equal to the sum of the fraction of the last weight change and the new weight change that is computed. If the network is trained on carefully selected feature vectors, it can be used to predict the output of other feature vectors.

The feature vector used was the greyscale values of the individual pixels in a squared window on the neighbourhood of the pixel under consideration. The sizes of the windows evaluated were 5×5 pixels, 7×7 pixels and 9×9 pixels, with the targeted pixel in the centre. Additionally, the Euclidean distance of the pixel to the pith (r_p) was fed to the input layer. Hence the input layer had from 26 nodes up to 82 nodes. The input was standardised to range from -1.0 to 1.0. Two different methods of setting the values of the window were compared. The standard method is simply to scan over the image pixel by pixel, reading out the neighbouring pixels. The other method was to align the window to the tangent given by the radii from the pith to the centre of the window (Fig. 3). With the tangential alignment method, the neighbouring pixel values were calculated through interpolation from the original image pixels. The output layer had only one node, whose output was set to 1.0 if the pixel belonged to a knot and was otherwise set to 0.0 in the training stage, and the nets

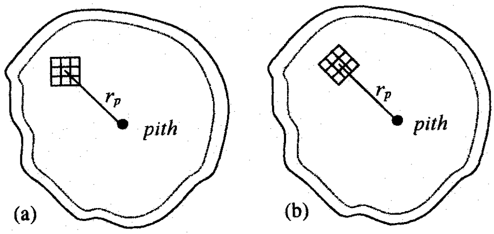

Fig. 3. Illustration of the two methods of aligning the window around the targeted pixel. (a) Horizontally aligned window, and (b) tangential alignment to the radii (r_p) from the pith to the centre of the window.

were initialised with random weight coefficients and bias terms. The learning rate was fixed at 0.15 and the momentum set to 0.5. Each topology evaluated was trained in 500 iterations. The software used was developed in C++ specifically for this study.

The performance of the networks was measured as a prediction rate defined as the number of correctly classified pixels divided by the total number of classified pixels. The search for a good working model was narrowed based on early results from the study. Thus, some combinations of window size, window alignment and size of the hidden layer were not evaluated. The evaluated topologies are shown in Table 1. The two methods of aligning the window were compared at three different topologies. A comparison between two hidden layers and one hidden layer was made. The evaluated topology in the two-layer case was 50:15:5:1, indicating 50 input nodes, two hidden layers with 15 and 5 nodes, respectively, and 1 output node, and the topology with one hidden layer was 50:15:1. The comparison indicated that one hidden layer was sufficient and subsequently one hidden layer was used in all the other cases. The number of nodes in the hidden layer in the other cases was 5, 9, 12, 15, 21 or 40. The prediction rate of the topology 50:15:1 was evaluated using cross-validation. One disc at a time was selected as a prediction set while training was done using the remaining 12 discs. This was repeated until all discs had been used to estimate the prediction rate.

RESULTS

The prediction rate due to different combinations of window size, window alignment, number of hidden layers and nodes in the hidden layers is summarised in Table 1. The prediction rate of the training set was

Table 1. *Summary of prediction rates achieved with the topologies evaluated on the training set*

Window size	Method	Nodes in hidden layer	Average prediction rate (%)	SD
7×7	Std	15	97.01	0.75
7×7	Std	21	97.34	0.66
9×9	Std	40	97.61	0.65
5×5	Tang.	5	97.06	0.85
5×5	Tang.	9	97.29	0.82
5×5	Tang.	12	97.40	0.71
5×5	Tang.	15	97.45	0.81
5×5	Tang.	21	97.34	0.76
7×7	Tang.	5	97.04	0.87
7×7	Tang.	9	97.48	0.69
7×7	Tang.	12	97.52	0.72
7×7	Tang.	15	97.76	0.56
7×7	Tang.	15:5	97.75	0.56
7×7	Tang.	21	97.82	0.53
9×9	Tang.	5	96.50	1.08
9×9	Tang.	9	97.62	0.65
9×9	Tang.	12	97.73	0.65
9×9	Tang.	15	97.79	0.57
9×9	Tang.	40	98.21	0.54

Std: standard method; Tang. tangential alignment method.

higher with the tangential alignment method than with the standard window method for the three different net topologies compared. Adding of a second hidden layer with 5 nodes, creating a net topology of 50:15:5:1, did not improve the prediction rate compared to the previously evaluated topology of 50:15:1. In general, the prediction rate increased with larger window size as well as with a larger hidden layer. The exceptions were the two combinations of a large window (9 × 9) with a small hidden layer (5) and a small window (5 × 5) with a large hidden layer (21), where better prediction rates were achieved with smaller window at the same size as the hidden layer and with a smaller hidden layer at the same size as the window, respectively.

Cross-validating the topology 50:15:1 gave an average prediction rate of 95.9% with a standard deviation of 1.16%. The prediction rate increased with the number of iterations (Fig. 4). After 200 iterations the prediction rate of the test set was already 95.8%.

Two examples of CT images classified by a net with the topology 50:15:1 trained on all 13 discs are shown in Fig. 5. It is visually apparent that all knots were found by the ANN and that the misclassifications are mainly located in the knot border areas. The prediction results of the two discs are shown in Table 2. For both discs more clear wood was misclassified as being knots than vice versa.

DISCUSSION

The classification accuracy achieved in this study was on a par with the results reported by Schmoldt et al. (2000) for various hardwood species. A probable source of error is the subjective marking of knots in the CT images. Although segmentation is intrinsic to human vision, the borders between knots and clear wood were not easy to outline in the CT images. A more accurate method would be to cut discs from a previously CT-scanned log, outline the knots on the discs and scan them with a camera and use them as a key during the training stage.

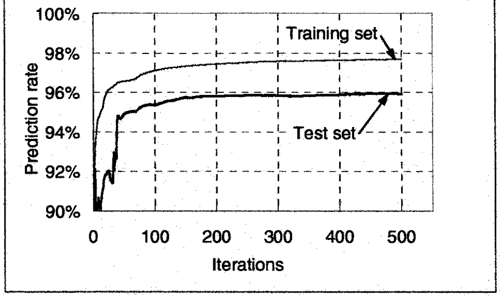

Fig. 4. Evolution of the prediction rate: averages from cross-validation of the topology 50:15:1.

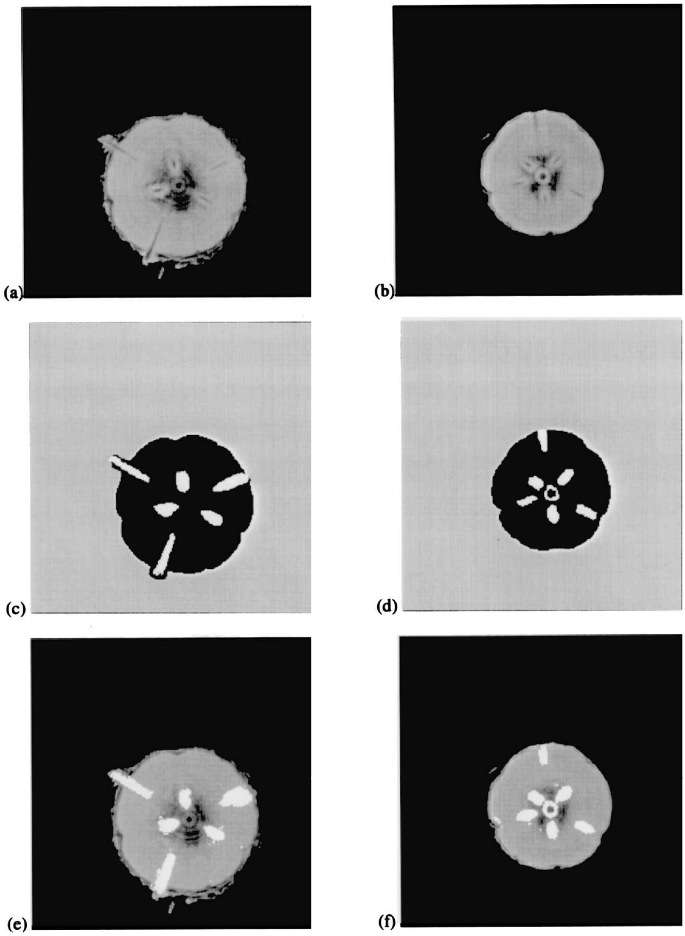

Fig. 5. Images of disc 6 (a, c, e) and disc 12 (b, d, f) classified by an artificial neural network (ANN) with the topology 50:15:1. (a, b) Original images; (c, d) manually classified images; (e, f) images classified by the ANN.

When training an ANN there is a risk that noise will be modelled. If this is the case, the prediction rate of the test set will have an optimum after a certain number of iterations. By observing how the prediction rate evolves, as in Fig. 4, and stopping the training if it starts to decline, the risk of overfitting the model can be reduced. The method of aligning the window in the tangential direction gave better predictions than simply keeping it horizontally aligned. This may be due to greater efficiency of the neural network when using the textural orientation. Growth rings will be orientated in the same direction in the window and all knots will be orientated in the same direction perpendicular to the growth rings. It is possible that preprocessing the images would improve prediction ability. However, the structure of an ANN with parallel processing of the input-feature vector allows the network to incorporate image filters into the model. The network has no knowledge of how previous pixels have been classified. On the contrary, this makes it likely that a postprocessing routine of filling out holes and removing small spurious knot areas would improve classification. Given the results presented here, it can be concluded that the number and position of knots will be quite accurate in a parametric description based on images classified with an ANN. Only after postprocessing the images and after the parametric description is made will it be possible to conclude how well the size of the knots are estimated. As the classifier is biased towards

Table 2. *Prediction (pred.) results of the 13 discs classified with the 50:15:1 neural network*

Disc no.	Disc area (pixels)	Correct pred. of knot (%)	Correct pred. of clear wood (%)	False pred. of knot (%)	False pred. of clear wood (%)	Prediction rate (%)
1	13 882	10.8	83.9	4.4	0.9	94.7
2	14 158	5.5	87.5	6.2	0.8	93.0
3	12 418	6.1	90.4	2.4	1.1	96.5
4	11 689	6.5	91.2	1.4	0.9	97.7
5	12 385	1.3	96.8	1.3	0.6	98.1
6	11 724	9.3	86.9	2.8	1.0	96.2
7	10 650	5.7	91.2	1.7	1.4	96.9
8	10 084	6.8	90.2	2.3	0.7	97.1
9	10 093	7.9	88.5	2.0	1.5	96.5
10	10 494	5.9	90.4	1.0	2.8	96.2
11	9 400	5.0	92.1	0.8	2.1	97.1
12	8 563	7.9	88.8	2.6	0.8	96.6
13	8 364	4.2	93.2	0.9	1.7	97.4
All	143 904	6.4	89.9	2.5	1.2	96.3

overestimation of the knot area in the images, it is possible that some improvements can be made within these steps.

It is easy to adapt the network to simultaneously classify other features such as bark, heartwood etc. It is simply a matter of adding nodes in the output layer, one node per added class. Since the scope of this study was limited to developing a method for identifying knots, multiple-feature classifiers have not been evaluated against the single-feature classifier used here. Others (Schmoldt et al. 2000, Nyström & Kline 2000) have reported improved accuracy when dividing wood features into more specific classes. Thus, it should be investigated whether this approach can improve the classification of knots further. A single log was used in this study for both training and testing the networks. In order to estimate the general prediction rate, images from different logs should be used for training as well as testing.

A drawback with the ANN is that there is no way of telling in advance which configuration will perform well. Different topologies and learning rates must be evaluated. This is tedious work since training a network on images can take several hours. Another drawback is that it is difficult to tell the importance of single variables in the input vector.

This study has shown that ANNs are feasible for feature extraction from CT images of young Scots pine sawlogs. Further improvements may also be possible, as discussed above. Hopefully, the method can be incorporated into a more complete algorithm in order to make a parametric description of the knot structure of CT-scanned logs for augmenting the Swedish Stem Bank with young Scots pine logs for further use in forest research. By using parametric descriptions of log and knot geometry and knot type, the quality and value of solid-wood products can be assessed by simulated sawing of the logs and used to analyse the yield of different strategies in forestry and sawmills.

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Paper II

Scand. J. For. Res. 18: 168–175, 2003

Models of Knots and Log Geometry of Young *Pinus sylvestris* Sawlogs Extracted from Computed Tomographic Images

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The value of solid wood products is largely determined by the sizes, types and distribution of the knots in the products. Hence, there is a great interest in describing the internal knot structure of individual logs. The Swedish Stem Bank has been extensively used for modelling the interior knot structure of Scots pine (*Pinus sylvestris* L.) and for simulating the outcome of sawing operations. The stem bank holds parametric descriptions, extracted from computed tomographic (CT) imagery, of mature trees. A method for extracting parametric descriptions, in compliance with the stem bank, from young Scots pine sawlogs is presented in this study. A key step in the algorithm is the use of an artificial neural network to find knots in the CT images. The accuracy of the extracted descriptions was evaluated by comparing the size and position of knots measured on 10 real boards with corresponding boards simulated based on the description. The study showed that the number of knots on the real boards was well predicted ($R^2 = 0.90$). The differences in tangential and longitudinal position were 0.3 ± 3.6 mm and 1.6 ± 4.2 mm, respectively. The differences in tangential and longitudinal diameter were 0.6 ± 4.0 mm and -0.6 ± 3.9 mm, respectively. Knot diameters were more accurately predicted on boards distant from the pith than on boards close to pith. *Key words: ANN, computed tomography, knots, log geometry, models, sawing, simulation.*

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INTRODUCTION

Knot properties are of great importance for many solid wood products. The quality and value of the product are largely determined by the sizes, types and distribution of its knots. Economic gains may be achieved by picking the right raw material and by processing it intelligently, based on knowledge of the interior knot structure of trees and logs (Steele et al. 1993, Grönlund 1995, Todoroki 2001). Thus, there is great interest in describing knot structure.

Traditional means of measuring knot properties (Koehler 1936, Liljeblad et al. 1988) involve a lot of work and are destructive. The medical computed tomographic (CT) scanner is suitable for automated, non-destructive measurement of knot properties (Grundberg 1999) and has been used in establishing the Swedish Stem Bank (Grönlund et al. 1995), a database of 200 Scots pine stems. Besides a detailed description of the stems' origins, stand characteristics and timber grading, the interior knot structure is available in parametric form. The database has been used in forest research for developing knot structure models (Björklund 1997, Moberg 1999) and in the wood technology sector for simulation of sawmill operations (Björklund & Julin 1998) and simulation of a log scanner (Grundberg & Grönlund 1997). The stems originate from mature stands with an age ranging from 70 to 153 yrs. Scanning the stems in a CT scanner revealed the knot structure in the Swedish Stem Bank. A semiautomatic algorithm was used on the CT images to obtain the parametric descriptions of knot structure. The high contrast between the dense knots and the lighter heartwood was used as a basis for the algorithm (Grundberg 1994).

Thinning in younger stands accounts for a large portion of the increase in the estimated potential harvest in Sweden. Combined with a change in demand towards smaller dimensions of wood products, the importance of young trees as a raw material is increasing. For this reason, there is an interest in augmenting the stem bank with young Scots pine logs. Initial attempts to apply the same method to images from young trees with little or no heartwood gave erroneous results. Nordmark (2002) has demonstrated the feasibility of using artificial neural networks (ANN) for the segmentation and labelling of

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knots in young Scots pine sawlogs. A new algorithm involving the use of ANN has been developed and used to extract parametric descriptions from a set of 89 logs originating from 48 trees.

The objective of this study was to evaluate the accuracy of parametric descriptions of young Scots pine sawlogs obtained with the new algorithm.

MATERIALS AND METHODS

Forty-eight trees were sampled from eight young, not previously thinned stands near Malå in the north of Sweden. In each stand a circular plot with a 7.0 m radius was subjectively located. On each plot the diameter at breast height was measured on all trees. Pine trees with a diameter greater than 125 mm were sorted according to diameter and stratified into three groups with the same number of trees in each group. Two trees were randomly sampled from each group, resulting in six trees per stand in eight different stands. The sampling strategy was chosen to allow for evaluation of different thinning strategies.

After field measurements, the stems were felled and cross-cut into one to three logs, depending on tree height, with lengths of 310–550 cm, yielding a total of 89 saw logs. The top of each stem was left in the forest, from the point where the diameter was less than approximately 10 cm, while the saw logs were transported to the laboratory and scanned in a medical CT scanner (Siemens SOMATOM AR. T). Digital images were produced, sized 256×256 pixels and with an 8-bit greyscale showing the density variations of transverse sections of the logs, one image cm^{-1} in the longitudinal direction. The scale of the images was 350 mm per 256 pixels, or approximately 1.37 mm $pixel^{-1}$.

Five trees from different stands were randomly chosen to develop algorithms for the extraction of log geometry and knot parameters from the CT images. A key step in the algorithm is the segmenting of knots in the images. In this study a feed-forward back-propagation ANN (Hassoun 1995) was used for pixelwise classification of the CT images. Each pixel was classified as being either in the border of a knot or not. To train the network, five images from each of the five trees were used. Images with whorls were taken from the longitudinal positions at 10%, 30%, 50%, 70% and 90% of the scanned tree length. Corresponding cross-sections were located in the logs, and cut and sanded to be used as a key to the CT images.

An ANN was trained to identify the border of the knots on the 25 images. The feature vector used was the greyscale values of the individual pixels in a 9×9 window, with the targeted pixel in the centre. The window was aligned to the tangent given by the radius from the pith to the centre of the window (Fig. 1). In addition, the Euclidean distance of the pixel to the pith was fed to the input layer. Hence, the input layer had 82 nodes. One hidden layer with 17 nodes was used, and the output layer had one node.

The geometry of the surface and the heartwood of a log were extracted following the sequence given below.

1. The position of the pith was manually pointed out on the first and last image in the image stack and on every image that was judged to contain knots (Fig. 2a). The position of the pith for images in between was calculated through linear interpolation.
2. Every image was filtered with a 7×7 median filter to reduce high-frequency noise (Fig. 2b).
3. The images were thresholded at a greyscale of 145, corresponding to a density of 733 kg m^{-3} (Fig. 2c), and the boundary was outlined (Fig. 2d).
4. Polar coordinates of the log surface, with the pith as an origin, were extracted from the image stack, one radius at every degree and at every 10 mm along the log. The results were mapped to a

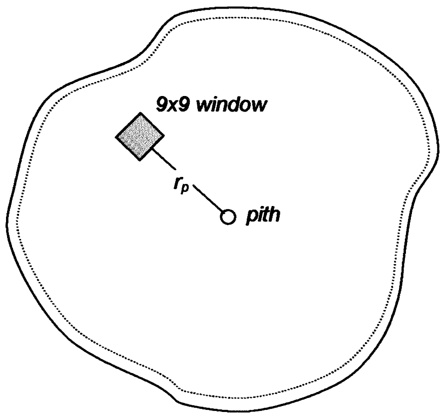

Fig. 1. Illustration of positioning of the window with the targeted pixel in the centre. As the targeted pixel scans over the computed tomographic image, interpolated greyscale values of the 9×9 pixels in the window and the distance to pith (r_p) are fed to the artificial neural network, which classifies the targeted pixel.

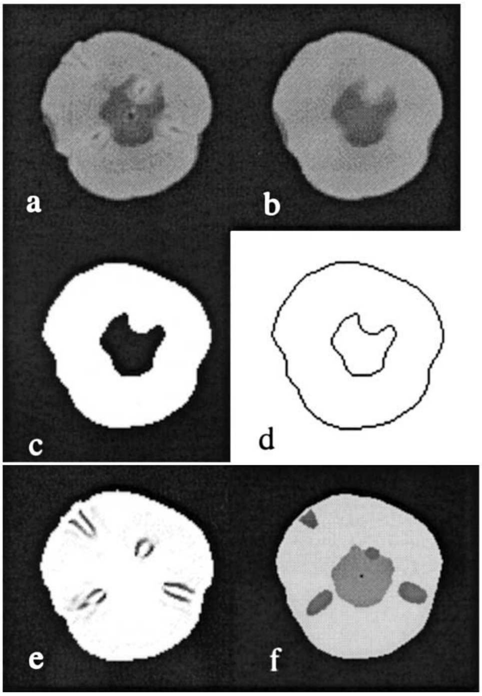

Fig. 2. Images of a log cross-section at different stages of parameter extraction: (a) original computed tomographic image; (b) after application of a 7×7 median filter on image (a); (c) thresholded binary of image (b); (d) boundary outline of image (c); (e) knot borders predicted by the artificial neural network; (f) cross-section as reconstructed from parametric description.

greyscale image with the height equal to log length and the width 364 pixels. In the horizontal direction, 360 pixels were used to store the radii; two pixels were used to store the position of the pith in Cartesian coordinates. The remaining two pixels were not used. The heartwood border was stored in the same way, but the created image was filtered with a 7×7 median filter to reduce the noise originating from whorls.

The knot parameters were extracted following the sequence given below.

1. Images marked in the previous step as containing knots were classified with the ANN and the output of the ANN was mapped to greyscale (0–255) (Fig. 2e).
2. Starting at a radial distance of 15 pixels from the pith, 75 images showing concentric surfaces were produced from the classified images (Fig. 3a). With an increment of 1 pixel in radial distance, one image per radius was produced.
3. The images were thresholded above levels given by the function (60 – radial distance in pixels) with a minimum threshold of 5.
4. A routine filled out the gaps in the knots.
5. The images were filtered with a 3×3 median filter (Fig. 3b).
6. The features were identified and characterized. Each feature's point of balance and width was recorded.
7. Starting with the knots in the first image, a search for matching knot cross-section in the following images was performed by measuring the Euclidean distance between the features' points of balance. If the Euclidean distance was less than 10 pixels, the two-knot cross-section was considered to belong to the same knot. Regression models for knot size and position of knot axis were calculated.

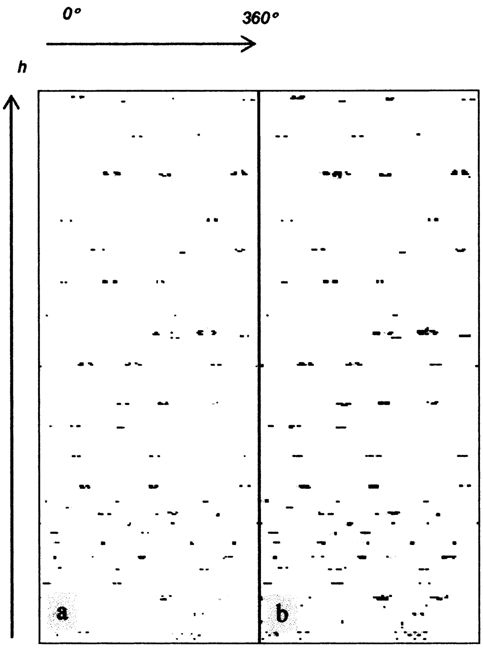

Fig. 3. Images of a concentric surface around the pith showing knots as classified by the artificial neural network (a) and after filtering (b).

With the parametric descriptions of log geometry and knot models, the log can be reconstructed (Fig. 2f). The description of every knot is made by 11 parameters (A–K), in compliance with the Swedish Stem Bank. Figs. 4 and 5 illustrate the notation used in the following equations. The knot angle in radians in a tangential direction at the distance r_p pixels from the pith is given by Equation (1). Knowing the scale in the original CT images, the diameter of the knot in mm can be calculated. Here, the scale was 350/256 mm pixel^{-1}.

The rotation of the knot axis is given in degrees by Equation (2), and the longitudinal position within the log is given in cm by Equation (3). In the Swedish Stem Bank, parameters E and F are used to describe the knot diameter in the longitudinal direction. Because the resolution is 10 mm between the CT images, the longitudinal knot diameter is better approximated using Equation (1), with the assumption that the knot cross-section is circular. Hence, the E and F parameters are not used here. Parameter I is the distance in mm from the pith to the end of the knot. Parameter J is the distance in mm from the pith to the dead knot border; here the dead knot border has not been assessed. Parameter K is the distance from the pith to the outer face of the log at the point where the knot axis intersects the outer face. For a non-occluded knot, $K = I$.

$$\O_p = A + B(r_p)^{1/4} \quad (1)$$

$$\Omega_p = C + D\ln(r_p) \quad (2)$$

$$Z = G + H\sqrt{r_p} \quad (3)$$

Logs from three trees were through-and-through sawn, yielding two or four unedged boards per log. On the sapwood side of the outermost pair of boards, the size and position of the knots were measured. Ten boards were measured, four boards from the inner positions and six boards from the outer positions. The knot size was measured in both longitudinal and tangential directions. The longitudinal position was measured with the butt end as a reference, and the tangential position with the left edge as a reference (Fig. 6). Corresponding boards were reconstructed by simulated sawing of the parametrically described logs (Fig. 7). Real knots and simulated knots were

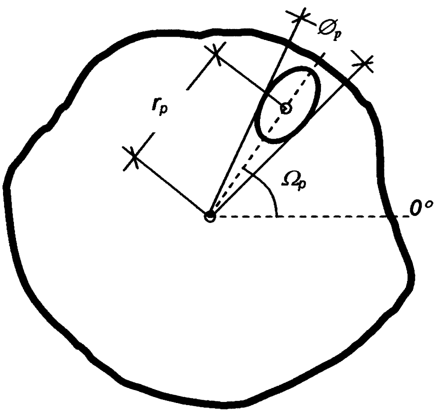

Fig. 4. Knot geometry notation, projection to a cross-section.

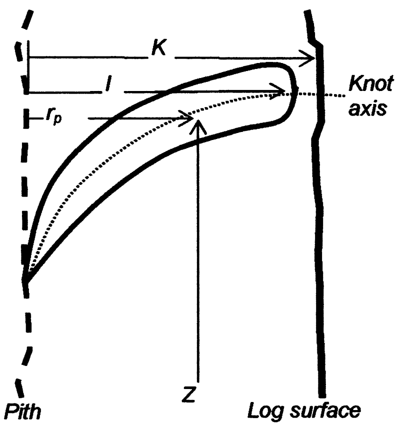

Fig. 5. Knot geometry notation, projection to a radial section.

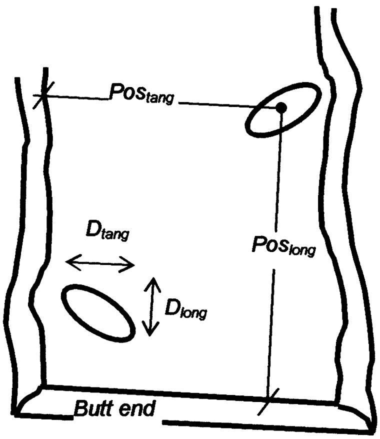

Fig. 6. Definition of measurements carried out on the real boards.

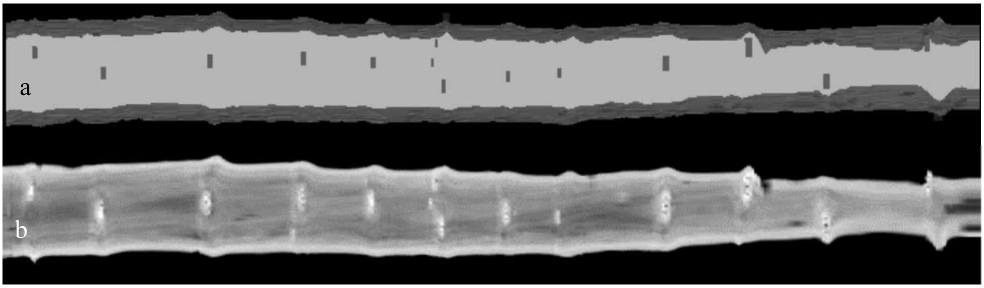

Fig. 7. Board reconstructed from simulated sawing based on parametric description of a log (a) and corresponding section of the computed tomographic image stack (b). NB. Horizontal and vertical scales are not equal.

matched together by means of the Euclidean distance of the knot position. The maximum distance was set to 20 mm. The number of correctly described knots and their size and position were evaluated.

RESULTS

A total of 224 knots was measured on the real boards, while the simulated boards gave a total of 219 knots. The correlation between predicted and real number of knots for the 10 boards examined was high ($R^2 = 0.90$) (Fig. 8). The proportion of real knots matched in position by simulated knots was $84 \pm 7\%$ (Table 1). In addition to the matching knots, there was an average of 3.4 ± 2.5 simulated knots not found on the real boards. Table 2 shows the precision and variation in predicting the size and position of knots. The difference in longitudinal knot position was on average 1.6 ± 4.2 mm (mean $\pm$ SD), and in tangential knot position the difference was 0.3 ± 3.6 mm. The predicted knot diameter was on average close to the real knot diameter. However, the SD of 4 mm indicates that the relative error can be rather large. In Fig. 9 the predicted tangential knot diameter is plotted versus the real tangential knot diameter for all matching knots on boards originating from the inner pair, while Fig. 10 shows the corresponding plot for the boards originating from the outer pair. The relative error is large, and the prediction is better on the outer boards ($R^2 = 0.72$) than on the inner ($R^2 = 0.52$). On the outer boards, one knot that had branched off into two small knots inside the log was recognized as one large knot by the algorithm, giving the outlier.

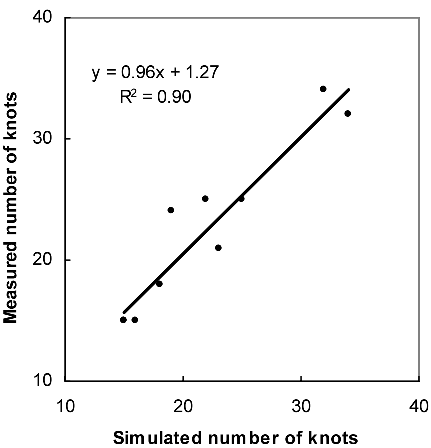

Fig. 8. Number of knots measured on the real boards as a function of simulated number of knots.

DISCUSSION

The number of knots on each board was well predicted by the number of simulated knots. In a study on 12 spruce logs (Oja 1998), the prediction of the number of knots had a correlation (R^2) between real and predicted knots of 0.81, compared with 0.90 in this study. The proportion of matching knots was also high.

The SD of the difference of predicted and real knot diameter was worse than reported by Grundberg (1999). Comparing 555 knots on boards from five Scots pine logs, that study reported a SD of 2.7 mm. Those logs were larger and were cant sawn to produce two centre planks (50×125 mm) and 19 mm side boards. The calculated knot diameter is sensitive to the positioning of the board face at positions close to the pith for two reasons. When the angle between

Table 1. *Number of matching knots on real and simulated boards*

Board	Tree	Log	Board position	Matching knots	
				n	Proportion of real (%)
1	1	1	R2	15	83
2	1	1	L2	19	90
3	1	2	R1	19	79
4	1	2	L1	20	80
5	2	1	R1	27	84
6	2	1	L1	24	71
7	3	1	R2	21	84
8	3	1	L2	12	80
9	3	2	R2	14	93
10	3	2	L2	14	93
All				185	84

Log refers to position in tree from ground; board position is right or left (R, L) and inner or outer pair (1, 2)

Table 2. *Differences in position and size between simulated and real knots*

Board	Difference Simulated – Real (mm)			
	Long. position	Tang. position	Long. diameter	Tang. diameter
1	1.9 ± 4.0	-0.5 ± 1.6	1.0 ± 2.9	1.5 ± 2.3
2	1.0 ± 2.8	0.4 ± 2.1	0.9 ± 5.1	2.5 ± 5.0
3	-1.5 ± 2.6	-0.8 ± 2.3	-2.5 ± 2.9	-2.0 ± 4.5
4	1.1 ± 2.8	0.2 ± 2.7	-2.3 ± 2.9	-1.0 ± 4.4
5	2.3 ± 3.4	1.3 ± 3.5	1.1 ± 4.3	2.9 ± 4.7
6	2.8 ± 4.6	-1.1 ± 6.3	-1.5 ± 4.8	0.1 ± 3.6
7	4.4 ± 2.9	1.0 ± 2.9	-1.5 ± 2.7	-0.4 ± 2.4
8	1.0 ± 3.1	2.4 ± 1.6	-0.6 ± 2.4	-0.2 ± 2.0
9	1.0 ± 8.0	-0.9 ± 2.2	0.1 ± 1.5	1.3 ± 1.6
10	1.0 ± 3.5	1.2 ± 4.0	0.0 ± 3.6	1.4 ± 2.3
All	1.6 ± 4.2	0.3 ± 3.6	-0.6 ± 3.9	0.6 ± 4.0

Data are means $\pm$ SD.
Long: longitudinal; tang.: tangential.

the knot axis and the board face is small, as it will be for knots near the wane, the projected knot diameter changes considerably, even with small changes in the angle. Knots close to the pith, such as knots at the centre of the board, are sensitive to the positioning owing to the rapid development of their diameter close to the pith. With a board thickness of 19 mm, the sapwood side of the inner pair of boards will be close to the pith. This may explain the better prediction of knot diameter on the outer boards (Figs. 9, 10) and the lower accuracy compared with Grundberg (1999). The manual measurement of knot diameter on the real boards is also expected to be a source of variation. Grundberg (1999) reported a SD of 1.2 mm between measurements on 92 knots performed by two different people.

The position of the knots was surprisingly well described, considering the low resolution in the longitudinal direction of the CT images and uncertainty of the shrinkage of the boards. By measuring the position on unedged boards, the good results indicate that both log geometry and knot position are well modelled by the parametric descriptions. The relatively large errors on knot diameter imply that grading simulated boards with the explicit Nordic Timber Grading rules will not produce reliable results at a single board level. However, for groups of logs larger than 100, the random error in knot diameter is expected to have a limited influence on the value and volume recovery calculated (Grundberg 1999). The dead knot border was not discriminated by the algorithms. Thus, all knots were classified as sound.

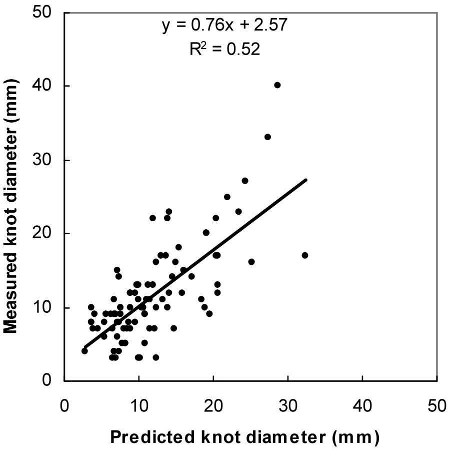

Fig. 9. Tangential knot diameter on the inner boards. Measured on real boards versus predicted by simulated sawing of corresponding boards based on parametric descriptions.

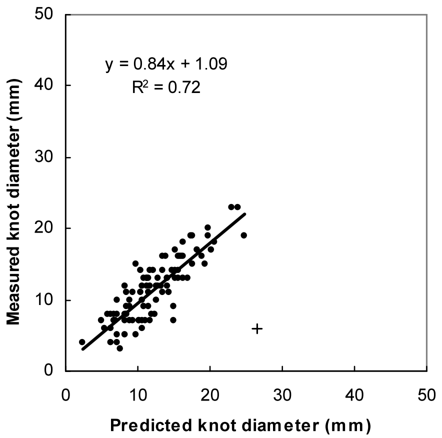

Fig. 10. Tangential knot diameter on the outer boards. Measured on real boards versus predicted by simulated sawing of corresponding boards based on parametric descriptions. Outlier (+) was excluded when fitting the regression line.

This would also affect grading accuracy, although the trees were young, and dead knots occurred mostly near the butt end of the first log and were therefore small in diameter. Accuracy in predicting the size and position of knots was evaluated on a limited validation set, i.e. 10 boards from five logs from three trees. As wood is a variable material, other validation sets may give different results.

It can be concluded that the parametric descriptions derived by the algorithms described here are accurate for log geometry and knot position, and that they predict knot diameter with an acceptable precision at distances to pith greater than 40 mm. Hence, the logs from young thinnings augment the Swedish Stem Bank and can be used for modelling the knot structure of trees and simulating the yield of different strategies in forestry and sawing. However, simulating board faces near the pith will give unreliable results.

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Paper III

Paper III

Predicting Lumber Volume and Grade Recovery for Scots pine Stems using Tree Models and Sawmill Conversion Simulation

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ABSTRACT

Through application of tree models, stem shape and internal knot structure of Scots pine stems could be predicted using site, stand and tree variables. Stem shape was described by stem taper and cross-sectional eccentricity. Knot properties included were knot diameter, sound knot length, loose knot length, number of knots per whorl and longitudinal inclination. This model system was then integrated in a sawmill conversion simulation system (Saw2003) in order to evaluate lumber recovery in terms of lumber dimension distribution, volume, grade and value. These applications showed that it was possible to predict the lumber grade recovery on the basis of stand and tree measurements. When comparing results of tree models against empirical data for 604 logs, the volume recovery of side boards was overestimated with the modeling approach, but the volume recovery of centre boards and the grade recovery showed good agreement. For both methods, the recovery of the strictest grade decreased slightly with increasing DBH-class, but increased with increasing lumber dimension. The results of this study illustrate how the Saw2003 system can be applied to estimate the lumber volume and grade recovery of standing Scots pine trees.

Key Words: Knot properties, sawing simulation, stem eccentricity, taper, timber utilization, wood quality.

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INTRODUCTION

The use of models to estimate wood quality attributes, and the application of such models in sawmill conversion simulation systems, has been identified as an important method in order to link end users' product requirements with properties of the forest resource (Barbour and Kellogg 1990, Houllier et al. 1995, Briggs 1996, Barbour et al. 1997, Ikonen et al. 2003). These models thereby provide a basis for grading simulated products in terms of defect allowances, lumber dimensions and values. Such integrated systems represent flexible tools for evaluating the product recovery from a standing timber resource, comparison of different conversion strategies or identification of suitable raw material sources for specialized products.

These research efforts recursively employ growth models together with taper, live crown and branch models over a long time period to simulate the external stem shape and internal knot structure of trees at the time of harvest. Although this method has biological appeal, recursive use of a large number of integrated models may have implications regarding precision and bias of the results, where errors in one model might be magnified over time or carried over into other models (Houllier et al. 1995); this would be especially a concern when the models are based on different data sources or simulations are extrapolated far beyond the original data. The calculations can also become cumbersome when used for a large number of trees.

In another approach to sawmill simulation, Usenius and Song (1997), Barbour et al. (1999), Chiorescu and Grönlund (2000), Lemieux et al. (2000), Todoroki and Rönnqvist (2002), and Nordmark and Oja (2004) use either destructive or non-destructive measurements to reconstruct the three-dimensional external shape and internal knot structure of logs in computer-simulated conversion into lumber. In these cases, the sample available for simulation studies is limited to the measured logs, which might be a problem given the expense of measurement techniques.

In Sweden, a national database of Scots pine (*Pinus sylvestris* L.) stems collected from experimental plots, and measured with a medical CT-scanner, has been created (Grundberg et al. 1995). Through digital image analysis, detailed information concerning internal knot properties is obtained: The radial resolution is 1 mm, and the longitudinal resolution is 1 cm. Each knot is described by 9 parameters defining location (longitudinal and radial), size (in the tangential direction) and quality (length of sound- and loose-knot segments). Also, the location of the pith and the radial distance to stem surface (under bark) is included in the database. This data material is used by Moberg (2000 and 2005) and Moberg et al. (2005) as a basis for developing statistical models of stem taper and internal knot properties with site, stand and tree characteristics as independent variables. These models directly predict stem shape and knot properties without the recursive use of growth models, and thus represent an alternative to the approach described above. This could be an advantage in applications where the historical silvicultural regimes might be unknown, and a relevant three-dimensional database might not be readily available, such as: Operational logging planning (e.g. harvest scheduling or allocation of logs to individual mills); calculating the stumpage fee for a harvestable timber resource; or comparing conversion strategies for a specific mill's catchment area.

A system for sawmill conversion simulations - called Saw2003 - has been developed by Nordmark (2002). This software can simulate the lumber volume and grade recovery from saw logs as described in the Swedish Scots Pine Stem Bank (SSPSB). The objectives of this study have been to investigate the possibilities of applying models, based on site and tree characteristics, describing internal knot properties and external stem shape in the Saw2003 system, and to compare the results from such model simulations with the results from the empirical data of the SSPSB in terms of lumber volume and grade recovery.

MATERIALS AND METHODS

The study was based on 192 Scots pine trees sampled from 33 stands. The stands were sampled in order to get a broad distribution of growing conditions for Sweden. In each stand, the stems were divided into three DBH-classes around the stand quadratic mean DBH, with class limits at half a standard deviation above and below this mean. From each DBH-class, two stems were randomly chosen (Grundberg et al. 1995). The variation of stand and tree properties have been summarized in Table 1.

Table 1. *Summary statistics of the data used to generate stem shape (Fig. 1) and knot structure (Fig. 2).*

Property	Abbre-viation	Unit	Min.	Mean	SD	Max.
Age, total	AGE	years	70	106	27.5	153
Altitude	ALT	m	50	218	93.8	420
Annual ring width, 1-20 years	RW1-20	mm	8	40	17	106
Crown length (Ht – Hllb)	CL	m	4.10	9.31	2.11	14.9
Crown ratio (CL/Ht)	CR		0.19	0.43	0.083	0.64
Diameter, stand mean at breast height	DBHmean	mm	215	288	54	401
Diameter, breast height	DBH	mm	176	285	66.1	476
Diameter, whorl k	Dk mean	mm	109	195	49.7	527
Height, total	Ht	m	14.1	21.6	3.29	29.0
Height, lowest live branch	Hllb	m	6.8	12.3	2.88	19.8
Height, whorl k	Hk	m	0.1	7.18	4.97	19.7
Height increment (Hk – Hk-1), whorl k	ΔHk	cm	7	28	9.9	67
Site index, dominant height at 100 years	SI	m	16	22.7	3.6	28
Temperature sum[a]	Tsum	°C days	606	1035	229	1370

[a]In Sweden, temperature sum can be estimated as a function of altitude and latitude (Moren and Perttu 1994).

The system of models, used in the calculations, has been illustrated in Figs. 1 and 2. First, stem shape is simulated in 1 cm intervals using a taper function Moberg et al. (2005). A series of functions were then used to calculate stem eccentricity as described by an ellipse (containing magnitude and direction of the main axis of eccentricity). Magnitude of eccentricity was described in a segmented, random coefficients model; direction of major axis used a circular-normal model assuming first level autoregressive error structure (Moberg et al. 2005). Finally, in order to get values compatible with the SSPSB, 360 radii from the pith were generated on the basis of these values at each cross-section.

Simulation of knot properties started with prediction of whorl location. A height increment function (Elfving and Kiviste 1997) was used for this purpose as Scots pine is a uni-nodal species lacking inter-whorl branches. Next, knot frequency (*KF*) and mean and maximum knot diameter (KD_{mean} and KD_{max}) of each whorl were calculated as described by Moberg (2005). Knot diameter of individual knots (*KD*) was based on azimuthal direction (*KDIR*) and a stochastic component (assuming a log-normal distribution around the mean). Sound- and loose-knot lengths (KL_{sound} and KL_{loose}), as well as longitudinal inclination (*KI*), were a function of this predicted knot diameter although a few tree descriptors also had some additional influence (Moberg 2005). Finally, the simulated stems were separated into sections corresponding to the lengths of the logs in the SSPSB. Through application of these integrated models and algorithms, a database containing 604 twin pairs of saw logs, containing compatible data from both model simulations and empirical measurements from the SSPSB, could be created.

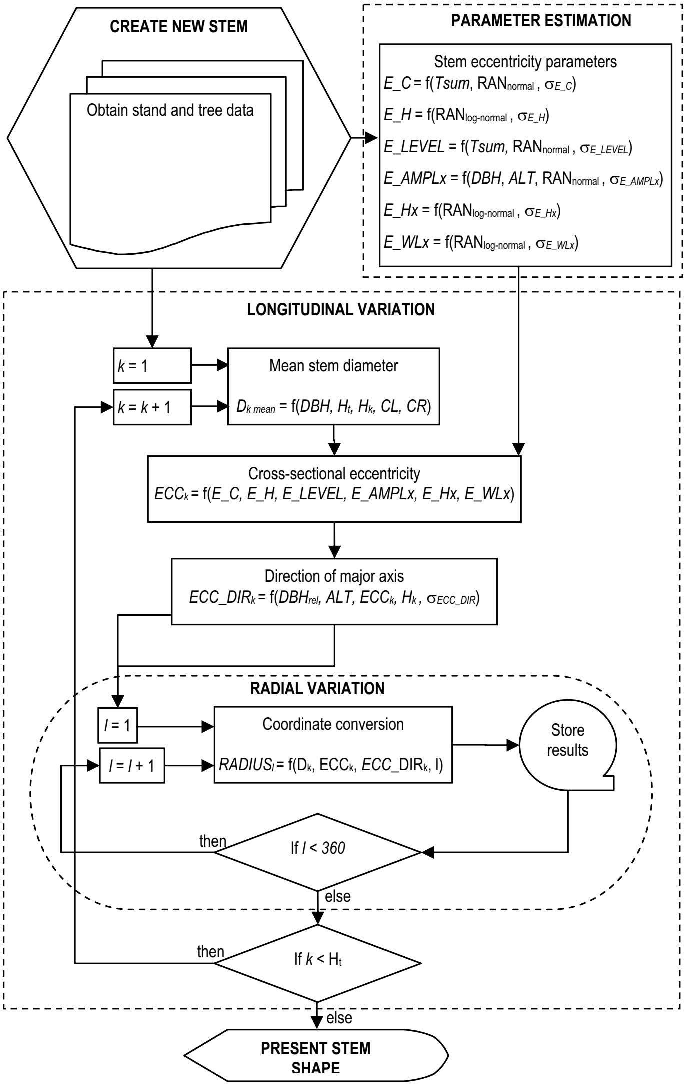

Figure 1. *Flow chart describing the system of equations used for simulating the external shape of a model stem.*

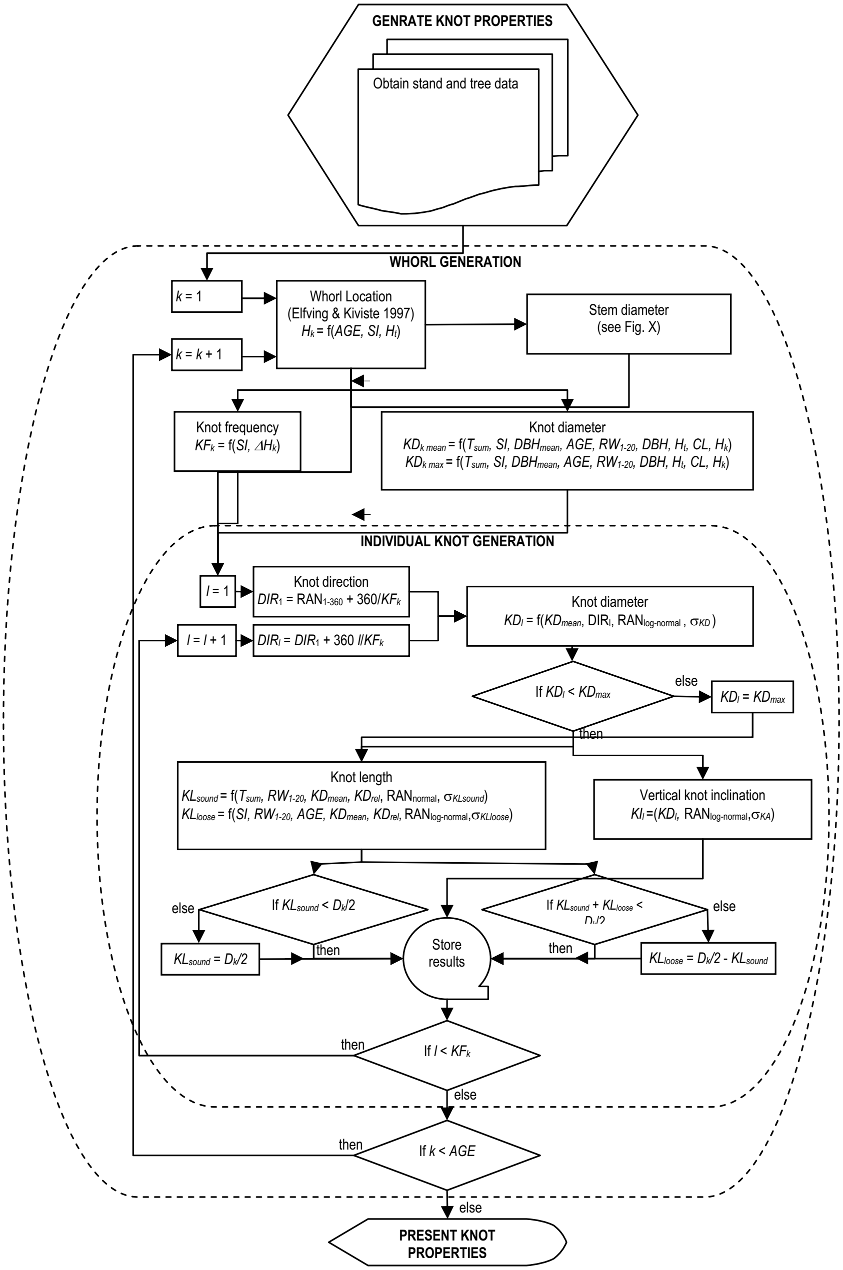

Figure 2. *Flow chart describing the system of equations used for simulating the internal knot properties of a model stem.*

The sawmill simulation system used in the study is a Windows™-based program developed in C++ (Nordmark 2002). The software has a graphical interface partly based on OpenGL, allowing the user to interact with logs and boards in three dimensions. The simulations were automated using a scripting module of the system which exposes most of its functionality to the user for custom applications. Cant sawing was used in the modeled sawmill, whereby the first sawing machine cut the log into a block and side boards, and the second saw cut the block into 2–4 centre boards and 2–4 side boards (Fig. 3). The logs were automatically rotated horns down (crook up) and centered in both saws. Curve sawing was applied throughout. The sawing patterns for different small-end diameter intervals are shown in Table 3. Side boards were edged and trimmed, while trimming was the only operation on centre boards; both operations were value-optimized based on lumber prices and grade.

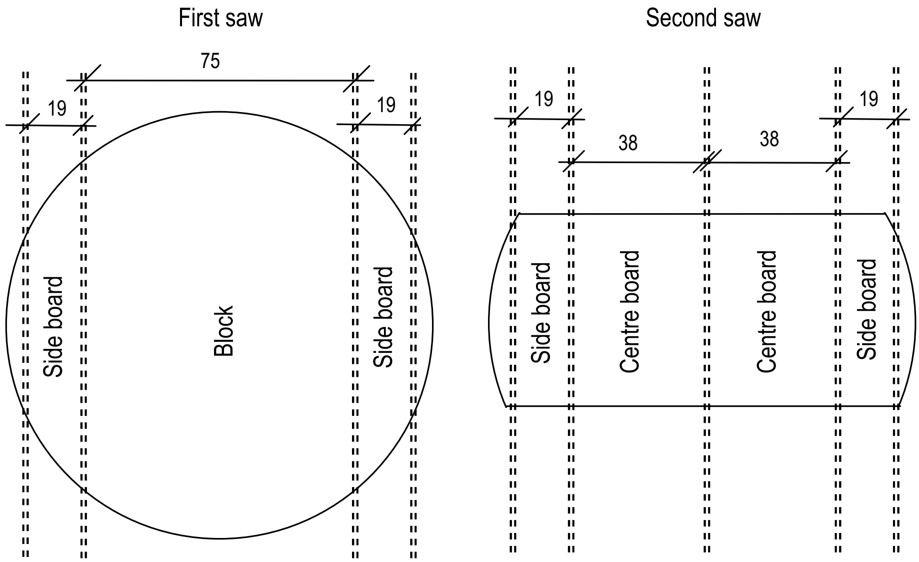

Figure 3. *Illustration of sawing patterns (using the pattern for the smallest log of Table 3 as an example) used with cant sawing.*

Grading was based on wane criteria and knot properties according to the Nordic Timber grading rules (Anon. 1994). The boards were graded into Grade A, B, or C, where A is the strictest grade. The grading rules define allowable wane, knot diameter, number of knots and sum of knot diameters on edges and faces. Separate limits are given for sound and loose knots in grades A and B. The boards were priced according to Table 2. In addition to the lumber produced, the volume of by-products was calculated (sawdust and chips). The price of by-products was 200 SEK m^{-3}.

Table 2. *Knot and wane allowances, as well as lumber values, for lumber grades (adapted from Nordic Timber, Anon. 1994).*

Board dimension		Nordic Timber grades		
Thickness	Width	A	B	C
		Maximum knot size (mm)[a]		
16-25	75-115	20	35	50
	125-150	25	40	55
	175-225	30	45	60
32-38	75-115	25	40	55
	125-150	30	45	60
	175-225	35	50	65
44-50	75-115	30	45	60
	125-150	35	50	65
	175-225	40	55	70
63-75	75-115	35	50	65
	125-150	40	55	70
	175-225	45	60	75
		Number of knots of maximum size per 1 m section		
All	All	4	5	6
		Wane Max depth at each edge (mm)		
19	All	4.9	5.9	6.8
25	All	5.5	6.8	8.0
32	All	6.2	7.8	9.4
38	All	6.8	8.7	10.6
50	All	8.0	10.5	13.0
63	All	9.3	12.5	15.6
75	All	10.5	14.3	18.0
		Wane Max width at each edge (mm)		
All	All	10	15	20
		Value ($\$ m^{-3}$)		
19-32	All	300	200	143
38-75	All	262	200	143

[a] Allowances are listed for sound knots; limits for loose knots are 70% of sound knots in grades A and B, 100% in grade C.

Table 3. *Sawing patterns and related log small-end diameter intervals (see Fig. 3 for an illustration).*

Log small-end diameter (mm)		Sawing pattern (mm)	
Min.	Max.	First saw	Second saw
100	129	19,75,19	19,38,38,19
130	149	19,100,19	19,38,38,19
150	169	19,100,19	19,50,50,19
170	184	19,125,19	25,50,50,25
185	194	19,125,19	19,63,63,19
195	209	19,19,150,19,19	19,25,50,50,25,19
210	219	19,19,150,19,19	19,25,63,63,25,19
220	229	19,19,175,19,19	19,25,50,50,25,19
230	249	19,19,175,19,19	25,25,63,63,25,25
250	264	19,19,200,19,19	25,25,63,63,25,25
265	284	19,19,200,19,19	19,25,75,75,25,19
285	304	19,19,225,19,19	19,25,75,75,25,19
305	324	19,25,200,25,19	19,25,50,50,50,50,25,19
325	344	25,32,225,32,25	25,25,50,50,50,50,25,25
345	384	25,32,200,32,25	19,25,63,63,63,63,25,19
385	449	25,32,200,32,25	19,25,75,75,75,75,25,19

RESULTS

The simulated stem shape and knot properties of a sample stem is illustrated in Fig 4. Knot diameter increased asymptotically above ground level to just below the live crown. Above this level, knot diameter increased in a second-order polynomial, reflecting the build up of biomass as the tree gets larger and older (Moberg 2000). After reaching a maximum at the base of the live crown, knot diameter became smaller, and was bounded to zero at the top of the stem. The log-normal distribution of individual knots around the mean was evident in the wider distribution at higher mean values, and that positive values were consistently obtained (Fig. 4a). Stem taper was estimated through a segmented polynomial function consisting of three sections. It was bounded to diameter at breast height and to zero at the top of the tree (Fig.4b). Whorl location has been illustrated by the pith in Fig 4b, whereby the maximum height increment was evident in the lower half of the stem. A more or less cylindrical zone of sound knots could be identified around the pith, and further outside there was a zone of loose knots. At the base of the stem, there was a zone of clear, knot-free wood (Fig 4b).

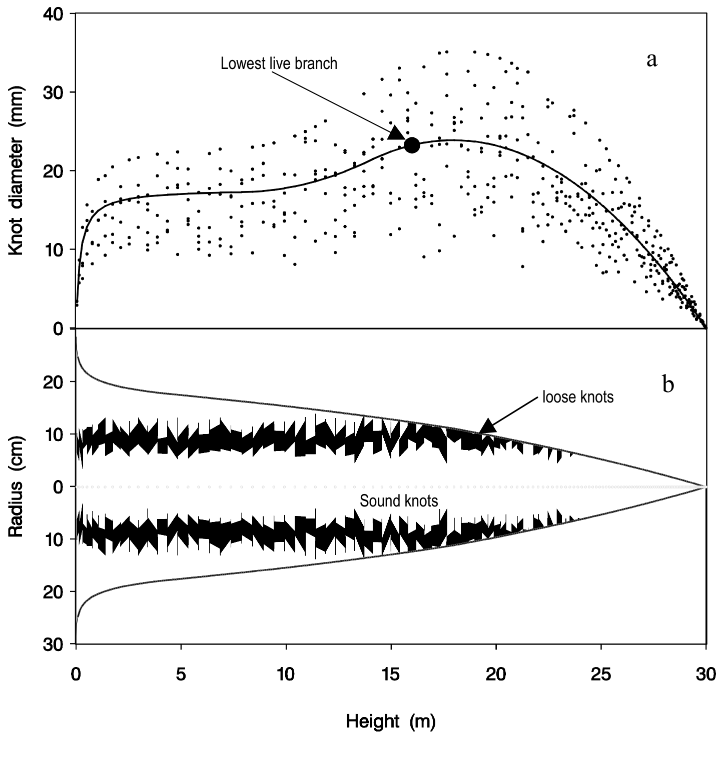

Figure 4. *Illustration of simulated knot diameter, knot type, whorl location and stem taper.*

A comparison of the results from model simulations with the equivalent data from measurements over the diameter strata from the sampling strategy of the SSPSB has been presented in Table 4 and Figs. 5 and 6. Both data sources indicated increasing lumber volume recovery with increasing diameter class, and the level of volume recovery of centre boards was about the same when comparing the data sources against each other. The volume recovery of side boards was overestimated, and the volume of chips was underestimated, in the modeling approach, but there was no apparent systematic relationship of bias to tree size. The grade recovery of Grade B increased slightly with the diameter size classes at the expense of Grade A recovery; Grade C recovery was about the same for all tree sizes. In comparison with the measurement data, the model simulations resulted in a slight underestimation of Grades A and C, with a corresponding overestimation of Grade B. The net effect on value recovery, expressed per unit volume, was a 2.7 % larger recovery for the modeling approach. The combined effect volume and grade recovery resulted in a total value recovery difference of 9.2 % between the two methods.

Table 4. *Total sawlog volume, lumber volume, volume recovery rate, total lumber value and relative product value using tree models and empirical measurements respectively.*

	Log volume (m^3)	Board volume (m^3)	Residue volume (m^3)	Volume yield (%)	Board value ($)	Value recovery ($ $\cdot m^{-3}$)
Model simulation	104.0	58.3	45.7	56.0	12,500	214.57
Empirical data	106.5	54.7	51.8	51.3	11,600	212.57

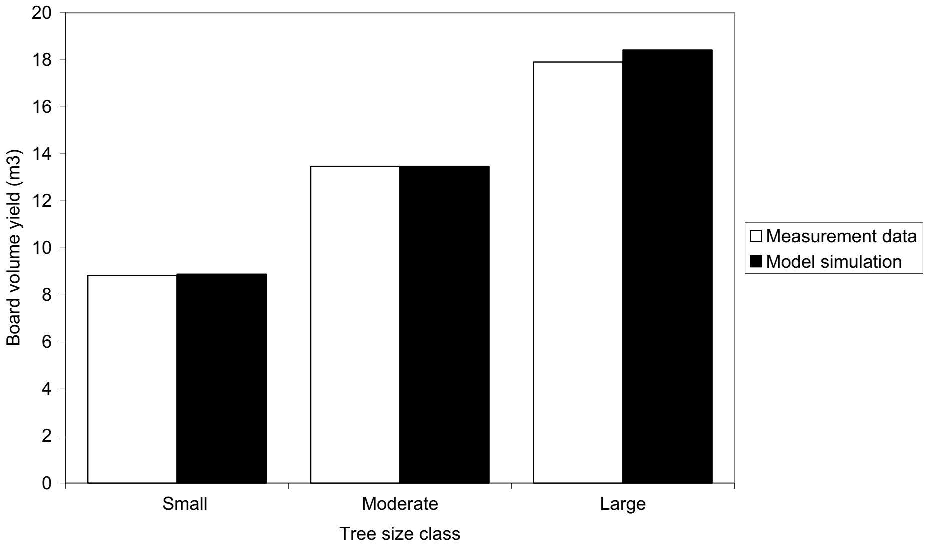

Figure 5. *Lumber volume yield by tree size class using tree model and empirical measurement data respectively.*

The results from model simulations have been compared with the equivalent data from measurements in terms of simulated board thickness in Figs. 7 and 8. The lumber volume recovery from the two data sources was quite similar, although the volume of side boards was overestimated by about 20% in the modeling approach due to the difference in the thinnest thickness class. However, there did not seem to be any systematic bias of estimates related to lumber thickness. The grade recovery level was very similar when comparing the two data sources: In both cases, recovery of Grade A increased over the thickness classes, primarily at the expense of Grade C recovery. The largest dimension class for both side and center boards did not follow this pattern, but these classes, on the other hand, contained only a small volume. The modeling approach overestimated the unit value of side boards by 2.7 % and center boards by 1.2 %.

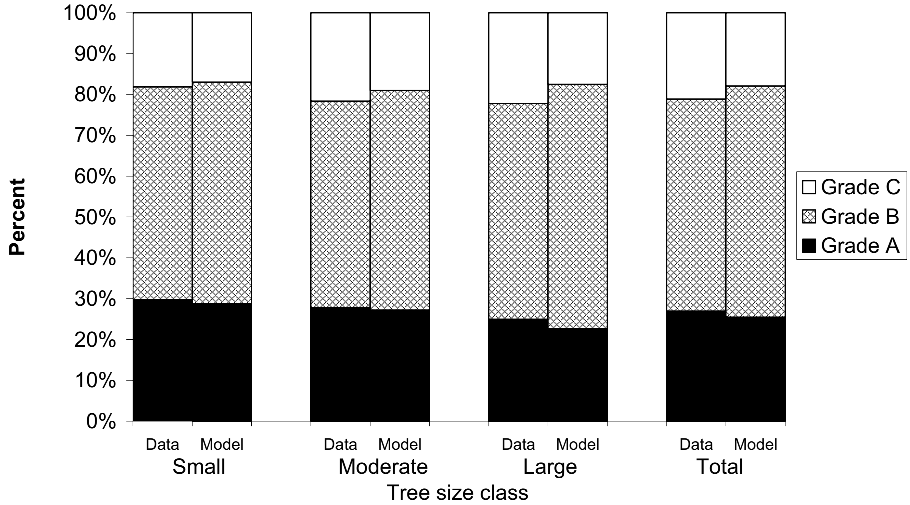

Figure 6. *Lumber grade distribution by tree size class using tree model and empirical measurement data respectively.*

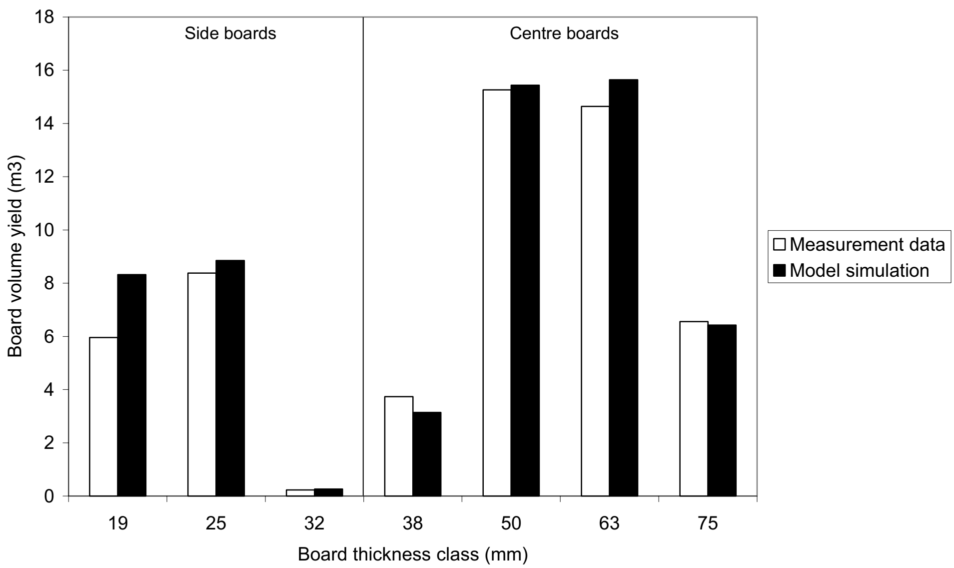

Figure 7. *Lumber volume yield by board thickness class using tree model and empirical measurement data respectively.*

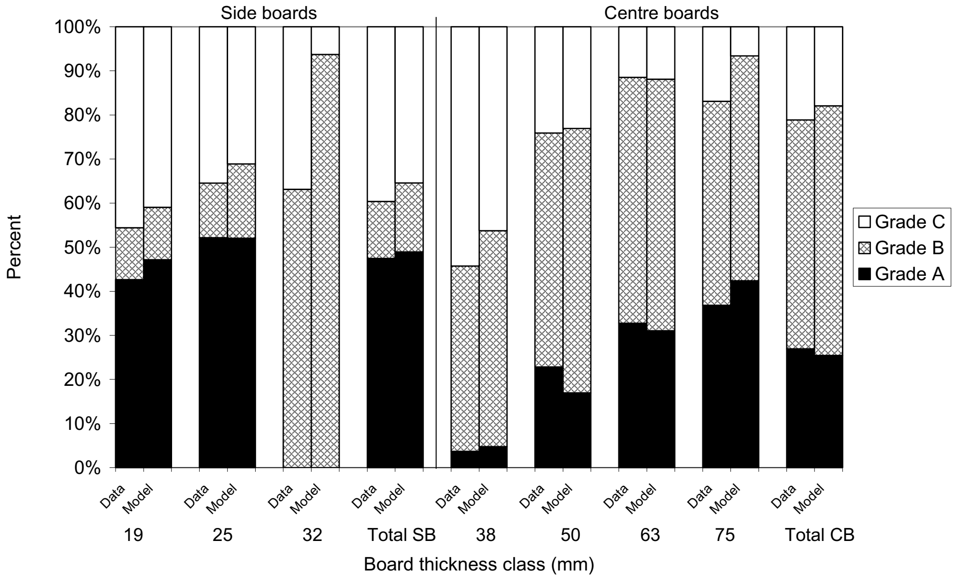

Figure 8. *Lumber grade distribution by board thickness class using tree model and empirical measurement data respectively.*

DISCUSSION

The conversion simulations results showed the possibilities to apply statistical models, based on tree, stand and site variables, to predict the lumber volume and grade recovery. The Saw2003 system is also used for conversion simulation by Nordmark and Oja (2004) to predict board values based on X-ray scanning and optical three-dimensional scanning measurements, and is judged to perform adequately. It is also successfully used by Nordmark (2002) to study the possibilities of controlling bucking and log sorting with respect to value recovery. The results of the present study therefore extend the functionality of the Saw2003 system for standing Scots pine trees. This could be useful in planning applications to support decisions early in the solid wood supply chain regarding industrial potential of a standing timber resource for assessing stumpage rate, allocation of sawlogs to different specialized mills or evaluation of future conversion strategies for a specific mill.

The volume of sawlogs was underestimated through the model approach, but yet resulted in a larger volume of lumber (Table 4). Fig. 7 indicated that the reason for overestimation of lumber volume was primarily the high recovery of thin side boards (19 mm). These boards were nearest the stem surface, making it likely that the models did not accurately reflect the irregular shape of the stem surface. Although recovery of by-products was not reported at the board level, this was also supported in Table 4, which showed higher recovery of chips (from slabs outside of the side boards or the trimmed ends of boards) in the empirical data. Another source for this inaccuracy could be that, although the modeling approach took stem eccentricity of stem cross-section into account through an ellipse shape, it assumed longitudinally straight stems. Curve sawing, as was applied in the modeled sawmill for the empirical data, compensates for some regular longitudinal miss-shapes such as sweep or crook that otherwise would result in volume losses (Wang et al. 1992, Todoroki and Rönnqvist 1998). However, the logs in the SSPSB also had multiple irregularities such sinuous shapes which would result in volume recovery losses even with curve sawing. In this study, it was not possible to explore if the higher volume recovery of modeling data was more due to longitudinal (e.g. multiple crooks) or radial stem irregularities (e.g. due to whorls or buttress).

Within-stand differentiation due to inter-tree competition leads to some trees, with improved micro-climates or genetic properties, increasing their girth at the expense of neighboring trees (Oliver and Larson 1990). These dominant trees will have larger crowns, branches and therefore knots than the co-dominant or suppressed trees (Larson 1969, Mitchell 1975). A number of studies find that lumber from larger stems, within stands, is down-graded due knot size: Johansson (1992) concerning Norway spruce graded according to the old Swedish lumber grading rules (Anon. 1982); Middleton et al. (1995) concerning lodgepole pine and the Standard Grading Rules for Canadian Lumber for Structural Light Framing and Structural Joists and Planks (NLGA, Anon. 1998); and Middleton and Munro (2001) concerning western hemlock for both the NLGA and the Japanese Agricultural Standard for Structural Lumber (Anon. 1991). Although the differences were slight, both the empirical and modeling approaches of the present study support these findings (Fig. 6).

Grading rules, including Nordic Timber (Anon. 1994), typically have a larger allowance for knot size with larger pieces of lumber. Although there is a positive correlation between knot size and tree size when comparing within-stand effects, when comparing the universal relationship between size of lumber and grade recovery in a broad sample such as the SSPSB, the effects of growth various conditions are mitigated by other factors. Large logs in this dataset could be the effect of high growth rates, or old age at the time of harvest. Likewise, small logs could either be the effect of slow growth rates, young age or height of the log in the stem. As a result, it is likely that it was the grading rules which were the reason for the improved grade recovery with board thickness (Fig. 8), and that the underlying biological factors were compounded together. Similar effects are observed with the old Swedish grading rules for Scots pine (Grönlund 1994), and the NLGA for Douglas-fir (Middleton and Munro 1989) and lodgepole pine (Middleton et al. 1995).

CONCLUSIONS

The conversion simulations showed that it was possible to predict the lumber volume and grade recovery on the basis of tree and stand measurements. However, the overestimation of volume recovery rate due to the assumption of straight stems using tree models needs further attention. For example, it would be possible to introduce stochastic elements in order to predict three-dimensional stem crook in order to obtain more realistic stem shapes.

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Paper IV

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Prediction of Board Values in *Pinus sylvestris* Sawlogs Using X-ray Scanning and Optical Three-dimensional Scanning of Stems

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As the sawmill industry strives towards customer orientation, the need for sorting of logs according to quality has been recognized, and automatic sorting based on measurements by three-dimensional (3D) optical log scanners has been implemented at sawmills. There is even a small number of sawmills using the X-ray log scanner for automatic log-sorting. At the log-sorting stage, the potential of the raw material to fulfil the needs has already been reduced by the decisions taken when the trees were bucked (cross-cut) into logs. Thus, the application of predictions of the boards' properties at the bucking stage is desirable. This study investigates the possibility of predicting board values from logs based on 3D scanning alone and 3D scanning in combination with X-ray scanning of stems. This study is based on 628 logs scanned by computed tomography that make up the Swedish Pine Stem Bank. Simulated sawing of the logs gave product values for each log. Prediction models on product value were adapted using partial least squares regression and x-variables derived from the properties of the logs and their original stems, measurable with a 3D log scanner and the X-ray LogScanner. The results were promising. Using a 3D scanner alone, R^2 was 0.68, and using a 3D scanner in combination with an X-ray LogScanner, R^2 was 0.72. *Key words: 3D scanning, automatic grading, bucking, cross-cutting, log scanning, PLS, sawlogs, simulation.*

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INTRODUCTION

Advances in research in the field of log-sorting at sawmills has reached the point where the quality of the centre boards yielded can be predicted for individual scanned logs. This is true for quality based on parameters such as stiffness (Aratake et al. 1992, Sandoz 1996, Ross et al. 1997, Oja et al. 2001) and knot structure (Grace 1994, Andersson 1997, Jäppinen 2000, Oja et al. 2000). Technologies used to scan the logs are ultrasonic measurement, measurement of longitudinal stress waves, two-axis shadow scanners, three-dimensional (3D) optical scanners and two-axis X-ray scanners. As the sawmill industry strives towards customer orientation, an efficient method of log-sorting is necessary so that the required combinations of the board dimensions and qualities can be produced. However, at the log-sorting stage, the potential of the raw material to fulfil requirements has already been reduced by the decisions taken when the trees were bucked (cross-cut) to logs, hence the desirability of the application of predictions of the boards' properties in the bucking operation.

The 3D optical scanner used for scanning of logs at high speed is able to provide a detailed model of the external log geometry. Variables derived from the log geometry such as different measures of taper and unevenness of the mantle surface (i.e. bumpiness) have proven useful for grading of logs according to knot properties on the centre boards of Scots pine (*Pinus sylvestris* L.) by Lundgren (2000) and Oja et al. (2003), and of Norway spruce (*Picea abies* (L.) Karst.) by Jäppinen & Beauregard (2000). The two-axis X-ray LogScanner (Grundberg & Grönlund 1997) provides images of the density variations within the scanned logs. Simulations have shown its ability to predict knot properties in Scots pine and Norway spruce sawlogs (Grundberg & Grönlund 1998), and real measurements confirmed its ability to classify logs by grade (Oja et al. 2003) based on density variations. In a

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bucking context, additional variables derived from 3D scanning and X-ray scanning describing the stem, and relations between different stem sections can be added to the prediction model.

The stem-bucking problem is usually addressed with dynamic programming (DP) (Dreyfus & Law 1977), where the objective is to maximize the summed value of the logs cut from the stem (Pnevmaticos & Mann 1972). The method finds the optimal combination of cuts out of thousands of possible combinations. The challenging part of the problem is not the DP algorithm, but rather the pricing of logs. For pulp logs this is not an issue as long as there is a simple volume and value relationship, but for sawlogs the price needs to be related to the expected quality of the boards sawn from the log. Faaland & Briggs (1984) and Reinders & Hendricks (1989) integrated a log-sawing algorithm that evaluates the value of the boards sawn from the logs into the bucking model. The log breakdown models assumed simplified geometric log descriptions. More realistic log breakdown models can be found in work by Lewis (1985), Funck (1993), Todoroki (1996) and Nordmark (2002), with more detailed levels of description of log shape.

The value of a log can be expressed as the sum of product values extracted from the log, while the value of each product can be expressed as the product of volume yield and product value per volume:

$$\text{Value of log} = V_{\text{sawdust}} \cdot P_{\text{sawdust}} + V_{\text{chips}} \cdot P_{\text{chips}} + V_{\text{boards}} \cdot P_{\text{boards}} \quad (1)$$

where V = volume (m^3) and P = price (SEK m^{-3}).

With the 3D optical log scanners and the use of log breakdown simulators it is possible to estimate the volume yield of boards, chips and sawdust, whether it is an actual log or a prospect log that is a segment of a scanned stem. Usually chips and sawdust have fixed prices without variation due to grade, while the price of boards varies with grade. With the volume yield estimated with a log breakdown simulator, the missing link in estimating the value of a log is the ability to predict the value of the timber per volume (P_{boards}). The aim of the present study was to assess the accuracy of predicting product values of boards in logs not yet cut, from measurements on stems with a 3D scanner alone or in combination with an X-ray LogScanner.

MATERIALS AND METHODS

The study was approached using simulation techniques. The Swedish Pine Stem Bank (SPSB) (Grundberg et al. 1995) served as the wood supply. Simulated sawing of the logs in SPSB gave product values for each log. Using partial least squares regression (PLS) (Geladi & Kowalski 1986), prediction models on product value were adapted with x-variables derived from the properties of the logs and their original stems, measurable with a 3D log scanner and the X-ray LogScanner (Grundberg & Grönlund 1997).

The SPSB is a database containing detailed information on 628 logs originating from 198 Scots pine trees. The project is based on computed tomography (CT) scanning of these logs, which were carefully selected from 33 well-documented sample plots all over Sweden. From each sample plot six trees were taken: two small, two medium-sized and two large trees. The trees were manually bucked, and the sawlogs obtained were CT scanned. Analysing the images achieved, parametric descriptions of the outer shape and knot properties of each log were compiled and stored in the database. The outer shape is given as cross-sections, at an interval of 1 cm, described using polar coordinates with the pith as the origin. The knots are described using a set of mathematical models. Each knot has its own coefficients in the models, making it possible to compute the position of the knot axis in three dimensions as well as the size of the knot at different positions along its axis. The order of the logs within the trees as well as their rotational position during the CT scanning was documented, thus allowing for reconstruction of the stems. From the descriptions of the logs' outer shapes, variables were derived describing surface unevenness, taper and diameter of the logs. This simulates what can be computed from the output of raw data from a commercial 3D optical log scanner. The two-axis X-ray LogScanner was simulated by processing the CT images of the logs as described by Grundberg & Grönlund (1997). By further processing of the simulated signals from the X-ray LogScanner each whorl within the logs was described by its longitudinal position, volume and longitudinal extension. Secondary variables describing the presence of whorls were formed. Variables describing the stem's properties and variables of the log's relation to the stem were added. These variables included length of stem, taper of stem, log position in stem, and the relation between log top diameter and diameter of the stem at breast height.

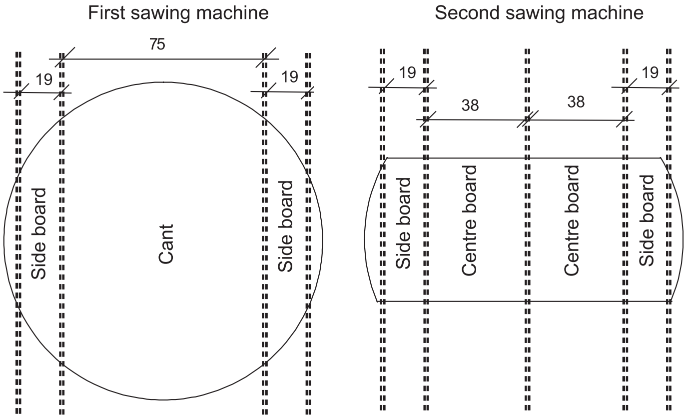

Fig. 1. Cant sawing. The first sawing machine cuts the log into side boards and a cant. The cant is then rotated by 90 degrees and cut by the second sawing machine into side boards and centre boards. Side boards are further processed by edging and trimming, while trimming is the only operation on centre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

Two models were fitted to the data, one using variables from both the 3D and X-ray (M:3D-X), and one using variables from the 3D scanner alone (M:3D).

The sawing simulator used is a Windows™-based program developed in C++. The software (Saw2003) has a graphical interface partly based on OpenGL, allowing the user to interact with logs and boards in three dimensions. The program is capable of reading log descriptions from the SPSB database and optionally assembling logs into stems. The sawmill modelled uses cant sawing, where the first sawing machine cuts the log into a cant and side boards, while the second sawing machine cuts the cant into two to four centre boards and two to four side boards (Fig. 1). Side boards are edged and trimmed, while trimming is the only operation on centre boards. Both edging and trimming are value-optimizing operations based on timber prices and grade. Grading is based on wane criteria and knot properties. The simulator also exposes a great deal of its functionality to a scripting module. Through scripts, simulations can be automated, and reports of the sawing process and properties of logs and boards can be tailored. In total, 615 logs from the SPSB were included in the study.

Table 1. *Sawing patterns and related log top end diameter intervals (see Fig. 1)*

Log top diameter (mm)		Sawing pattern (mm)	
Min.	Max.	First saw	Second saw
100	129	19, 75, 19	19, 38, 38, 19
130	149	19, 100, 19	19, 38, 38, 19
150	169	19, 100, 19	19, 50, 50, 19
170	184	19, 125, 19	25, 50, 50, 25
185	194	19, 125, 19	19, 63, 63, 19
195	209	19, 19, 150, 19, 19	19, 25, 50, 50, 25, 19
210	219	19, 19, 150, 19, 19	19, 25, 63, 63, 25, 19
220	229	19, 19, 175, 19, 19	19, 25, 50, 50, 25, 19
230	249	19, 19, 175, 19, 19	25, 25, 63, 63, 25, 25
250	264	19, 19, 200, 19, 19	25, 25, 63, 63, 25, 25
265	284	19, 19, 200, 19, 19	19, 25, 75, 75, 25, 19
285	304	19, 19, 225, 19, 19	19, 25, 75, 75, 25, 19
305	324	19, 25, 200, 25, 19	19, 25, 50, 50, 50, 50, 25, 19
325	344	25, 32, 225, 32, 25	25, 25, 50, 50, 50, 50, 25, 25
345	384	25, 32, 200, 32, 25	19, 25, 63, 63, 63, 63, 25, 19
385	449	25, 32, 200, 32, 25	19, 25, 75, 75, 75, 75, 25, 19

Thirteen were excluded owing to missing or corrupt data. The logs were automatically rotated horns down (crook up) in the first saw and centred in both saws. Curve sawing was applied. Normal sawing patterns for different intervals of the small end diameter of the logs are shown in Table 1. Two or three sawing patterns were evaluated for each log, the normal pattern and the patterns with diameter intervals above and below. For the smallest logs, only the pattern with a diameter interval above was added. The boards were graded A, B or C following the Nordic Timber Grading Rules (Anon. 1994). The grading rules define allowed wane, and the rules also state limits on knot diameter and sum of knot diameters on edges and faces for sound and dead knots, respectively. Grade A has the strictest allowances on the above-mentioned properties and grade C has the widest allowances. The boards were priced according to Table 2. The processing of a log results in a list of priced boards. Dividing the summed value of the boards by their summed volume gives the average value per volume for boards sawn from that particular log with a specific breakdown pattern. An average (AVG) for each log was calculated on the two or three different breakdown patterns for each log sawn using eq. (2). The AVG was used as the response predicted by PLS regression.

$$\mathrm{AVG} = \frac{1}{P}\sum_{p=1}^{P}\frac{\sum_{b=1}^{B_p} Value_b}{\sum_{b=1}^{B_p} Volume_b} \qquad (2)$$

where AVG = mean of value per volume for a log (SEK m^{-3}), P = number of breakdown patterns, and B = number of boards.

PLS regression was chosen because it is based on the assumptions that the x-variables are correlated, that there is noise in the data and that there can be structures in the residuals (Lindgren 1994). Because of this, PLS regression was well suited to this investigation, and the PLS analysis was carried out using the software SIMCA-10.0 (Anon. 2002). One-hundred observations were excluded so as to be used as an independent test set. Two models were calibrated for the remaining 515 observations in the dataset. The coefficient of determination (R^2) and a Q^2 value based on cross-validation (Martens & Naes 1989*a*) were calculated. When cross-validating, N models are built, each time excluding an Nth part of the observations and thereby creating a training set. Each model is then tested on the observations that were excluded when building the model (the test set). Q^2 represents the proportion of variance of y-values in the test set that is explained by the model. Hence, Q^2 is a measure of the model's ability to predict future observations, i.e. observations that were not included when building the model. A model that explains random variations in the training set will fail when tested on new observations; hence, Q will be low for such a model (Martens & Naes 1989*b*).

Table 2. *Timber price list used*

	Price by board type (SEK m^{-3})	
Grade	Side boards	Centre boards
A	3000	1850
B	1400	1600
C	1100	1000

Table 3. *Volume yield by grade and relative distribution of volume: output from simulated sawing of the Swedish Pine Stem Bank with normal sawing pattern*

	Grade	Volume (m^3)	Share (%)	
Centre boards	A	7.8	20	13
	B	21.2	54	37
	C	10.0	26	17
		39.0	100	68
Side boards	A	8.6	46	15
	B	2.7	15	5
	C	7.2	39	12
		18.5	100	32

RESULTS

The output of the simulated sawing with normal sawing patterns is given in Table 3. Centre boards account for 68% of the produced volume. However, the centre boards' share of total value is lower, at 61%. This is due to the high share of high-value grade A side boards. The high price given to grade A side boards, compared with grade B and C side boards, is

Table 4. *R^2 and root mean square error (RMSE) for the two partial least squares regression models*

	R^2		RMSE (SEK m^{-3})	
Model	Training set	Test set	Training set	Test set
M:3D-X	0.72	0.75	183	178
M:3D	0.68	0.72	195	189

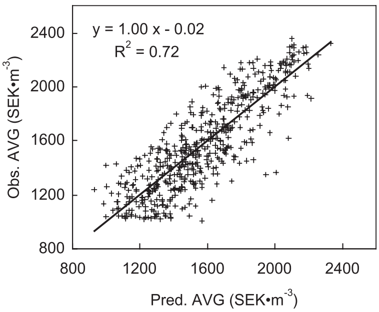

Fig. 2. Predicted and observed average board value (AVG) for the training set of 515 logs using model M:3D-X.

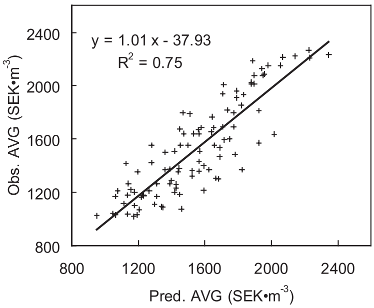

Fig. 3. Predicted and observed average board value (AVG) for the independent test set of 100 logs using model M:3D-X.

also the cause of the high share, as the edging and trimming operations are value optimizing. Results for the two PLS models calibrated are shown in Table 4. The model M:3D-X was calibrated with three principal components and with $R^2 = 0.72$ and $Q = 0.71$. The model based on 3D alone (M:3D) was calibrated with three principal components and with $R^2 = 0.68$ and $Q = 0.67$. The difference between the models is not significant. Plots of predicted AVG versus observed AVG for the training set and the independent test set are shown in Figs 2 and 3. Variables found to be significant are shown in Table 5. Model M:3D-X comprises 21 significant variables. In summary, high values (AVG) are achieved with large-diameter, smooth (no bumps) butt logs with large butt end taper from tall trees, and with low to moderate values on X-

Table 5. *Significant variables and their coefficients in the partial least squares regression models*

		Coefficient	
Variable	Description	M:3D-X	M:3D
topDiam	Small end diameter of log	0.074	0.062
buttDiam	Large end diameter of log	0.076	0.084
relDiam	Diameter of log relative to stem's diameter at breast height	0.104	0.088
volume	Log volume	0.054	0.040
taper	Taper of log	–	0.110
buttTaper	Taper of log at large end	0.090	0.143
logPos	Height position of log within stem	−0.093	−0.089
relPos	Log's position relative to stem length	−0.121	−0.122
bump0–5	Proportion of log with bumpiness in the interval 0–5	0.128	0.186
bump5–10	Proportion of log with bumpiness in the interval 5–10	−0.132	−0.159
bump10–15	Proportion of log with bumpiness in the interval 10–15	−0.087	−0.159
bump15–20	Proportion of log with bumpiness in the interval 15–20	−0.042	−0.090
bump20–30	Proportion of log with bumpiness in the interval 20–30	−0.057	−0.082
bump30–50	Proportion of log with bumpiness in the interval 30–50	–	−0.070
nWhorls	Number of whorls within log	−0.067	–
wDist0–20	Proportion of log with distance between whorls in the interval 0–20	−0.087	–
wDist20–40	Proportion of log with distance between whorls in the interval 20–40	0.081	–
wSumLgt	Summed longitudinal extension of all whorls within log	−0.108	–
wLgt0–5	Proportion of whorls within log having longitudinal extension in the interval 0–5	−0.080	–
wLgt15–30	Proportion of whorls within log having longitudinal extension in the interval 15–30	−0.067	–
wVol25–50	Proportion of whorls within log having a volume in the interval 25–50	0.042	–
wVolButt	Average volume of whorls in the butt log section of the stem	−0.038	–
wLgtButt	Average longitudinal extension of whorls in the butt log section of the stem	−0.050	–

Coefficients are scaled and centred, making their respective contributions comparable.

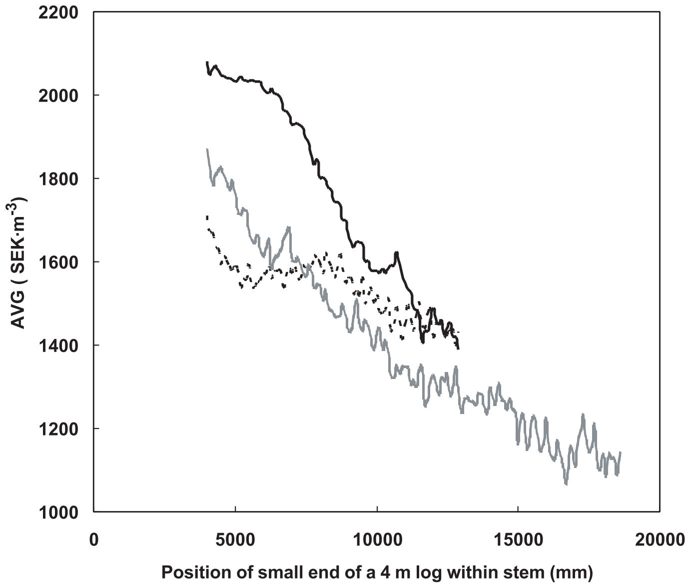

Fig. 4. Average board value (AVG) predicted with model M:3D on a 4 m log at different positions within the stem. Example with three stems.

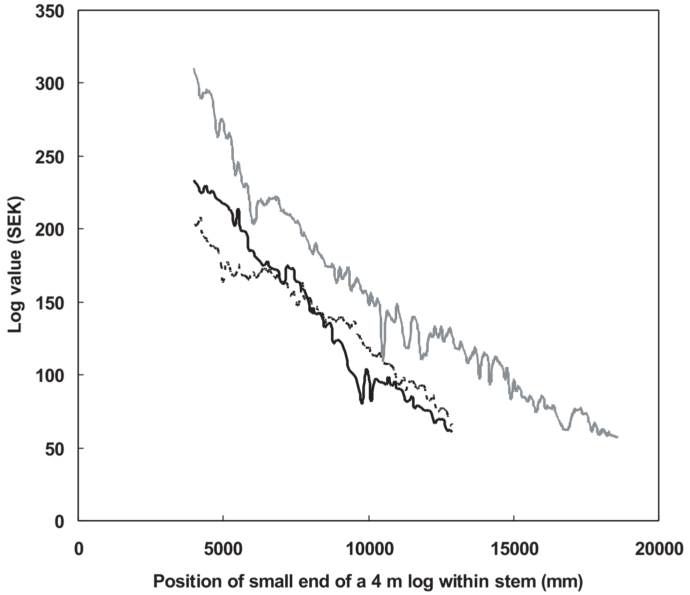

Fig. 5. Gross value of a 4 m log at different positions within the stem estimated by combining predictions of board values with model M:3D and volume yield predicted with the sawmill simulator software Saw2003 and adding the value of byproducts. Example with three stems.

ray-measured knot properties in the log and in the lower part of the stem. Model M:3D comprises 14 significant variables. The variables and the sign of the coefficients were the same as in model M:3D-X, with the exception of the X-ray LogScanner variables that were excluded and two variables added. An example of the application of model M:3D on three stems is provided in Fig. 4 and the example is extended to the prediction of log values in Fig. 5. In both examples a log 4 m long was assumed, but values can be predicted on logs with any length between 3.0 and 5.6 m.

DISCUSSION

The results obtained show the ability to predict board values from logs based on measurements on stems with a 3D optical log scanner and a 3D optical scanner in combination with an X-ray LogScanner. By combining one of the models with the results of log breakdown simulations log values can be predicted for any segment of a scanned stem and used in a DP algorithm finding the optimal bucking pattern. The application of such predictions in a bucking algorithm needs to be evaluated before their usefulness can be established. When assessing the results, one must bear in mind the stochastic nature inherent in log breakdown. With discrete limits on maximum knot diameter allowed in different grades, simply rotating the log by a few degrees in the first saw will change knot diameters on the boards, and thus the boards' grades might change. Furthermore, severe defects near the board's ends are likely to be trimmed off, avoiding downgrading, while a defect in the board's midsection is more likely to cause downgrading. Without precise knowledge of internal defect location in a log, it is not possible to predict reliably the grade, and from this the value, of the boards to be sawn from that particular log.

Earlier research on log-sorting using 3D scanner data (Jäppinen 2000) or X-ray LogScanner data (Oja et al. 2000), or both in combination (Oja et al. 2003), has shown its good ability to predict grade on centre boards. The average board values (AVG) predicted in this study are a fusion of the values of centre boards and side boards, and can be regarded as prediction of grades on the boards weighted by their price. It is possible that the influence of the previously discussed randomness in board grades is reduced as more boards contribute to the AVG.

The combined use of 3D and X-ray scanners gives a moderate improvement in prediction accuracy compared with using 3D alone. If grading were based on properties other than knots, e.g. heartwood, density or distance between whorls, the difference could be larger, as the X-ray LogScanner has proven useful for such predictions (Grundberg & Grönlund 1998). Another advantage of using the X-ray LogScanner in combination with 3D log scanning is that more collinear variables in the PLS model make it less sensitive to noise.

This study was based on a nationwide origin of the wood supply by using the SPSB. The relatively strong result from this study suggests that unevenness and density variations in logs and stems are general indicators of knot properties and that models developed will be robust to changes in a sawmill's raw material catchment area. Without further analysis it is not possible to foresee how locally adapted models will perform in relation to those presented here. However, when there is a change in the relative prices of the different grades the models need to be recalibrated. Once the variables and structure of the model used have been established, recalibration can be done quite easily.

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Paper V

Value recovery and production control in bucking, log sorting, and log breakdown

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Abstract

This study investigates how value recovery and production control are affected by the measurement techniques used in bucking and log sorting. The study was approached using simulation techniques. A database of 48 well-described young softwood stems (*Pinus sylvestris* L.) served as the wood supply, and a sawmill simulator able to read and process the stems was used to predict the outcome of the sawing process. In the simulations, five bucking alternatives and three log-sorting alternatives were evaluated. In addition, combinations of production control were employed in bucking, log sorting, and log breakdown with the target set to produce a given volume share of four specific products. In total, 28 simulations were carried out. The results indicate that the bucking method has greater influence on value recovery than the method of log sorting has. Results also indicate that the more process stations involved in production control, the better the demand targets are met (the degree of apportionment), but the lower the value and volume recovery become. Production control in bucking, log sorting, and log breakdown had almost equal effect on the degree of apportionment.

The process of converting trees to lumber with grades and dimensions specified by the customer's need is a chain of closely linked operations. At an early stage of the process, the bucking operation occurs. In Scandinavia, bucking is typically done at the harvesting site, while in North America the bucking is often done at the sawmill. At this stage, where the stem is cut into sawlogs, the dimensions of a particular log (i.e., length and small-end diameter) place upper limits on the length, width, and thickness of the lumber that can be sawn from it. While shorter and smaller lumber dimensions can be sawn from the same log, production economy will suffer as the volume yield drops. This means that undersized logs, as well as oversized logs, are undesirable, and it emphasizes the importance of high measurement accuracy (Chiorescu and Grönlund 2000).

With the cut-to-length system, logs delivered to the sawmill do not carry information on their individual dimensions as recorded by the harvester. It is therefore necessary to measure the logs in order to assign an appropriate breakdown pattern to each log and optionally sort them into diameter classes representing different sawing patterns so that a batch of logs can be processed with the same sawing pattern. The measuring device used in log sorting measures the shadow of the log in one, two, or three directions, or the true outer shape with laser triangulation. Log sorting can be done before debarking, admitting the difficulties with varying bark thickness and missing bark on parts of the log, or it can be done on debarked logs for higher accuracy. With the tree-length system, the bucking and log sorting can be performed in one operation or in two separate operations using any of the these measuring devices.

The number of possible bucking patterns increases quickly with the length of the stem and the number of feasible log lengths. The number of possible bucking patterns can easily exceed 10,000. The optimization problem is usually addressed with dynamic programming (DP) (Dreyfus and Law 1977) maximizing the value of the logs cut from the stem (Pnevmaticos and Mann 1972). The challenging part of the problem is not the DP algorithm, but rather the pricing of logs. One way of pricing the logs is the use of a log price list with individual prices for different log dimensions. The log price list then controls the bucking, and as a consequence it acts as the interface through which the sawmill communicates its need for the supply of specific log dimensions. Another way of pricing the logs is by using a log breakdown simulator for estimating the value yield of a log. The integration of log breakdown into the bucking problem has been addressed in earlier research (Faaland and Briggs 1984,

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Table 1. — Study set-up: combinations of bucking, log sorting, and production control.

Simulation	Bucking	Log sorting	Production control		
			Bucking	Log sorting	Breakdown
1	Manual	3D	No	No	No
2	Manual	3D	No	Yes	Yes
3	Manual	CT	No	No	No
4	Manual	CT	No	Yes	Yes
5	Manual	Diameter	No	No	No
6	Manual	Diameter	No	Yes	Yes
7	2D	3D	No	No	No
8	2D	3D	Yes	Yes	Yes
9	2D	CT	Yes	Yes	Yes
10	2D	CT	No	No	No
11	2D	Diameter	Yes	No	No
12	2D	Diameter	Yes	No	Yes
13	2D	Diameter	No	No	No
14	2D8	3D	Yes	Yes	Yes
15	2D8	3D	No	No	No
16	2D8	CT	Yes	Yes	Yes
17	2D8	CT	No	No	No
18	2D8	Diameter	Yes	No	No
19	2D8	Diameter	Yes	No	Yes
20	2D8	Diameter	No	No	No
21	3D	3D	No	No	No
22	3D	3D	Yes	Yes	Yes
23	3D	CT	No	No	No
24	3D	Diameter	No	No	No
25	CT	3D	No	No	No
26	CT	CT	No	No	No
27	CT	CT	Yes	Yes	Yes
28	CT	Diameter	No	No	No

Reinders and Hendriks 1989, Maness and Adams 1991), where simplified log geometry models free from defects were used. A full 3D profile of a log with high accuracy opens up the possibility of simulating the outcome of products from a sawing operation with high precision. In such a simulation, it is possible to rotate the log, apply curve sawing and, finally, edge and trim the boards with respect to wane criteria. Different sawing patterns and positioning in the saws can be evaluated, and the set-up yielding the highest value can be chosen for each log.

In addition to 3D profiling of stems, their inner properties can be revealed using a computed-tomography-based (CT) scanning system, allowing for even more realistic simulation of the product's grades in production control. Due to high cost and low throughput, CT-based log scanners have not yet been deployed in bucking or log sorting, but they might well be in the future.

Further downstream, sideboards are processed by an edger in which the width is set and all boards are eventually trimmed to their final length. Both edging and trimming are based on optimizations that, preferably, are value based. Prices then can be used to control the operation in bucking, log sorting, and breakdown. Optimizing each process independently of the others may lead to solutions that are not globally optimal to the chain of operations converting trees to lumber (Nordmark and Chiorescu 2001). However, in order to reach a globally optimal solution for a sawmill's production, thorough knowledge of the entire wood supply for the targeted planning period is required. One alternative is to pass information about the ongoing production to all process stations to ensure that they all optimize on the same premises. Though still not globally optimal, it's a workable solution in real production.

The bucking and sawing model described by Faaland and Briggs (1984) operates on a single stem at a time, while Maness and Adams (1991) focused on the log allocation problem where sawmill production was optimized on a weekly level. Maness and Adams (1991) also accounted for inelastic demand by controlling price/volume relationships. In this study, realistic log geometry and knot properties are considered to varying degrees in the bucking and sawing model, which accounts for inelastic demand by continuously controlling price/volume relationships.

The aim of this study was to investigate how value recovery and production control are affected by the measurement techniques used in bucking, log sorting, and log breakdown.

Material and methods

The study was approached using simulation techniques. A database of 48 well-described softwood stems served as the wood supply, and a sawmill simulator able to read and process the stems was used to predict the outcome of the sawing process. In the simulations, five bucking alternatives and three log sorting alternatives were evaluated. In addition, combinations of production control were employed in bucking, log sorting, and log breakdown with the target set to produce a given volume share of four specific products. In total, 28 simulations were carried out (**Table 1**). The results that were monitored were value and volume recovery and how well the targeted volume share of the four products was met. Results were further evaluated using partial least squares regression (PLS) (Geladi and Kowalski 1986).

Wood raw material

The wood raw material was a database consisting of 48 young Scots pine (*Pinus sylvestris* L.) stems with detailed descriptions in parametrical form collected from real trees. The diameter at breast height of the sampled stems ranged from 126 mm to 234 mm with an average of 161 mm and their heights ranged from 990 cm to 1603 cm with an average of 1328 cm. After felling, the trees were manually bucked and limbed. The sawlogs were transported to Luleå University of Technology where they were scanned in a CT scanner. Through image analysis of the obtained CT images, the outer shape and the internal knot structure of the logs were extracted.

Table 2. — Timber price list used.

Grade	Price by board type	
	Side boards	Center boards
	- - - - - - - (SEK/m^3)[a] - - - - - -	
A	3000	1850
B	1400	1600
C	1100	1000

[a]SEK = Swedish krona.

The format of the parametric descriptions is in concordance with the previously established Swedish Pine Stem Bank (Grundberg et al. 1995). During the whole process from the felling of the trees to the final database, great care was taken in order to allow for a correct reconstruction of the stems from the logs.

A validation of the parametric descriptions against real boards, sawn from three of the logs after CT scanning, showed that the number of knots and their positions were well described, as well as the log geometry, while the sizes of the knots had relatively large errors at positions close to the pith (Nordmark 2003). Although the descriptions deviate to some extent from the logs they were derived from, it was concluded that they could be used for simulating the yield of sawing.

Sawing simulator

The sawing simulator used (Nordmark 2002) is a Windows™-based program developed in C++ with a graphical interface partly based on Open GL, allowing the user to view and interact with logs and boards in three dimensions. The software is capable of reading logs from the database and optionally assembling logs into stems for bucking into other lengths.

The sawmill modeled uses cant sawing, where the first sawing machine cuts the log into a block and side boards, while the second sawing machine cuts the block into two to four center boards and two to four side boards. Side boards are edged and trimmed, while trimming is the only operation on center boards. Both edging and trimming are value-optimizing operations based on lumber prices and grade. Grading is based on wane criteria and knot properties. The simulator also exposes a great deal of its functionality to a scripting module. Through scripts, simulations can be automated, and reports of the sawing process and properties of logs and boards can be tailored. The sawmill simulation software's ability to correctly predict wane and knot properties on boards from the database was validated in an earlier study (Nordmark 2003). In this study, logs were automatically rotated horns down (crook up), centered in both saws, and curve sawn. A minimum trimming of 50 mm at each board end was applied. The boards were graded A, B, or C following the Nordic Timber Grading Rules (Anon. 1994) where A is the highest grade. The grading rules define allowed wane, and the rules also state limits on knot diameter and sum of knot diameters on edges and faces for sound and dead knots, respectively. The boards were priced according to **Table 2**. A price penalty related to board length was introduced to account for production costs related to length. The relative value was set to 100 percent for length class 5400 mm and reduced in steps of 2 percent for each length decrement of 300 mm down to a relative value of 76 percent for length class 1800 mm. Without such price deduction, it is likely that most logs will be cut to minimum length due to log taper and volume yield relationship. No other costs were considered. By-products were given the price 200 SEK/m^3.

Bucking

The bucking patterns of the stems were value optimized using dynamic programming, with the exception of one manual alternative where the crosscuts were arbitrarily chosen. The discretation was 100 mm, meaning that crosscut positions were evaluated every 100 mm along the stems. Five bucking alternatives were evaluated:

Manual. — This is how the original logs were cut in reality when they were sampled from the forests. Logs were cut with lengths between 3100 mm and 5500 mm with a 300-mm length module. No optimizing calculations were done.

2D. — This is a value-optimizing bucking where the value is given by a log price list with individual prices for different combinations of log small-end diameter and log length. Diameters of the stems were derived from the stems' cross-section areas with the interval 10 mm lengthwise. The diameter profile of each stem was then filtered so that no increases in diameter were allowed in the direction from the butt end towards the top. The stem feature array passed to the bucking algorithm was the diameter profile along the length of the stem without any information on out of roundness or crooks, hence 2D.

2D8. — This alternative follows the method of 2D, but with an error added to the diameter profile in order to simulate the accuracy of a harvester-based bucking system (Möller and Sondell 2000). Each stem was given a random error on the diameter with a normal distribution of $N(0, \sigma^2)$ with the standard deviation set to 8 mm.

3D. — The full 3-D profile of the stems was used. Prospective logs as segments of the stem were passed to the sawmill simulator, which simulated the breakdown and outcome of products. The returned estimated value was used to price the logs; i.e., no log price list was used. As no knot parameters were passed, the optimization approaches maximization of volume recovery.

CT. — Like 3D, but in addition to the full 3-D-profile, the interior knot structure of the stem is known. Thus, the bucking is truly value optimized.

The log price list used in the 2D and 2D8 bucking cases (**Table 3**) was compiled from the results of an optimized bucking and log sorting, i.e., the CT bucking/CT log sorting case.

Log sorting

In this study, the meaning of log sorting is restricted to determination of the appropriate breakdown pattern for individual logs. Three alternatives in log sorting were evaluated:

Diameter. — Based on the log's small-end diameter, the breakdown pattern is given by a look-up table (**Table 4**).

3D. — The full 3-D profile of the logs was used for simulated sawing. Two or three sawing patterns were evaluated for each log: the normal pattern given by the look-up table and the patterns with diameter intervals above and below. For the smallest logs, only the pattern with a diameter interval above was added. The pattern giving the highest value in the simulated sawing was chosen. No knot parameters were passed to the simulated breakdown, so the optimization approaches maximization of volume recovery.

CT. — As 3D, but in addition to the full 3-D profile, the interior knot structure of the logs is known. Thus the log sorting is truly value optimized.

Table 3. — Log price list used in 2D bucking.

	Log small-end diameter									
Length	100 mm	130 mm	150 mm	170 mm	185 mm	195 mm	210 mm	220 mm	230 mm	250 mm
(mm)	(SEK/volume by top measurement)									
2200	630	699	736	768	791	804	824	836	847	869
2500	682	756	796	831	856	870	891	904	917	940
2800	734	813	856	894	920	936	959	973	986	1011
3100	775	859	905	945	972	989	1013	1028	1042	1068
3400	827	916	965	1008	1037	1055	1080	1096	1112	1140
3700	858	951	1001	1045	1076	1094	1121	1137	1153	1182
4000	889	985	1038	1083	1115	1134	1161	1179	1195	1225
4300	930	1031	1086	1134	1167	1187	1215	1233	1251	1282
4600	951	1054	1110	1159	1193	1213	1242	1261	1278	1311
4900	982	1088	1146	1197	1232	1253	1283	1302	1320	1353
5200	1013	1123	1182	1234	1271	1292	1323	1343	1362	1396
5500	1034	1146	1207	1260	1297	1319	1351	1371	1390	1425

Table 4. — Sawing patterns and related log small-end diameter intervals.

Log small-end diameter interval		Sawing pattern	
Minimum	Maximum	First saw	Second saw
(mm)			
100	129	19,75,19	19,38,38,19
130	149	19,100,19	19,38,38,19
150	169	19,100,19	19,50,50,19
170	184	19,125,19	25,50,50,25
185	194	19,125,19	19,63,63,19
195	209	19,19,150,19,19	19,25,50,50,25,19
210	219	19,19,150,19,19	19,25,63,63,25,19
220	229	19,19,175,19,19	19,25,50,50,25,19

Production control

Production control was implemented by an algorithm continuously adjusting the prices of the controlled boards and, in the case of 2D bucking, the price of corresponding log dimensions (Eq. [**1**]). When the desired share of a particular product is lower than the target share, and the share is decreasing, the product price is raised. If the target share is higher than desired, and the share is increasing, the price is lowered. Whenever the share is moving towards the target, the price remains.

Equation [**1**]: Production control algorithm:

$$\begin{aligned} ds_n &= Sp_{n,i} - Sp_{n,i-1} \\ dt_n &= So_n - Sp_{n,i} \\ \Delta c_n &= u \cdot \lambda \cdot Dm \cdot \left(\frac{dt_n}{So_n}\right) \\ \lambda Dm &\geq \Delta c \geq -\lambda Dm \\ C_{n,i+1} &= C_{n,i} + \Delta c_n \\ 1 + Dm &\geq C \geq 1 - Dm \\ Pc_n &= P \cdot C_n \end{aligned} \qquad [\mathbf{1}]$$

where:

ds = change of share (‰)
i = stem being processed
n = product under control
dt = deviation from target (‰)
Sp = share produced (‰)
So = share ordered (‰)
Δc = change of coefficient
Dm = allowed deviation of price coefficient (%)
λ = step control parameter
$u = \begin{cases} 1, & \text{if}(ds \cdot dt) \leq 0 \\ 0, & \text{otherwise} \end{cases}$
C = price coefficient
Pc = control price
P = selling price

In this study, maximum price deviation (Dm) was set to 50 percent, and the step control parameter (λ) was set to 0.1. Price coefficients (C) were initialized to 100 percent and volume share produced was initialized to 0. Recovered volumes and coefficients were updated after each processed stem. The list of controlled products is given in **Table 5**. Log dimensions corresponding to the controlled center boards are shown in **Table 6**. The dynamic prices of boards and logs (Pc) were only used for controlling the production. In the summation of values presented, all boards were priced according to **Table 2**.

A measure of how well the target shares of the controlled products were met is given by Equation [**2**]. The measure is further referred to as the apportionment degree. The interpretation is that the better the orders are met the closer to 1000‰ will the apportionment degree be. Any deviation from the target will give a lower value.

Equation [**2**]: Definition of apportionment degree:

$$\text{Apportionment degree} = 1 - \sum_{n=1}^{N} \left| So_n - Sp_n \right| \qquad [\mathbf{2}]$$

where:

N = number of controlled products

In order to allow for the production control parameters to stabilize, the set of 48 stems was run in two consecutive runs without resetting the parameters in between in all simulations.

Partial least squares

Partial Least Squares (PLS) regression was chosen because it is based on the assumptions that the x-variables are correlated, that there is noise in the data, and that there can be structures in the residuals (Lindgren 1994). Because of this, PLS regression was well suited to this

Table 5. — *Order specification used in the production control studies.*

Thickness	Width	Length	Grades	Desired share of board volume
- - - - - - - - - - - - - (mm)	- - - - - - - - - - - - -			(‰)
19	75	2400	B, C	20
38	75	3000	A	20
38	100	3900	A, B	20
50	100	3300	B	20

Table 6. — *Log tally specification used in the production control studies.*

	Log specification		
Board dimension	Small-end diameter	Length	Desired share of log volume
- - - - - - - - - - - - - - - - - - - -	(mm) -		(‰)
19 by 75 by 2400	--	--	--
38 by 75 by 3000	100 to 129	3100	20
38 by 100 by 3900	130 to 149	4000	20
50 by 100 by 3300	150 to 169	3400	20

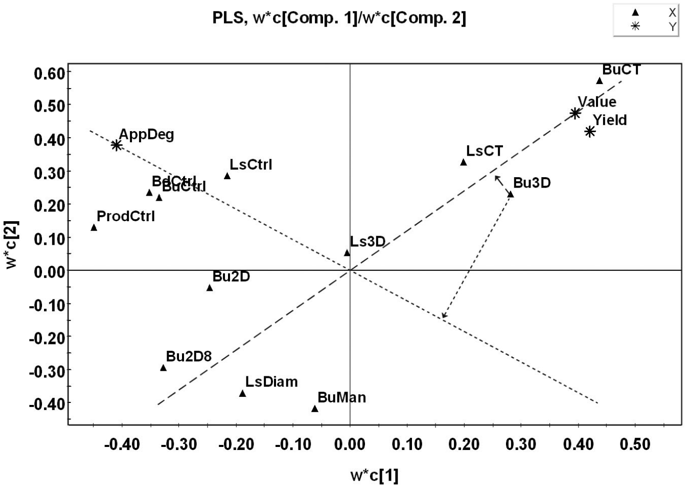

Figure 1. — PLS scatter plot. Y-variables are the modeled responses. AppDeg = apportionment degree; Value = gross value of the products; Yield = volume yield. X-variables are binary, indicating the presence of a treatment in the simulations. ProdCtrl = production control; BuCtrl = production control in bucking; LsCtrl = production control in log sorting; BdCtrl = production control in log breakdown; Bu2D8 = bucking based on diameters with errors and a log price list; Bu2D = bucking based on diameters and a log price list; Bu3D = bucking based on the stems' full 3-D profile; BuCT = bucking based on the stems' full 3-D profile and interior knot structure; LsDiam = log sorting based on the logs' small-end diameters; Ls3D = log sorting based on the logs' full 3-D profile; LsCT = log sorting based on the logs' full 3-D profile and interior knot structure. Variables close to each other are positively correlated. Projecting the x-variables to the line drawn from a y-variable through origin gives the prediction coefficients of the scaled and centered x-variables (e.g., Bu3D) for that y (e.g., Value, AppDeg), i.e., the relative importance of the predictors. In the example, B3D is positively correlated to value but negatively correlated to the apportionment degree.

investigation, and the PLS analysis was carried out using the software SIMCA-10.0 (Anon. 2002). Coefficient of determination (r^2) and a Q^2 value based on cross validation (Martens and Naes 1989a) were calculated. Q^2 represents the proportion of variance of *y*-values in the test set that is explained by the model. Hence Q^2 is a measure of the model's ability to predict future observations, i.e., observations that were not included when building the model. A model that explains random variations in the training set will fail when tested on new observations; hence Q^2 will be low for such a model (Martens and Naes 1989b). In the analysis, dummy variables were used to indicate the treatments engaged in each simulation. A dummy variable was given the value 1 if the treatment was used in a simulation and given the value 0 if it was not.

Results

Value recovery and volume recovery resulting from the simulations without any production control are shown in **Table 7** and **Table 8**, respectively. *Manual, 2D*, and *2D8* bucking had low value recovery compared to *3D* bucking. The highest values were achieved with *CT* bucking. Value recovery is also influenced by the method of log sorting used. The results rank *Diameter* log sorting as giving the lowest values and *CT* log sorting as giving the highest values. Furthermore, the bucking method is shown to have greater influence on value recovery than does log sorting. Volume recoveries follow the same pattern in general, but with a few exceptions. The relative differences between treatments are smaller, and *Manual* bucking gave higher volume recovery than *2D8*, although value recovery was lower.

Results of the simulations with production control employed are shown in **Table 9**. The apportionment degree was on average 981±11‰ with production control compared to 949±18‰ in the simulations without production control. The highest degrees of apportionment were achieved with *2D* and *2D8* bucking. The degree of apportionment varied less with the type of log sorting applied. Value recovery and volume recovery rank the combinations of bucking and log sorting in the same order with production control employed as with no production control.

The PLS model was calibrated with two principal components and with r^2 =

Table 7. — Value recovery, no production control.

	Bucking					
Log sorting	Manual	2D8	2D	3D	CT	All
	(SEK)					
Diameter	7931	7963	7986	8398	8771	8210
3D	8081	8116	8184	8496	8782	8332
CT	8167	8234	8299	8556	9088	8469
All	8060	8104	8157	8484	8880	8337

Table 8. — Volume recovery, no production control.

	Bucking					
Log sorting	Manual	2D8	2D	3D	CT	All
	(%)					
Diameter	41.9	41.4	42.2	43.4	44.0	42.6
3D	42.2	42.0	42.4	44.0	43.5	42.8
CT	42.2	42.2	42.6	43.4	45.3	43.1
All	42.1	41.8	42.4	43.6	44.2	42.8

Table 9. — Simulation results with production control employed.

			Production control					
Simulation	Bucking	Log sorting	Bucking	Log sorting	Breakdown	Vol. yield	Value	App. degree
						(%)	(SEK)	(‰)
2	Manual	3D	No	Yes	Yes	41.8	7986	985
4	Manual	CT	No	Yes	Yes	42.0	8193	973
6	2D	Diameter	No	Yes	Yes	41.4	7836	965
8	2D	3D	Yes	Yes	Yes	41.8	8084	988
9	2D	CT	Yes	Yes	Yes	42.2	8235	990
11	2D	Diameter	Yes	No	No	42.0	7946	975
12	2D	Diameter	Yes	No	Yes	41.7	7901	996
14	2D8	3D	Yes	Yes	Yes	41.3	8030	990
16	2D8	CT	Yes	Yes	Yes	41.6	8195	997
18	2D8	Diameter	Yes	No	No	40.8	7828	964
19	2D8	Diameter	Yes	No	Yes	41.3	7879	983
22	3D	3D	Yes	Yes	Yes	44.0	8487	969
27	CT	CT	Yes	Yes	Yes	44.9	9039	977

0.76 and $Q^2 = 0.59$. A plot of the weights used to combine *x*-variables and *y*-variables (w*c) in the two components is shown in **Figure 1**. Value and volume recovery are strongly correlated to each other, and the type of bucking applied has a large influence, while the type of log sorting has a somewhat smaller influence on value and volume recovery. Whenever production control is employed, indicated by the variable ProdCtrl, volume and value are decreased. The more process stations involved in production control (variables BuCtrl, LsCtrl, and BdCtrl), the lower the value and volume recovery, but the apportionment degree increases. The type of log sorting has low influence, while the type of bucking has a moderate influence on the apportionment degree.

Discussion

First, it must be emphasized that this study was based on a wood supply of a limited origin both geographically and biologically, and the results are discussed within this context. Furthermore, if production costs had been included, other results might have been achieved. However, the results may serve as indicators of relationships in a broader sense.

Simulating the process of converting trees to lumber made it possible to compare alternative ways of bucking and log sorting while eliminating differences in the raw material input between runs. Simulating reality is a cost-efficient way of screening for relationships, but the relationships found should be verified in reality before they are considered true. However, no indications within the results arrived at in this study lead towards the conclusion that the relationships found are inconsistent with real-world practice.

The bucking method had the greatest influence on value and volume recovery. In order to extract maximum value from the wood raw material, bucking of stems and sorting of logs into sawing patterns must be based on knowledge of the stem's outer shape and a precise description of its knots. CT scanning of stems is a future possibility to provide such information. It was included in this study to provide a benchmark of the value potential of the wood raw material. At the other end of the spectrum is *Manual* bucking, which is rare in practice due to the mechanization of forest operations. *2D8* bucking with a log price list resembles a harvester operating in the cut-to-length system where diameters under bark are predicted from measurements over bark. This is the dominant practice in Scandinavia. *2D* bucking, i.e., correct measurement of diameters under bark, was included to make it possible to compare the method of *2D* bucking with other methods without the effect of measurement accuracy. *3D* bucking without errors was superior to *2D* bucking without errors in this study.

The log price list was compiled from the results of an optimal processing in bucking and log sorting. In practice, the construction of log price lists is more complicated and it is likely that the log price list used in this study was more correct than one would expect a log price list used in reality to be. The desired shares of the controlled products were directly translated to shares of log dimensions for production control in *2D*/*2D8* bucking. However, the volume yield of boards varies with log dimension, and in order to make a correct apportionment of logs to fit the targeted products, this log/yield relationship should preferably be accounted for.

The method of log sorting also influences value and volume recovery in the way that the more information about the logs that is processed, the better the performance. The spread in value recovery was lower in terms of the method of log sorting used than it was in terms of the bucking method. This reflects the situation that dimensions and knot properties of a log to a large extent also determine the dimensions and grades of the boards sawn from it. Thus, the alternatives for processing the logs originating from a stem are fewer compared to the alternatives available when the stem is being bucked.

The purpose of including production control was not to evaluate the algorithm, but rather to investigate how different treatments in bucking, log sorting, and log breakdown affect the degree of apportionment. There may be better, more efficient algorithms applicable, and the applied algorithm could have been better tuned. The obtained PLS model showed that in order to achieve a high apportionment degree it is almost equally important to employ production control in the process stages of bucking, log sorting, and log breakdown. Furthermore, the model shows that all process stages should be employed. At the start of production, where the volume produced is low, the volume share of a controlled product takes a large leap whenever such a product is produced. As a consequence, the volume share and the control price coefficient will oscillate around the target until a large total volume has been produced. The limited number of stems processed when evaluating production control in the simulations may have been insufficient for avoiding that type of randomness in the apportionment degree. *2D* and *2D8* bucking had a positive effect on the apportionment degree compared to *3D* and *CT* bucking. One reason may be the randomness just mentioned. Another likely reason is that the value of a log given by a breakdown simulation is the sum of the value of the products extracted from it. A board with specified dimensions and grade is only part of the summed value. From this it follows that the value of logs will be less sensitive to changes of the controlled products price coefficients when predicted from a breakdown simulation, compared to the case where the log's price coefficient is changed directly, as in the case of *2D* bucking with a log price list.

Using 3D optical scanners in combination with a log breakdown simulator in bucking and log sorting makes it possible to extract high value from the wood raw material. With the concept, log price lists become obsolete, easing communication between different processing stages. Until industrial CT scanning is available, there are other possibilities for implementing the inclusion of lumber quality in bucking and sorting decisions. The detailed model of the log mantel obtained from 3D scanning can be used for predicting the quality of the sawn goods (Lundgren 2000). The two-way x-ray log scanner is also applicable for predicting board quality with high accuracy alone (Grundberg and Grönlund 1997) or in combination with an optical 3-D scanner (Oja et al. 2003). Further studies should focus on including quality predictions in bucking and log sorting decisions and on validating the results presented here on a larger and more heterogeneous raw material.

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Paper VI

Satisfying Consumer Demand –

a Comprehensive View of Sawmill Economy using Simulation Techniques

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ABSTRACT

There is an ongoing shift in production strategy in the sawmill industry in Scandinavia from bulk production of standard grades towards customer-oriented production of well-defined products. Satisfying a consumer's need for special grades will have implications for the outcome of other products and perhaps for productivity as well. This makes it difficult to foresee the profitability of a business offer where a change in production is involved. We have estimated the outcome of products, productivity, value and economy in a scenario where a consumer asks for large volumes of the dimensions 50x100 mm, 50x125 mm and 50x150 mm, and with lengths of either 240 cm or 480 cm. In the scenario the sawmill buys a standing volume of Scots pine (Pinus sylvestris L.). This is represented by the logs in the Swedish Pine Stem Bank. Four different strategies of bucking operations were simulated, a reference strategy with varying lengths as found in real-world practice, two with fixed lengths (255 cm and 495 cm resp.) and one with mixed fixed lengths (495+255 cm).

The product flow of a sawmill with an annual production capacity of 100,000 m3 was modeled and productivity, expressed as pieces per hour, was calculated for the average log lengths derived from the bucking operations. Using a virtual sawmill, the outcome of products in terms of volume and value were estimated. Putting it all together, the contribution per hour was calculated. From a timber input of 110 m3, the volume of the desired products ranged from 3.0 m3 in the reference alternative up to 15.8 m3 in the mixed length alternative. The gross value of the produce was highest for the 255 cm alternative, but the same alternative had the lowest production rate. All in all, the highest profitability was achieved with the reference alternative, even with a 10% bonus on the price for the desired products. Although this was a limited study, we conclude that a holistic approach, as taken here, will be necessary for good decision making within the supply chain. Optimizing forest operations, value recovery and production as separate entities will not produce optimal results.

INTRODUCTION

There is an ongoing shift in production strategy in the sawmill industry in Scandinavia from bulk production of standard grades towards customer-oriented production of well-defined products. Satisfying a consumer's need for special grades will have implications for the outcome of other products and perhaps on productivity as well. This makes it difficult to foresee the profitability of a business offer where a change in production is involved. The common strategy in Sweden of bucking trees into lengths gives a widely spread distribution of lengths, usually ranging from 31 dm to 55 dm and width an average length of 46 dm. In a scenario, a consumer asks for large volumes of the dimensions 50x100 mm, 50x125 mm and 50x150 mm, and with lengths of either 240 cm or 480 cm. Our hypothesis is that by length adapting the bucking to the consumer's demand, the volume of the desired products can be increased as well as the total economy of the operations given a bonus on the price of the desired products. The objective of this study was to estimate the outcome of products, productivity, value and economy for different bucking strategies using simulation techniques.

MATERIALS AND METHODS

The Swedish Pine Stem Bank (SPSB)

The Swedish Stem Bank (6) is a large database containing detailed information on 200 Scots pine (*Pinus sylvestris* L.) trees. The project is based on computed tomography (CT) scanning of these 200 stems, which were carefully chosen from 33 well-documented sample plots all over Sweden. From each sample plot six trees were taken: two small, two medium-sized and two large trees. After harvesting the selected trees, the logs obtained were CT-scanned in a fourth generation medical tomograph (Siemens SOMATOM AR.T.). The images achieved through CT scanning of logs were analyzed automatically using image analysis algorithms (4). These images describing the logs consist, however, of a large amount of information. In order to reduce the amount of data, a method for parameterization of the log has been developed (3). The parameter files issued describe the outer shape of the log and the heartwood border using polar coordinates having the pith as origin. One radius at every degree every 10 mm along the log describes the outer shape, whilst a mean radius for twelve degree sectors every 10 mm along the log describes the heartwood border. The location of the pith is given every 10 mm along the log using an X-Y reference system. The description of every knot (location, size and type) is made by using 11 parameters acquired from CT images by semiautomatic image-processing algorithms.

The virtual SawMill (vSM)

The virtual SawMill is sawing simulation software that is able to utilize the digitized logs acquired from CT scanning and stored in the SPSB. The program is capable of reconstructing a 3-D representation of the outer shape and the internal structure of the log and of generating boards through a sawing procedure that is easily controlled by the operator. When generating boards, vSM can identify internal and external defects such as knots and wane. The grading procedure is based on explicit grading rules (1) and the value for each generated board is determined. Once the sawing procedure is completed, a detailed sawing report is available. A previous study has successfully dealt with the validation of the vSM at the single log level (5) and even a large-scale validation approach of the vSM along with the Swedish Pine Stem Bank has been carried out versus a real sawmill yield (2).

The virtual SawMill reads the logs from a Stem Bank CD/ROM and automatically creates an internal database from which different log selections can be made. The user interface allows not only the 3-D visualization of the log, but also allows the visualization of diverse sorts of sawing parameters. A main feature of the code is its "open architecture": the vSM is endowed with a particular programming aid (WoodScript) which allows users to adjust the program according to their specific needs. If, for instance, only the outer shape of the log is in focus, the knot structure can be easily removed and different hypotheses can be tested in a nondestructive environment through sawing simulation. Wane criteria adjustment or automatic batch sawing mode are some other facilities that vSM offers.

Extend

Extend is software designed for simulating material flow in a process. Buffers and interruptions can be modeled, as well as diverging and merging of flows along with processing times of different operations. A medium-sized sawmill with a production of 100,000 m^3 was previously modeled (7). The model incorporates operations from sawing to trimming and has been validated versus a real sawmill.

Simulation approach

The original stems were reconstructed from the parametric descriptions of the logs in the Swedish Pine Stem Bank. The stems were then bucked according to three different strategies in addition to the original one, and new versions of the stem bank were formed. The targeted lengths of the timbers were 240 cm and 480 cm. With a trimming allowance of 10 cm and an extra 5 cm due to the harvester's measurement inaccuracy, the targeted log lengths were 255 cm and 495 cm. The bucking strategies chosen are shown in Table 1.

Table 1. *Bucking strategies evaluated.*

Strategy	Explanation
Reference	Normal bucking (SPSB)
255 cm	Fixed lengths of 255 cm from the butt end upwards and with a residual top log shorter than 255 cm
495 cm	Fixed lengths of 495 cm from the butt end upwards and with a residual top log shorter than 495 cm
495+255 cm	Fixed lengths of 495 cm from the butt end upwards as far as possible, then a 255 cm log and a residual top log shorter than 255 cm

The properties of the four cases are shown in Table 2. The total volume in the SPSB was 110.04 m^3. The volume used was lower in the alternatives with fixed lengths. This is because some of the residual top logs fall below the minimum length of 185 cm.

Table 2. *Properties of wood raw material for the bucking strategies.*

Strategy	Used volume (m^3)	Average diam (mm)	Average length (cm)	Number of logs
Ref.	110.0	196.1	445.94	627
255 cm	107.0	209.2	253.21	1046
495 cm	109.0	194.5	455.23	605
495+255 cm	106.9	196.3	422.16	626

The sawing operation was simulated with the vSM. The same sawing pattern and same price list were used in all cases, and the boards were graded according to the Nordic Timber Grading Rules. Byproducts, including residual top logs shorter than 185 cm, saw dust and chips, were priced at 186 SEK/m^3. It was assumed that it is possible to get a higher price for the desired products if large quantities can be offered. Hence, the desired products were given a 10% price bonus.

The Extend model of a sawmill was used to assess the productivity of the different strategies by simulation. Simulations were made with the different average log lengths keeping all other parameters constant.

The contribution per hour was calculated for each of the alternative bucking strategies. A raw material cost of 650 SEK/m^3 was assumed. The calculations were based on a 10% bonus on the desired products.

RESULTS

The volume of the desired products was substantially increased with the fixed length alternatives (Fig. 1). The volume increased from 3.0 m^3 in the reference alternative to 15.8 m^3 in 495+255 alternative.

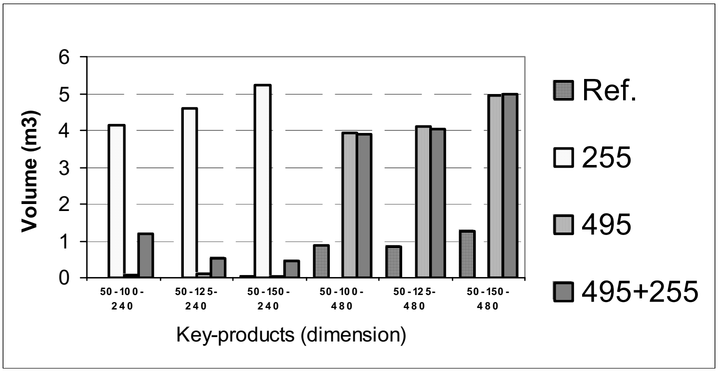

***Fig. 1**. Volumes of the desired products.*

The quality outcome was best with the 255 cm alternative, while the other alternatives all had similar distributions (Fig. 2).

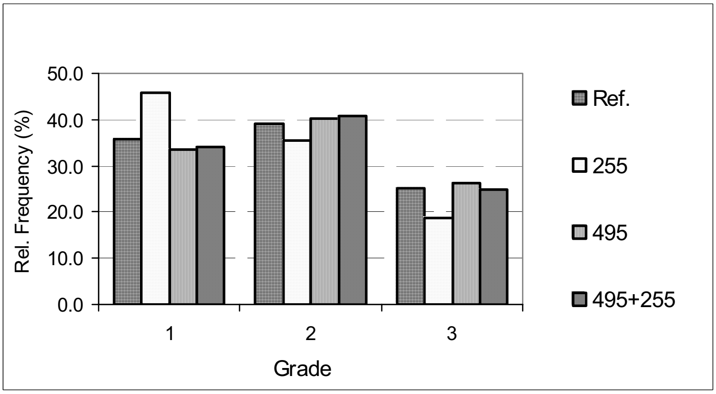

***Fig. 2.** Distribution of board grades, (1 = high grade, 3 = low grade).*

The value of the products, including byproducts, was highest in the 255 cm alternative, with the reference alternative almost as high (Table 3). The 495+255 cm alternative had the lowest value . With the value expressed per volume of raw material input, the difference between the 255 cm alternative and the reference was 1 SEK/m^3. With a 10% bonus on the desired products, the difference increased with 15 SEK/m^3.

Table 3. *Values of boards and byproducts.*

Alternative	Value boards (SEK)	Value by-prod. (SEK)	Total value (SEK)	Total value (SEK · m^{-3})
Ref.	102 351	10 112	112 463	1022.00
255 cm	102 525	10 054	112 580	1023.07
495 cm	98 408	10 224	108 632	987.19
495+255 cm	96 692	10 443	107 135	973.59
Ref.+ 10% bonus	102 767	10 112	112 879	1025.80
255 cm + 10% bonus	104 589	10 054	114 643	1041.83
495 cm + 10% bonus	100 232	10 224	110 455	1003.77
495+255 cm + 10% bonus	98 765	10 443	109 208	992.44

The productivity analysis gave the highest piecewise flow with the 255 cm alternative and the lowest flow with the 495 cm alternative (Table 4). Recalculated to flow of volume of raw material, the highest flow was with the 495+255 cm alternative. The bottleneck was the trimmer in the 255 cm alternative, while it was the saw in the other alternatives.

Table 4. *Flow of boards and raw material.*

Alternative	Flow, (pieces ·h^{-1})	Flow (m^3 ·h^{-1})
Ref.	2 436	57.1
255 cm	3 426	46.1
495 cm	2 274	55.9
495+255 cm	2 598	61.7

The contribution per hour from each alternative is shown in Fig. 3. The reference alternative gave the highest contribution, while the 255 cm alternative gave the lowest.

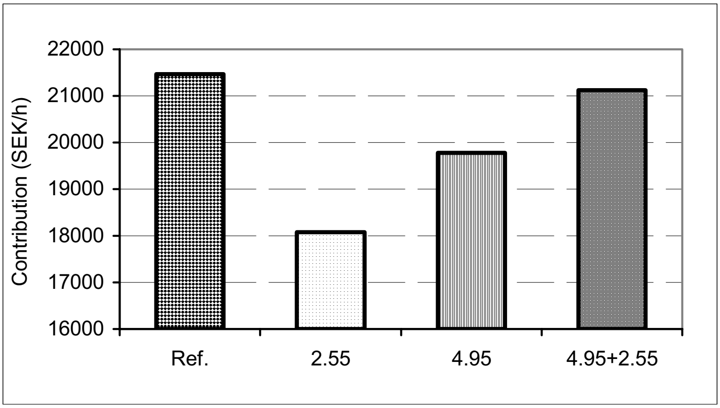

Fig. 3. *Contribution per hour.*

DISCUSSION

A quite important part of this study involved the simulation technique. Simulating reality is a very efficient, economical and interesting approach when complex situations are to be studied. In this study, different proposed strategies for satisfying a consumer's need for certain products could be evaluated in a cost-efficient way. Doing such things as trials at a sawmill would be very time-consuming and would require great effort to get comparable results between the different set-ups.

In the fixed-length bucking strategies, all logs were cut to the same length without regard to diameter at the top end. Since the desired dimensions usually are sawn from an interval of diameters, approx. 155 mm – 225 mm, there is no point in cutting logs with other diameters at fixed lengths. A better bucking strategy would have been to optimize the bucking by maximizing the value given by a log price list where the sought-after combinations of length and diameter were given a higher price than other combinations. It is likely that the volume of the desired products would increase, as well as the proportion of the raw material utilized, which would result in a higher contribution from the length-adapted alternatives.

The results of the simulated sawing gave the highest value from the 255 cm alternative. This alternative would have been chosen if the objective was to maximize the value obtained from a given wood supply. More high-quality boards, along with a high yield of products with a bonus on the price, out balanced the low utilization of raw material. A likely cause of the high quality is that the probability of a board containing sections with low quality increases with increased length. Since the grade of a board is determined by its worst section, longer boards will be more likely to receive a lower grade. The same alternative (255 cm) had the highest productivity on a piece-per-hour basis. This is a poor criterion for selection of strategy. A better measure of productivity is volume per hour. Based on volume per hour, one would have chosen the 495+255 cm alternative. However, only when the value is combined with the production rate, forming a measure of contribution per hour, does one have the appropriate criteria for evaluating different strategies and picking the most profitable one.

CONCLUSION

Although this was a limited study, we conclude that a holistic approach, as taken here, will be necessary for good decision making within the supply chain. By using simulation techniques it is possible to foresee the outcome of different operations along the production line and thus avoid expensive surprises. Optimizing forest operations, value recovery and production as separate entities will not produce optimal results.

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Paper VII

Targeting the Length of Lumber - a Case Study of a Small Dimension Softwood Sawmill

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ABSTRACT

This work is a study of a softwood sawmill in Sweden where the length of the lumber is of current interest. This paper discusses the length dimension with respect to bucking, log sorting and log breakdown typical of Scandinavian practice—cut-to-length harvesting system, presorting of logs and batch conversion using cant sawing. Twenty-four thousand five hundred and five (24,505) virtual Scots pine (*Pinus sylvestris*) sawlogs were used as input to a sawmill simulator. The simulator was set up to model the studied sawmill with respect to machinery, product prices, processing costs and positioning error of the logs within the first saw. The results were post-processed to account for measurement error in the log sorting station. A Linear Programming (LP) model was used to maximize the economic contribution from the sawmill's actual log supply with constraints on the products produced. Finally, bucking simulations were used to find a set of log prices that will produce the desired log length distribution when used to control the harvesters' bucking operation. By using realistic log geometries and by accounting for imperfections in the process, we were able to model the mismatch between log length and board length for smaller dimension lumber. Optimizations carried out indicate that the contribution can be increased by 2.4% with current log distribution. In order to meet demand, the log length distribution has to be altered, but this will also allow for an increase in contribution by 6.1%.

INTRODUCTION

The process of converting trees to lumber with grades and dimensions defined by the customers' needs is a chain of closely linked operations. One aspect of customers' needs that is receiving increased interest is the length of the lumber. That is, customers also want specific lengths aside from thickness, width and quality of the boards. Historically and to some extent yet ongoing, a wide distribution of lengths has been produced, and the lumber has been sold with varying lengths in a package. This paper discusses the length dimension of the lumber with respect to bucking, log sorting and log breakdown according to Scandinavian practice with the cut-to-length harvesting system, presorting of logs and batch conversion using cant sawing.

At an early stage of the process, the bucking operation occurs. In Scandinavia, bucking is typically done at the harvesting site. The dimensions of a particular log (i.e., length and small-end diameter) place upper limits on the length, width and thickness of the lumber that can be sawn from it. While shorter and smaller lumber dimensions can be sawn from the same log, production economy will suffer as the volume yield drops.

The second step in the conversion chain determining the dimensions of the lumber is the assignment of breakdown patterns to the logs, either in a log sorting station for batch processing or in line with the breakdown machinery. In Sweden, almost 95% of the sawmills practice presorting of logs. At the log sorting station, logs are sorted into bins representing different sawing patterns for batch processing. In its simplest form of sorting, the small-end diameter of the log is matched with a look-up table. In the look-up table, each bin has an interval of log diameters that are accepted. Defining these intervals has a large impact on the profitability of a sawmill. As an aid in deciding the sorting limits, software that simulates the conversion of logs to lumber can be used. Using cant sawing, each log yields 2–4 center boards. After drying, the boards are trimmed to their final length, and the operation ensures that each piece has an acceptable quality with respect to checks, wane, knots and other features.

In order to efficiently produce boards with desired thickness, width and length in desired quantities we need the ability to predict the outcome of boards from different log dimensions and link this via the bucking operation to the available forest resources in an optimizing model. The target of such an optimization would then be to minimize raw material consumption while fulfilling production needs, or preferably the target would be to maximize profit. Linear Programming (LP) (Hillier & Lieberman 1995) is a widely used tool for allocating limited resources among competing activities in the best possible way. Sampson and Fasick (1970) used LP to allocate logs to competing conversion stations within a single mill facility. Maness & Adams (1991) combined LP so as to optimize sawing patterns with dynamic programming (DP) (Dreyfus & Law 1977), optimizing the bucking patterns and thus allowing for an integrated approach to optimizing the forest–wood chain. While LP and DP optimizing technologies are interesting in themselves, the usefulness of the derived results relies heavily on how well the underlying activities and processes have been modelled. In earlier research where the log breakdown was integrated into the bucking problem (Faaland and Briggs 1984; Reinders and Hendriks 1989; Maness and Adams 1991), simplified log geometry models free from defects were used. The bucking and sawing model described by Faaland and Briggs (1984) operates on a single stem at a time, while Maness and Adams (1991) focused on the log allocation problem where sawmill production was optimized on a weekly basis. Maness and Adams (1991) also accounted for inelastic demand by controlling price/volume relationships. Nordmark (2005) used realistic stem geometries in a combined log bucking and log breakdown model that continuously controlled production by adjusting control prices of the products. In order to correctly model the log breakdown process it is important to consider measurement errors as well as errors in machinery (van Wyk, 2001) or otherwise the yield will be overestimated.

This work is a case study of a large sawmill in northern Sweden where the length of the lumber is of immediate interest. In order to meet market demands for particular lengths of lumber, the sawmill and the company supplying the logs have agreed upon a desired length distribution of the logs and have succeeded fairly well in producing such logs. The desired log lengths have a length offset of 150 mm to accommodate a total trimming allowance of 100 mm and the harvesters' length measurement error. However, the length distribution of the lumber produced deviates from the length distribution of the logs; e.g., a log class with lengths in the interval 4300 mm to 4600 mm sawn to the dimensions 38 x 100 yields a surprisingly low share of board volume with the desired length 4200 mm. The first question that arises is why this happens. Secondly, how can it be dealt with? The aim of this study was to develop a model that explains the mechanisms behind this behavior and to use the model to optimize the process of converting trees to lumber by improved log sorting and bucking using static demand profiles.

MATERIAL AND METHODS

The study was approached using simulation techniques. A database of 246 well-described unique softwood stems served as the wood supply, and a sawmill simulator able to read and process the stems was used to predict the outcome of the sawing process. Segments of the stems with varying lengths and at different positions within the stems were used to create a large number of logs representing all combinations of log length and small-end diameter (SED). The simulator was set up to model the studied sawmill with respect to machinery, product prices, processing costs and positioning error of the logs within the first saw. Each log was sawn with several sawing patterns, and the results were postprocessed to account for measurement error in the log sorting station. The compiled results were then used in a Linear Programming (LP) model capable of maximizing the profit from the sawmill's log supply with constraints on the products produced and available logs. Finally, bucking simulations were used on a virtual stand, compiled from forest inventory data, to find a set of log prices that would produce the desired log length distribution when used to control the harvesters' bucking operation.

Sawmill studied

The sawmill studied produces 280,000 m^3 of sawn goods annually, and it uses 650,000 m^3 of Scots pine logs as input to the process. The logs are presorted into log classes by small-end diameter, which is derived from measurements of the logs' outer shape. The sawmill operates two sawing lines, each consuming half of the log volume. One sawing line processes logs with small diameters. It is a high-speed circular saw where no sideboards are produced. The other line, which processes larger logs, is a band saw where sideboards usually are extracted. Side boards from the band saw are edged. All boards are kiln-dried either in batch kilns or in progressive kilns to moisture contents between 8% and 18%. The dried boards are graded and trimmed to their final lengths. The minimum board length is 1800 mm, and the maximum length is 5400 mm. In between, the boards are typically cut with a 300 mm module giving 13 lengths. A small proportion of the boards are freely cut within the minimum and maximum length limits.

Wood supply

The wood raw material used for simulations was 198 Scots pine (*Pinus sylvestris* L.) stems from the Swedish Pine Stem Bank (SPSB) (Grundberg et al. 1995) and an additional set of 48 young Scots pine stems (Nordmark 2003). The representativeness of the SPSB has been verified by Chiorescu & Grönlund, 2000. The 3-dimensional outer shapes of the stems are stored in files that can be read and processed by a computer. Sections of the stems were then used to create logs representing all combinations of small-end diameter and length. The creation of logs from a stem starts with setting the first cut position of the log small end at a distance from the stem's butt end equal to the minimum log length (3100 mm). Only one log is cut at this position. The cutting position of the small end is then moved 500 mm towards top of stem. Keeping the small end fixed at this new position, all log lengths feasible within the section down to the stem's butt end are then cut, and the procedure is repeated until the small-end position is less than 500 mm from the top of the stem. In total, 24,505 logs were created with small-end diameters ranging from 113 mm to 301 mm. Nine different lengths were cut, from 3100 mm to 5500 mm, with 300 mm increments, thus adding a 100 mm trimming allowance to the target lengths of the boards. The large number of logs ensured that each combination of diameter and length was represented by several logs from different stems. The log volume distribution by diameter and length delivered to the sawmill during year 2004 was used to set the available volume of logs in each diameter and length combination as a constraint when the process was optimized.

Sawing simulation

The sawing simulator used (Nordmark 2002) is a Windows™-based program developed in C++ with a graphical interface partly based on Open GL, allowing the user to view and interact with logs and boards in three dimensions. The simulator also exposes a great deal of its functionality to a scripting module. Through scripts, simulations can be automated, and reports on the sawing process and properties of logs and boards can be tailored. The actual sawmill was modeled as accurately as possible. Properties of the sawmill process modeled were breakdown patterns, saw kerfs, sawing allowances, drying allowances, positioning error in first saws, edging and trimming practices. Cost functions were integrated into the simulations, giving the cost of processing a log. Together with the value of the produced boards and by-products, the contribution of every log type with every breakdown pattern applicable was calculated. Each log was sawn with the breakdown pattern given by a look-up table (Table 1) and the two patterns above and the two patterns below, if available. Grading of boards was done with respect to wane only, following the rules for wane in the Nordic Timber Grading Rules for grade A (Anon. 1994). Allowed wane depth on each edge was 3 mm + 10% of board thickness. Allowed wane width on the outside face was 10 mm, independent of board width. The decision not to include other quality features was partly due to the difficulty of modeling the large number of customer adapted grades and partly based on the desire to focus on the geometric aspects of the problem. Special attention was directed towards those activities that affect final lengths of the boards in order to get a reliable estimate of the lengths produced. The activities recognized and dealt with were the log geometries used in the simulation, the positioning error at the first saw and measurement errors at the log sorting station. First, irregularities affecting the yield, such as crook and out of roundness, are accounted for by using realistic log geometries. Second, the irregular shapes of logs together with the inaccuracies of the machinery are known to influence the positioning of the logs with respect to the saw blade's cutting line; i.e., the log is offset from the centered position. An offset of the log increases the probability of getting wane on the center boards, which in turn may require extra trimming of the boards, reducing their length. Offsets in the first saw, where the faces of the cant are opened, affect both the lower and upper center board, whereas offsets in the second saw usually only affect one center board. A parallel offset in the first saw was simulated with a standard deviation (σ) of 4.0 mm. Each log was sawn with the same pattern at nine offsets from -2σ to $+2\sigma$ with a step of 0.5σ. The result at each offset was given a weight coefficient (Table 2) derived from the normal distribution frequency function (Eq. [1]) and normalized so that the sum of weights equals 1.0. The consequence of this procedure is that a log in combination with a sawing pattern with two center boards yields 18 center boards that are individually trimmed. The weighted sums of the boards, costs, byproducts, etc. were then used when calculating the contribution and yield of that log.

Equation [1]: Normal distribution frequency function

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \cdot e^{-(x-\mu)^2/2\sigma^2}$$

where

μ = average

Table 1. *Sawing patterns and related log small-end diameter intervals.*

	Log small-end diameter interval			Sawing pattern	
No.	Min.	Max.	Saw line	First saw	Second saw
	-(mm)-			-(mm)-	
1	114	125	1	75	38,38
2	126	142	1	100	38,38
3	143	160	1	100	50,50
4	161	171	1	115	50,50
5	172	182	2	125	19,50,50,19
6	183	195	2	19,125,19	25,50,50,25
7	196	206	2	150	25,50,50,25
8	207	214	2	19,150,19	25,50,50,25
9	215	228	2	19,150,19	25,63,63,25
10	229	236	2	25,150,25	19,75,75,19
11	237	247	2	25,150,25	25,75,75,25
12	237	247	2	19,175,19	25,63,63,25
13	248	260	2	200	25,50,50,25
14	261	267	2	19,200,19	19,25,63,63,25,19
15	268	300	2	25,200,25	19,25,75,75,25,19

The third activity dealt with was the log sorting measurement error. Any given log used in simulating the breakdown and predicting the outcome is considered to have an exact description of its geometry and hence an exact measure of its diameter. However, the diameter measured at the log sorting station will have an error added. Modern measuring devices use laser point triangulation. Measurements are made on bark, and functions are used to predict the double bark thickness (Zacco 1974), which is subtracted from the measured diameters. Variations in bark thickness and missing bark on parts of the log surface result in errors in the estimated diameters under bark. Evaluation of several 3D log scanners at sawmills resulted in an estimation that the error in a well-calibrated measuring device will have a normal distribution $N(0, \sigma)$, with σ being 3.5 mm (Grundberg et al. 2001) including the inaccuracies of the devices. The error limits the possibility of sorting the logs into correct log classes when the classes are separated by log diameter. The solution used to account for the error was to post-process the results with a 1-D Gaussian filter. The initial results were aggregated into log classes separated by small-end diameter and log length. Weight coefficients were calculated in analogy to the procedure used with the positioning error. The coefficients were then used to calculate a filtered value at each log class as the weighted sum of the results in the neighboring log classes with the same length but a different diameter. The width of the filter was $\pm 2\sigma$. An example of the interpretation of the procedure is that a log class measured to 170–171 mm will consist of logs with actual diameters between 163 mm and 177 mm, and the result of sawing that class with a specific sawing pattern is the weighted sum of sawing the actual logs in that class.

Table 2. *Weight coefficients used when simulating positioning errors in first saw and measurement errors in log sorting.*

Deviation	Weight
-2.0σ	0.028
-1.5σ	0.066
-1.0 σ	0.124
-0.5 σ	0.180
0 σ	0.204
0.5 σ	0.180
1.0 σ	0.124
1.5 σ	0.066
2.0 σ	0.028

Optimization

In this study, an LP software package was used which adds on to and is well integrated into the Microsoft Excel spreadsheet. The software was Frontline Systems Premium Solver Platform v. 5. With the high-level interface brought by the software, setting up and solving the LP problem was quick and easy. This has made it possible to focus the study on obtaining a realistic model of the sawmilling process to populate the LP problem with. The objective function maximized was the contribution, i.e., the gross value of the products minus the processing costs and excluding the cost of purchasing the logs, which translates to maximizing the profit from the given wood supply. Alternatives where the objective function was maximum volume yield were also evaluated. Variables were log volume in the 3-dimensional matrix of log diameter, log length and sawing pattern. Assigning a volume of logs to a cell in that matrix yields its own set of products, and the objective function is calculated as the summed yield of all cells. The LP algorithm finds the optimal distribution log volumes in all cells under constraints. Constraints were set on minimum and maximum volume of the boards specified by thickness, width and length. Constraints were also set on volume used in each log class, defined by small-end diameter and log length, which had to be less than or equal to the supply in that class. In a second step, the constraints on the log classes were relaxed by only constraining the volume by small-end diameter and not by length. The LP software used was limited to 2000 variables. In order to fit the problem within the limit, the number of log classes was reduced by aggregating the results into 2-mm-wide small-end diameter intervals. However, further reduction of the number of combinations of log diameter, log length and sawing pattern was necessary. In each log class there are four to five alternative sawing patterns. Comparing the net values of each pattern with the pattern giving the highest net gives a calculated optimality loss. By discarding variables with an optimality loss worse than a threshold of 100 SEK, the number of variables was decreased to 1989.

Bucking simulation

Based on results of the optimizations, a log length distribution was manually selected as a target for the bucking. The criterion used was that it would be practically feasible considering the harvesters' diameter-measuring error, which has been estimated to have a standard deviation of 8 mm on Scots pine (Möller & Sondell 2000). Data from preharvest inventories of final fellings in the sawmill's catchment area were used to compile a virtual stand which was used as input to the bucking simulations carried out. The breast height diameter (DBH) distribution was based on measurements on 33,700 Scots pine trees from 448 stands. 5300 trees were measured by both height and DBH. The diameter distribution along with the height relationship (Fig. 1) was used to create a virtual stand of 1400 trees with different DBH and height and with weights on their respective representation. A segmented stem taper function (Edgren & Nylinder 1949) was used to calculate the diameters along the stems at increments of 10 mm.

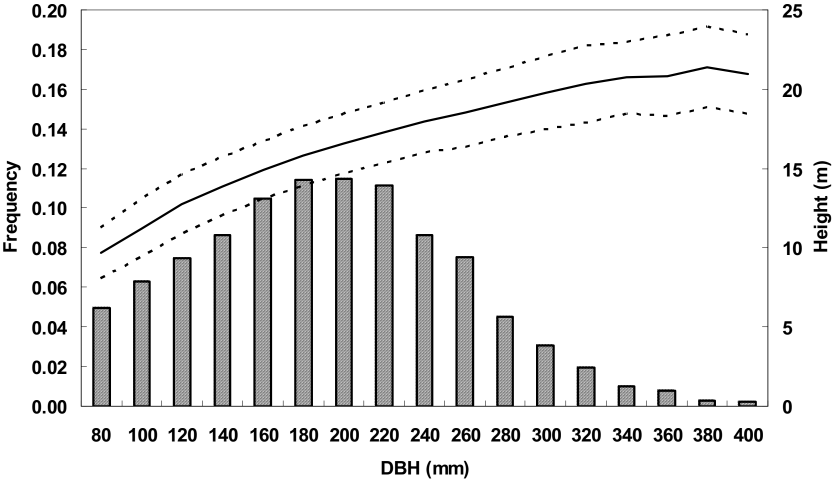

Figure 1. *Stem distribution and tree height of virtual Scots pine stand compiled from preharvest inventory of 448 stands. Average tree height is given by solid line, while dashed lines indicate standard deviation of tree heights. Stand was used as input to bucking simulations carried out.*

An application was developed that maximizes the value of stems given a log price list. The application uses dynamic programming to find the optimal bucking pattern of each stem. As input the program takes a log price list and a description of the virtual stand previously described. The log price list has a format known as StanForD (http://www.skogforsk.se) which is widely used in Scandinavia for exchange of information with harvesters. An option in the StanForD format was used which allows for specifying the desired distribution of lengths in each diameter class. An adaptive production-control algorithm (Nordmark 2005) was used to adjust the prices in order to meet the desired distribution of logs. The stand was bucked 50 times in sequence starting with current market log price list, and the log prices were updated after each time. The maximum allowed price deviation was set to 15%. The final log prices achieved (if working as supposed) should then be used when harvesting final fellings and bucking for the sawmill.

RESULTS

The proposed model for assessing the product yield in different log classes gives a reasonable explanation of why the lengths of the boards do not match the lengths of the logs and why this is more pronounced with smaller dimensions of lumber. Two lumber dimensions are used to illustrate the findings. In Fig. 2 the volume-yield length distribution of 38 x 100 center boards sawn from logs with the length 4300 mm is shown together with total volume yield for the competing dimensions 38 x 75 mm and 50 x 100 mm. The yield of targeted length 4200 mm shows a sigmoid pattern. Even from the smallest logs, a low yield is produced. With increasing log diameter, the yield of 4200 mm boards increases up to a point where it flattens. At that point the increase in log volume is equal to the increase in board volume and thus gives a constant yield. The maximum total yield is achieved if 38 x 100 mm is sawn with logs in the approximate interval 130 mm to 145 mm. If log volumes are evenly distributed among diameter classes in the interval, the yield of 4200-mm-long boards then becomes 61% of the total board volume produced. The log-sorting limit applied at the sawmill is 127 mm to 142 mm. The model estimates that this strategy will produce 50% of the board volume at the targeted length. In order to increase the volume share above 61% it is necessary to differentiate prices among the lengths and dimensions to offset the sorting limits from the highest volume-yield solution. Applying volume maximization to the other log lengths between 3100 mm and 5500 mm reveals one more interesting finding. The optimal interval of diameters is 134 mm to 150 mm for 3100-mm-long logs. The interval moves towards smaller diameters as log length increases, ending at 128 mm to 142 mm with 5500-mm-long logs. The other lumber dimension examined was 50 x 200 (Fig. 3). The yield of 4200-mm-long boards shows a different pattern. A very small share of the boards is predicted to be trimmed below the target length due to wane. The lines in the figure representing total yield of the three competing dimensions 63 x 175, 50 x 200 and 63 x 2000 include the volume of side boards. Current sorting limits practiced by the sawmill are 248 mm to 261 mm. The sorting limits depicted by maximum total yield are preferably lower. It is noticeable that the yield loss that arises when the sorting limits are offset is much less than in the case with the 38 x 100 dimension. In Figs. 4 and 5 the distribution of log volumes and board volumes recorded by the sawmill is shown together with the distribution of board volumes as predicted by the model using the sawmill's current sorting limits. The figures present examples of the general pattern found when comparing the simulated length distribution with observed distributions from the sawmill's production. For small dimensions the model underestimates volume recovery by predicting shorter lengths, while the model overestimates the volume recovery for large dimensions by predicting too long lengths. For intermediate dimensions the model gives a good estimate of recovered volumes. The model estimates total yield to 44.9% compared to 43.2% recorded by the sawmill. The volume of side boards is very well predicted, while the volume of center boards is overestimated by the model.

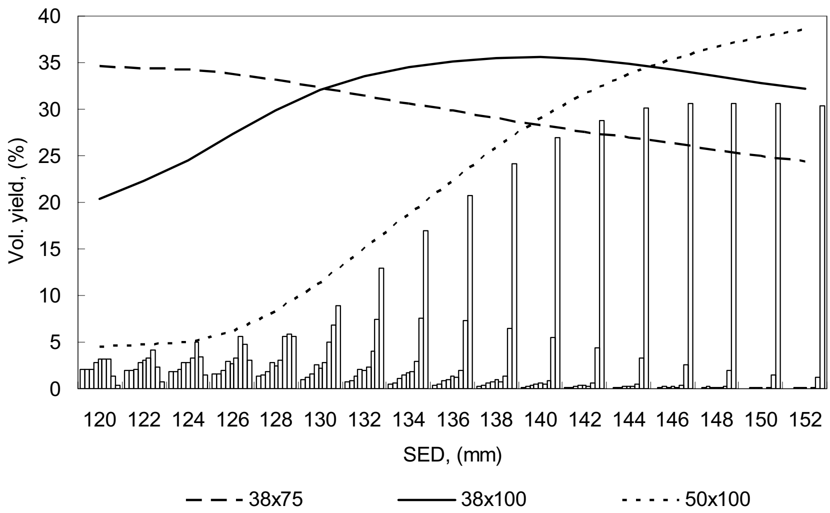

Figure 2. *Predicted volume yield length distribution of 38- x 100-mm boards yielded from 4300-mm-long logs with varying small-end diameter. Yield is expressed as proportion of log volume. In each presented 2-mm-wide log class, the leftmost bar represents boards 1800 mm long, and succeeding bars show boards with a 300-mm length increment up to the rightmost bar representing 4200-mm-long boards. Lines show total volume yield for three competing dimensions.*

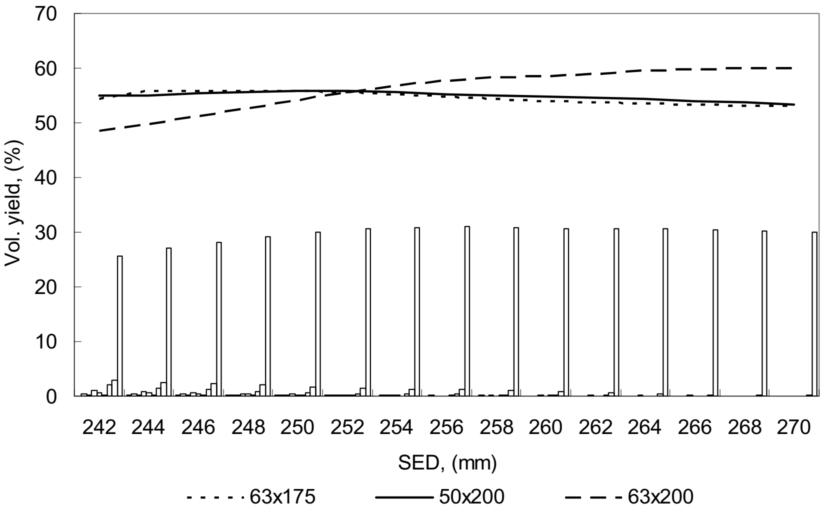

Figure 3. *Predicted volume yield length distribution of 50- x 200-mm boards yielded from 4300-mm-long logs with varying small-end diameter. Yield is expressed as proportion of log volume. In each presented 2-mm-wide log class, the leftmost bar represents boards 1800 mm long and succeeding bars shows boards with a 300-mm length increment up to the rightmost bar representing 4200-mm-long boards. Lines show total volume yield for three competing dimensions.*

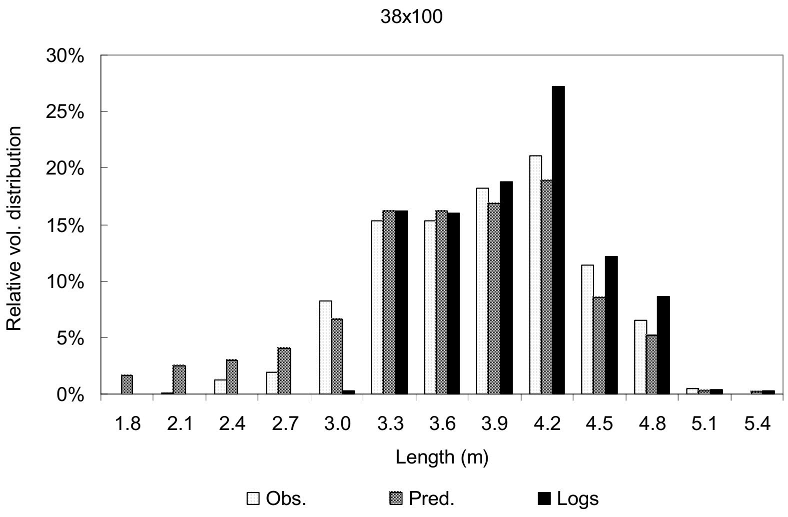

Figure 4. *Sawmill's distribution of logs by length classes within diameters 127 mm to 142 mm SED and predicted and observed length distribution of 38- x 100-mm boards yielded from sawing the same logs. Actual log lengths within a length class were 100 mm to 399 mm longer, while logs used for simulation were 100 mm longer than length class shown.*

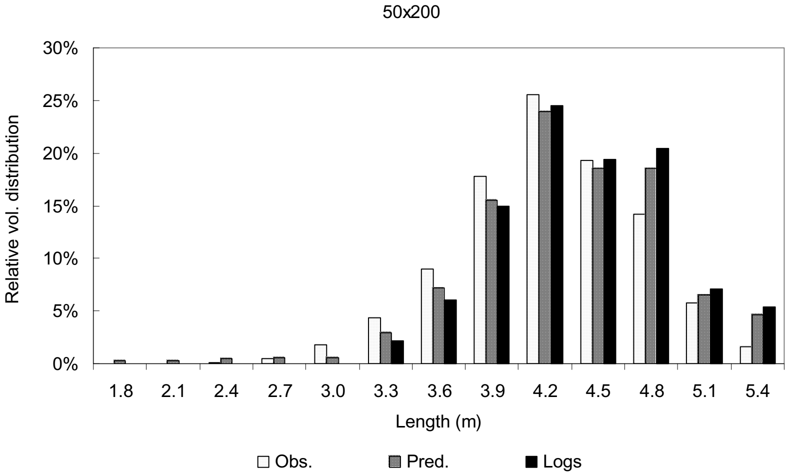

Figure 5. *Sawmill's distribution of logs by length classes within diameters 248 mm to 261 mm SED and predicted and observed length distribution of 50- x 200-mm boards yielded from sawing the same logs. Actual log lengths within a length class were 100 mm to 399 mm longer, while logs used for simulation were 100 mm longer than length class shown.*

Results from optimization of log sorting, i.e., allocation of log classes to sawing patterns, are compared to the sawmill's current practice in Table 3. With open market conditions and current log distribution (setup alternative no. 1), contribution was increased by 5.5% when value was maximized. Excessive production of certain dimensions makes this alternative hard to realize. In alternative no. 2, realistic constraints were set on minimum and maximum volumes of boards by thickness and width. The increase in contribution then amounted to 2.4%. The log-sorting schema resulting from alternative 2 is presented in Fig. 6. The schema shows a rather complex pattern that differentiates sawing patterns by log length as well as by log SED. Introducing constraints on the length distribution of the boards made the problem unfeasible with the current log distribution. Free distribution of log lengths within each 2 mm wide diameter class shows a potential of 10% (alternatives 3 and 4). Considering the harvesters' measurement accuracy, these two alternatives will not be practically feasible, as the solution requires very narrow intervals on the diameters for certain lengths. Setting the log length distribution equal at all diameters (alternative 5), the constraints were fulfilled and the contribution increase was estimated to 6.1%. It can also be noted that the volume recovery was decreased in most cases when the objective was to maximize value. Maximizing the volume yield shows a rather low potential (1.6% in alternative 2) indicating that the sawmill has been good at this.

Table 3. *Value and volume yield relative to the sawmill's current log supply and log sorting strategy.*

Setup No.	Log length distribution	Constraints on boards produced: Thick. Width	Constraints on boards produced: Length	Optimization objective: Value — Value	Optimization objective: Value — Vol.	Optimization objective: Volume — Value	Optimization objective: Volume — Vol.
				-(%)-			
1	Current	No	No	105.5	100.6	102.6	102.6
2	Current	Yes	No	102.4	99.9	101.0	101.6
3	Free lengths within diameter classes	Yes	Yes	109.4	99.7	100.5	102.6
4	Free lengths within diameter classes	Yes	No	110.5	99.4	94.1	103.5
5	10% 3700, 30% 4300, 20% 4600, 30% 4900, 10% 5200	Yes	Yes	106.1	99.3	105.7	100.2

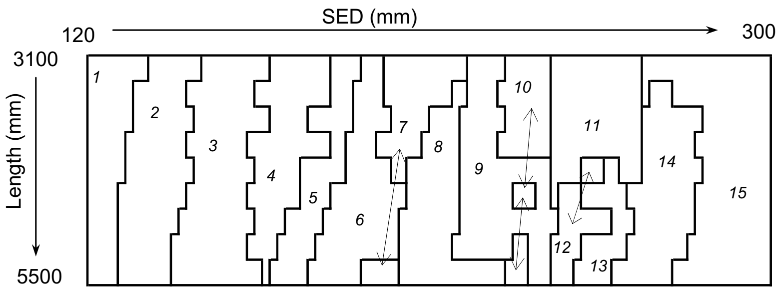

Figure 6. *Log sorting schema obtained from value optimization with sawmill's current log distribution and with constraints on volume produced in each dimension (thickness x width). Numbers correspond to sawing classes as in Table 1.*

Simulations of bucking with production control showed that the desired log length distribution could be fulfilled. In Fig. 7, developments of volume shares are shown. After approximately 40 iterations, targets are met. The original log prices were adjusted by less than 5% in 67% of the log classes; 18% had their prices adjusted by 5% to 10% and the remaining 15% had their price adjusted by more than 10%. However, the final set of prices arrived at after 50 iterations does not exactly yield the desired log length distribution when the volume produced is reset and the prices are applied to the virtual stand and not allowed to change. In fact, it does not seem to be possible to find such prices, at least not using integer log prices in SEK as in this study.

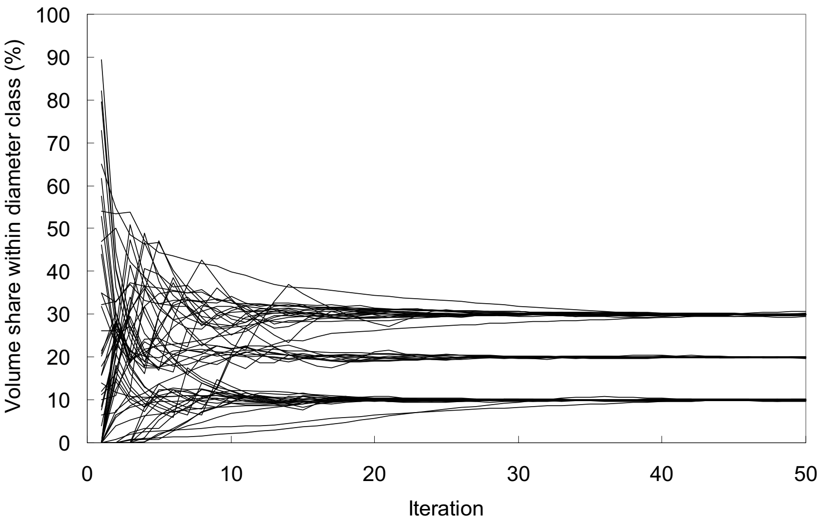

Figure 7. *Evolution of volume shares of sawlogs within diameter classes using adaptive log prices for production control in bucking. Targeted shares were 10% 3700-mm-long logs, 30% 4300 mm, 20% 4600 mm, 30% 4900 and 10% 5200 mm within each 20-mm-wide diameter class.*

DISCUSSION

By using realistic log geometries and by accounting for imperfections in the process, we have achieved a model of the conversion process that reflects reality rather well. The model is explains the mismatch between log length and board length for smaller dimension lumber. It also shows that increasing the share of target lengths at small dimensions can only be done at a relatively high cost in terms of volume yield. Deviations between yield predicted by the model and the sawmill are mainly found in length distributions of center boards at larger dimensions sawn with the band saw. The sorting limits practiced on large dimensions are set to accommodate side boards. The risk of getting wane on the center boards then becomes low. Instead, trimming is necessary due to quality features other than geometry, which the model presented here did not deal with. Larger dimensions are often trimmed to and sold as commodity grades, while smaller dimensions often are sold saw falling. As the volume of sideboards is predicted accurately, the simulations are believed to model the sawing process realistically in other respects as well. The aspect of quality is treated briefly, as the prices used are the average prices of the lumber. Such an average price may reflect the quality distribution of the lumber as well as the market's desire of certain lengths. For instance, when statistics on lumber sales during 2004 were examined, several large dimensions showed decreasing prices with increasing length. However, in each grade the prices were positively correlated to length, but longer lengths shifted the distribution of grades towards cheaper (poorer) quality, giving a lower average price. Hence altering the log lengths will have an effect on grade distribution, which is not estimated by the model, though it is partly reflected in the product prices used. In order to include quality features in log sorting practice, it is possible to use compiled data such as bumpiness, taper, etc., from a 3-D measuring device at the log sorting station to predict the quality distribution of a log's boards and use the prediction for stratified sorting (Lundgren 2000; Oja et al. 2003). Nordmark and Oja (2004) showed the possibility of using the 3-D geometry of stems to include the quality feature in automated bucking. Sondell et al. (2004) has shown the successful implementation of automatic prediction of furniture grades in a harvester's bucking system using the relation of log small-end diameter and stem DBH.

In this paper we have restricted the work to the set of sawing patterns in use by the sawmill. The search for optimal sawing patterns is an interesting task in itself which has been addressed by Maness and Adams (1991). More sawing patterns can easily be included in this model. However, LP software capable of dealing with more than 2000 variables is needed.

The log sorting instructions emanating from this study differentiate logs by small-end diameter and length. It is likely that log taper should be included as a primary feature used in log sorting. A more elaborated approach to log sorting has been proposed by Nordmark (2005) in which simulated sawing of the 3D profile acquired on an individual log was used to predict the value yield with several competing sawing patterns and the pattern giving the highest value being chosen. Furthermore, that model is well suited to production control, as it operates with product prices directly rather than sorting criteria derived from product prices.

With the sawmill's current log distribution, the results suggest that gains in value recovery can be made by altering the log-sorting instructions. Part of the value gain is realized if sorting limits are varied over log lengths, in contrast to today's situation where log sorting is based on SED alone. The contributions computed, expressed as SEK/m^3, show a positive correlation with length. This means that processing costs and market price outweigh the effect of a lower volume yielded with longer logs. Part of the value gain of 6.1% achieved when altering the bucking pattern (alternative 5) is due to longer logs. The average log length was increased by 299 mm. This setup also satisfies the desired length distribution of the boards. It is likely that increasing the volume of products with high demand at the expense of products that are hard to sell will generate further gains by reduced stocking. A prerequisite for realizing the value potential is that the log distribution can be changed as assumed. An appropriate log price list together with the option of apportionment within log diameter classes provides the means of controlling the harvesters' bucking. In practice, severe defects on the stems being bucked force the operator to override the computed optimal cross-cutting positions in order to avoid costly downgrading to pulpwood. Such imperative cuts reduce the ability to fulfill the desired apportionment.

Introducing the length dimension of lumber as an important feature in the chain of converting trees to lumber makes it necessary to address bucking as well as log sorting. The system model developed could be even more detailed and perhaps better tuned. However, we conclude that a good first step has been taken towards a better customer orientation, and we intend to implement the results gradually while carefully monitoring the outcome.

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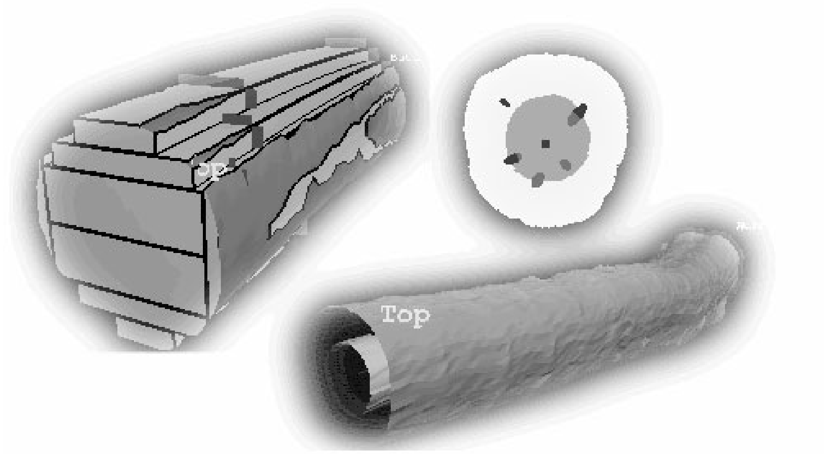
Sondell, J., L. Moberg, and J. J. Möller. 2004. Automatic bucking of sound-knot logs works well in practice. Result 15, SkogForsk, The Forest Research Institute of Sweden, Uppsala, Sweden. 4 pp. ISSN 1103-4173. (In Swedish with English summary.)

van Wyk, L. 2001. Dimensioning and tolerancing when sawing logs into lumber. Proc. of the 7th international conference on sawing technology. Szymani, R. (Ed.). November 7-9, 2001, Seattle, Washington, USA.

Appendix A

Saw2003 Quick Start



Urban Nordmark
2004-10-29

INTRODUCTION

The Saw2003 software is capable of reading log description files from the Swedish Pine Stem Bank (SPSB). It is also able to simulate the disintegration of the logs, in a manner similar to a real saw mill. This is a quick guide of how to operate the software through its graphical user interface.

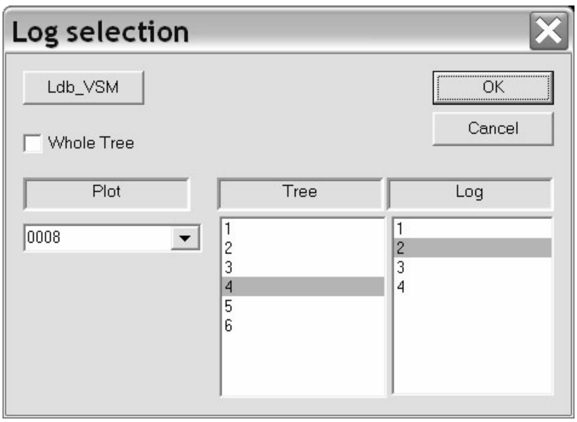
MAIN WINDOW

The main window holds 6 child windows referred to as views.

Depending on which view is active the menu and toolbar buttons change. In the image above the Script view is active and the menu option Script is visible and the Run button is enabled. Activating other window will hide Script from the menu and disable the Run button. Commands always active are listed below.

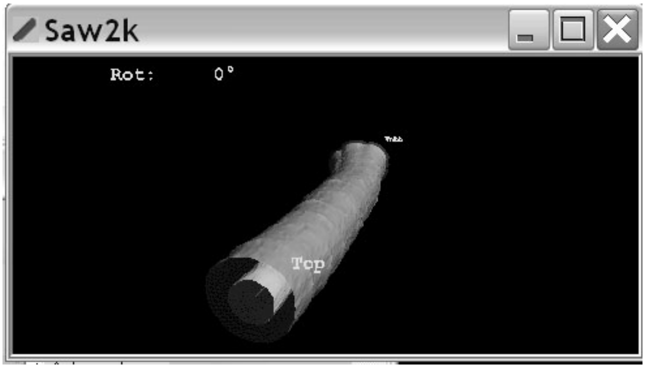
Command		Short Cut	Description
		CTRL + "L"	Open the Stem Bank dialog for selecting a log
		CTRL + "S"	Saw current log
Settings	/PostList…		Select a post list file. The selected file will be loaded. It will also be loaded next time program starts.
	/PriceList…		Select a price list file. The selected file will be loaded. It will also be loaded next time program starts.
	/QualDef…		Select a quality definition file. The selected file will be loaded. It will also be loaded next time program starts.
	/StemBank…		Selects log database.
	/Dump		Writes the various settings of the machinery to Info view and the selected control files.
View	/Log /Boards /Slice /Info /Positioner /Script		Select or create view

The log selection dialog allows the user to load a selected log to the saw mill, or by checking the **Whole Tree check box** a stem can be loaded.



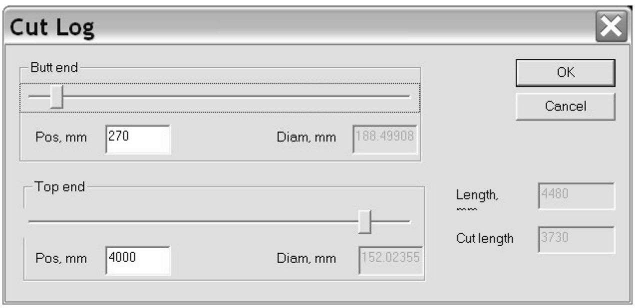
LOG VIEW

The Log view shows the currently loaded log.



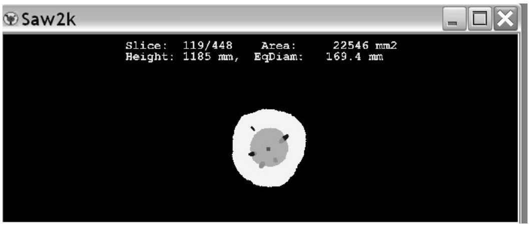
Command	Short Cut	Description
Left Mouse button + Mouse move up/down		Rotates the log around its long axis.
Right Mouse button + Moves move		Rotates the log around its mid height
	"S"	Toggle Surface ON/OFF
	"H"	Toggle Heart wood ON/OFF
	"K"	Toggle Knot axis ON/OFF
Log /CutLog…		Brings up the cut log dialog allowing for shortening of the log or rebucking of loaded trees.

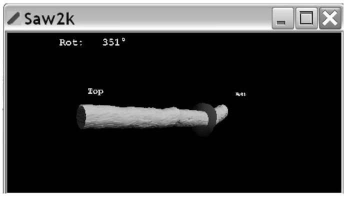
With the cut log dialog it is possible to shorten the current log/stem by cutting it at the butt end and top end. The program keeps the original log in memory so it is possible to restore its full length by calling up the dialog and readjust the sliders.



SLICE VIEW

The slice view shows a cross-section (slice) of the log as viewed from the top end of the log. Knots are color coded, green for sound knots and blue for dead knots.



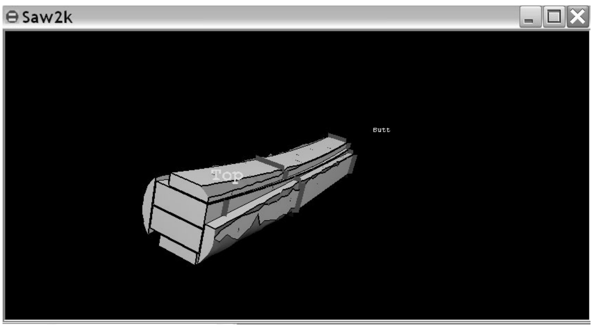


The position of the current slice is reflected in the Log view by a red shadow as shown in right image (surface removed for clarity).

Command	Short Cut	Description
Left Mouse button + Mouse move up/down		Rotates the log around its long axis.
Right Mouse button + Moves move		Move up/down the log
	“P”	Tri-state. Toggle 1:st saw cuts, both saw’s cuts, no cuts.
	“D”	Dump a detailed report of current slice to Info view

BOARD VIEW

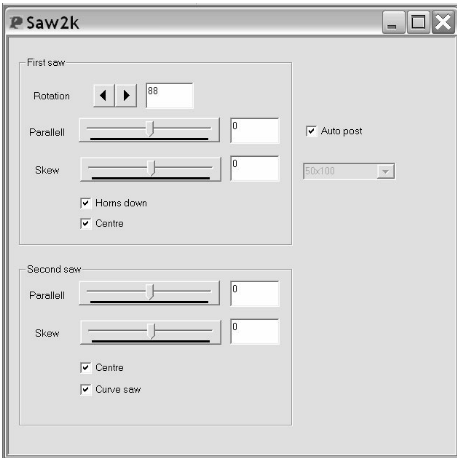
The board view shows boards with wane and knots.



Command	Short Cut	Description
Left Mouse button + Mouse move up/down		Rotates the boards around its long axis.
Right Mouse button + Mouse move up/down/left/right		Rotates the boards around their mid height
	"Space bar"	Iterate through the boards.
	"T"	Tri-state. Boards not trimmed. Boards not trimmed but with trim marks. Boards trimmed.
	"Q"	Show color coded qualities on board. Knot diameter, sum of knot diameters, wane.
	"D"	Dump a detailed report of the current board to Info view.
	"+-"	Change scale proportions.

POSITIONER

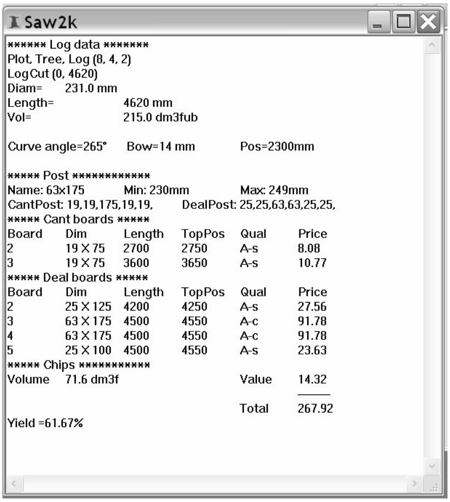
The positioner is an interface to the sawing machines and how the log is positioned there.



Command	Short Cut	Description
Horns down		Log gets automatically rotated horns down (crook up) prior to sawing
Centre		Log get automatically centered prior to sawing
Curve saw		The cant will be curve sawn
Auto post		Pattern is automatically selected based on log small-end diameter

INFO VIEW

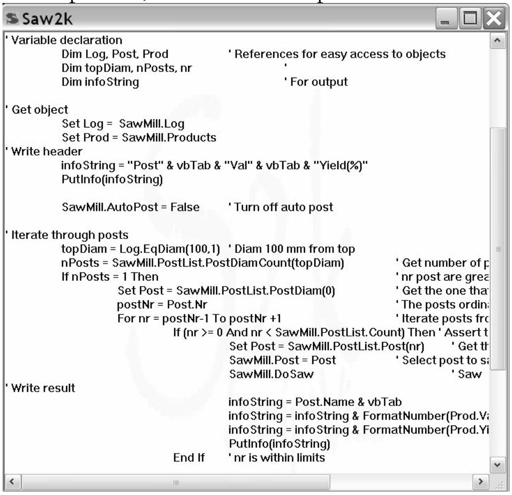
The Info view receives reports from various operations such as sawing a log or dumping slice data.



Command	Short Cut	Description
Clear		Clears the info view

SCRIPT VIEW

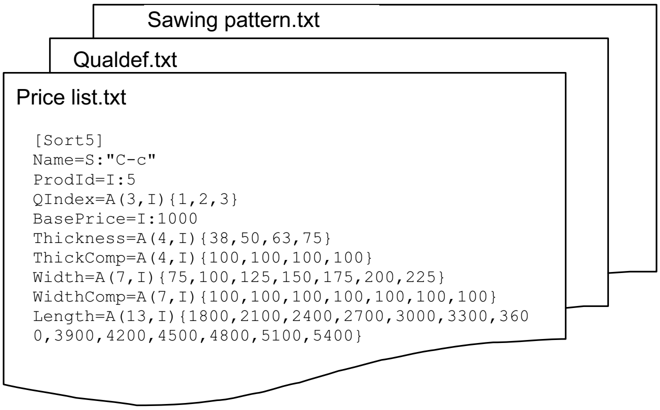
In Script view, Visual Basic scripts can be edited and used to automate the sawing simulations.



Command		Short Cut	Description
Clear			Clears the script view
Run		CTRL+"R"	Start current script
Stop			Stops running script
Script	/Load script		Load a script from a text file
Script	/Save script		Save a script to file

Appendix B

Saw2003 Control Files



Urban Nordmark
2005-04-12

INTRODUCTION

The sawing simulation software Saw2003 depends on a few control files. These files define how a log can be cut and how boards are graded and priced. In addition, files for production control and cost assessments are optional. The files are text files (ASCII) which allows for editing with any text editor. The format used (S2k) is native to the software and gives a structured and hierarchic representation of the data. Variables are easy to look-up and their type is given. The format is a home-brewed variant of the XML-standard which unfortunately was unknown to the author at the time of programming. The control files are listed in Table 1.

Table 1. *Control files used in Saw2003.*

File	Format	Importance	Description
Sawing patterns	Table	Necessary	A look-up table with log small-end diameter as the key to patterns of nominal widths of cuts at first and second saw.
Quality definition	S2k	Necessary	Grading rules following the system in Nordic Timber Grading Rules.
Price list	S2k	Necessary	Products and prices. A product is defined by grade and dimension.
Order	Table	Optional	Order book which can be used for adaptive control of production.
Costs	S2k	Optional	Cost coefficients of various operations in the sawing process. Allows for calculating a net value at log level.

S2K FILE FORMAT

S2k files are divided in sections. A section starts with the section name `[SectionName]`. Sections contain variables, one per row. First section is always the `[Header]`. In this section a variable `Separators` define characters that should be switched to a common separator such as TAB (ASCII 9). The use of different separators in the file serves the purpose of increasing readability when editing directly in the text file. Variables are typed and data can be scalar, array or matrix. The variable name is separated from data definition with "=".
A scalar has the format: `Var=type:value`.
Arrays have the format `Var=A(nValues,type){value1,…,valuen}`.
A matrix has the format: `Var=M(mRows,nColumns,type)`
`{{row1col1,…, row1coln }{…}{ rowmcol1,…,rowmcoln }}`.
Types defined are integer (`I`), decimal (`D`), string (`S`) constant (`CT`) and byte (`B`). Strings and constants are enclosed in `" "`. The format also allows for user types which must be defined in the header section, e.g. `E` and `F` denotes Edge and Face in `nKnots=A:(2,I)` `{E(2),F(4)}`. A user type is an extra tag on a value. Finally, a variable can be defined as an interval, e.g. `Thickness=A(4,IV:I){16 25,32 38,44 50,63 75}`. This should be interpreted as an array of four integer intervals.

SAWING PATTERNS FILE

The structure of a sawing pattern file is given in Table 2. Data is row based. Each row corresponds to a sawing pattern. Columns are separated with TAB. Explanations of data is given in Table 3. Column headings are not interpreted by the software which implies that the order of columns cannot be changed. Last three columns are optional.

Table 2. *Sawing patterns file structure. See Table 3 for explanation of columns.*

ID_NR	ID_NAME	MIN_D	MAX_D	KS_POST	DS_POST	KS_BOARDS	DS_BOARDS	SAW_LINE	SAW_SPEED	LOG_GAP
1	38x75	114	126	75	38,38	b	c,c	2	110	1900
2	38x100	126	143	100	38,38	b	c,c	2	110	1900
3	50x100	143	161	100	50,50	b	c,c	2	105	1800
5	50x115	161	172	115	50,50	b	c,c	2	100	1700
6	50x125_1	172	183	125	19,50,50,19	b	s,c,c,s	1	68	2300
7	50x125_2	183	196	19,125,19	25,50,50,25	s,b,s	s,c,c,s	1	68	2900
8	50x150_1	196	207	150	25,50,50,25	b	s,c,c,s	1	68	2300
9	50x150_2	207	215	19,150,19	25,50,50,25	s,b,s	s,c,c,s	1	65	2500
10	63x150	215	229	19,150,19	25,63,63,25	s,b,s	s,c,c,s	1	65	3300
11	75x150_1	229	237	25,150,25	19,75,75,19	s,b,s	s,c,c,s	1	65	3800
12	75x150_2	237	248	25,150,25	25,75,75,25	s,b,s	s,c,c,s	1	60	3500
13	63x175	237	248	19,175,19	25,63,63,25	s,b,s	s,c,c,s	1	60	3500
14	50x200	248	261	200	25,25,50,50,25,25	b	s,s,c,c,s,s	1	50	5500
15	63x200	261	268	19,200,19	19,25,63,63,25,19	s,b,s	s,s,c,c,s,s	1	50	5500
16	75x200	268	300	25,200,25	19,25,75,75,25,19	s,b,s	s,s,c,c,s,s	1	50	5500

Table 3. *Description of columns in sawing pattern control file.*

No.	Name	Description
1	ID_NR	Numerical tag.
2	ID_NAME	Name. This name is shown in the sawing pattern selection list box in the graphical user interface.
3	MIN_D	Minimum small-end diameter. When automatic selection of sawing patterns is enabled the log small-end diameter is compared with MIN_D as greater than or equal to.
4	MAX_D	Maximum small-end diameter. When automatic selection of sawing patterns is enabled the log small-end diameter is compared with MAX_D as less then.
5	KS_POST	Nominal widths of cuts in first saw. Widths are the material between the kerfs. Sawing allowances, kerf widths and shrinkage allowances at first saw is set in the program.
6	DS_POST	Nominal widths of cuts in second saw.
7	KS_BOARDS	Type of product corresponding to a cut in first saw. s = side board, will be edged b = block, will be processed in second saw
8	DS_BOARDS	Type of product corresponding to a cut in second saw. s = side board, will be edged c = centre board
9	SAW_LINE	Tag that can be used when several sawing lines are simulated.
10	SAW_SPEED	Speed of sawing in meters per minute. To be used with cost assessments.
11	LOG_GAP	Gap between logs when sawing (mm). Used with cost assessments.

Min. and max. diameter intervals may overlap. If so, the software picks the first in list that matches log diameter when automatic selection of sawing patterns is enabled.

QUALITY DEFINITION FILE

The quality system used is built around the Nordic Timber Grading Rules. Limits on knot diameter, number of knots and wane can be changed within this system. An excerpt from the file is shown in Fig. 1. An explanation is given in Table 4.

```
[Sort2]
Name=S:"B"
Index=I(2)
nKnots=A:(2,I){E:3,F:5}
nKnotsUnit=EF:CT("w1m")
Thickness=A(4,IV:I){16 25,32 38,44 50,63 75}
Width=A(3,IV:I){75 115,125 150,175 225}
EdgeKnotSize=A(4,I){CT("*"),30,40,50}
FaceKnotSize=M(4,3,I){{35,40,45},{40,45,50},{45,50,55},{50
,55,60}}
DryKnotRel= EF:I(70)
WaneLength_LE25= A(2,I){30,40}
WaneLength_GT25= A(2,I){20,30}
WaneDepth= I(15)
WaneWidth= I(12)
```

Fig. 1. *Definition of a quality within a quality file.*

Table 4. *Description of variables in a quality definition file.*

Variable	Unit	Description
`[Sort2]`		Section start of individual quality. These tags must be listed in the header section in variable `SortNames`. Tags not listed will be ignored.
`Name`		Name of quality.
`Index`		Pricelist is matched with index. A product in price list has a defined quality which is given by same index. Each quality defined must have a unique index.
`nKnots`	No.	Number of knots with maximum size. Actual interpretation is that the number multiplied with maximum knot size gives a maximum knot sum that is allowed. "`E`" is for Edges and "`F`" is for Faces.
`nKnotsUnit`	Constant	A constant "`w1m`" is the only allowed value. "w1m" means that the worst 1000 mm section of board is considered for measurement of knot quality properties.
`Thickness`	mm	Thickness classes given as intervals.
`Width`	mm	Width classes given as intervals.

`EdgeKnotSize`	mm	Maximum sound knot size on edges corresponding to thickness classes given in variable `Thickness`. Constant "*" means maximum size of sound knots equal to thickness.
`FaceKnotSize`	mm	Maximum sound knot size on faces corresponding to the combination of thickness classes and width classes given in variables `Thickness` and `Width`.
`DryKnotRel`	% of sound	Dry knot size relative to sound knots.
`WaneLength_LE25`	% of length	Maximum length of wane for boards with thickness less than or equal to 25 mm.
`WaneLength_GT25`	% of length	Maximum length of wane for boards with thickness greater than 25 mm.
`WaneDepth`	% of thickness	Maximum wane depth on edges. In software, 3 mm is added to get actual limit.
`WaneWidth`	mm	Maximum wane width on outside face. In software, 3 mm is added to get actual limit.

The maximum number of qualities that can be defined in a file is 32.

PRICE LIST FILE

The price list is organized in price sheets. Such a sheet defines dimensions and prices and acceptable qualities. Several sheets can refer to the same quality. An excerpt from the file is shown in Fig. 2. Variables are explained in Table 5.

```
[Sort1]
Name=S:"A-c"
ProdId=I:1
QIndex=I:1
BasePrice=I:1000
Thickness=A(4,I){38,50,63,75}
ThickComp=A(4,I){100,100,100,100}
Width=A(8,I){75,100,115,125,150,175,200,225}
WidthComp=A(8,I){100,100,100,100,100,100,100,100,100}
Length=A(13,I){
1800,2100,2400,2700,3000,3300,3600,3900,4200,4500,4800,510
0,5400}
LengthComp=A(13,I){  70,  70, 100,  80,  80,  80, 110,
100, 120, 110, 120, 100, 100}
ThickWidthComp=M(12,3,I){{38,75,125},{38,100,125},{50,100,
137},{50,115,136},{50,125,146},{50,150,138},{50,200,130},{
63,150,140},{63,175,135},{63,200,140},{75,150,138},{75,200
```

Fig. 2. *Definition of products by a price sheet in a price list file.*

Table 5. *Description of variables in a price list file.*

Variable	Unit	Description
`[Sort1]`		Section start of price sheet. These tags must be listed in the header section in variable `SortNames`. Tags not listed will be ignored.
`Name`		Name of product.
`ProdId`		Index of product.
`QIndex`		Qualities allowed. Can be several indexes.
`BasePrice`	$SEK \cdot m^{-3}$	All dimensions in the price sheet starts with this default value.
`Thickness`	mm	Nominal thickness classes of products.
`ThickComp`	%	Price coefficient on thicknesses as given by variable `Thickness`.
`Width`	mm	Nominal width classes of products.
`WidthComp`	%	Price coefficient on widths as given by variable `Width`.
`Length`	mm	Nominal length classes of products.
`LengthComp`	%	Price coefficient on lengths as given by variable `Length`.
`ThickWidthComp`	%	Price coefficient on combinations of thickness and width. Format is (`thickness, width, coefficient`). The variable is optional and only affects explicitly given dimensions.
`ProdComp`	%	Price coefficient on combinations of thickness width and length. Format is (`thickness, width, length, coefficient`). The variable is optional and only affects explicitly given dimensions.

As a price sheet is read the defined dimensions are expanded to a three-dimensional matrix ($nThickness \cdot nWidth \cdot nLength$). The initial base price then is multiplied with the price coefficients at the individual dimension, that is, the price of a board is the product of all coefficients and the base price.

ORDER FILE

The order file is to use with production control. Production control is employed through scripting in the software. Production can be controlled by number of pieces or by volume share. First row specifies total volume produced at start. The following table defines products under control (Table 6). Explanations are given in Table 7. Piecewise control is not well tested, thus it is recommended to use volume share control.

Table 6. *Example of ordered products in an order file.*

Quant	Prod	Volume	Prod	Thick	Width	Length	Products
-1	0	20	0	19	75	2400	"B-s","C-s"
-1	0	20	0	38	75	3000	"A-c"
-1	0	20	0	38	100	3900	"A-c","B-c"
-1	0	20	0	50	100	3300	"B-c"

Table 7. *Description of variables in a quality definition file.*

Column	Unit	Description
`Quant`	No.	Ordered number of pieces, if piecewise control.
`Prod`	No.	Produced number of pieces, if piecewise control.
`Volume`	‰	Ordered volume share, if volume based control.
`Prod`	‰	Produced volume share, if volume based control.
`Thick`	mm	Nominal thickness of products.
`Width`	mm	Nominal width of products.
`Length`	mm	Nominal length of products.
`Products`	Names	Products targeted. Names as given in price list file.

COST FILE

The cost file gives coefficients which are used for calculating the cost of processing a log. The sections in a cost file is presented and explained in Figs. 3-8. The cost functions were designed with special attention towards the influence of length of logs and boards.

```
[Header]
Separators= ,:(){}
Magic=S:"Saw2k"
FileType=S:"Cost"
SawLines=A(2,S){"Saw1","Saw2"}
UserTypes=
Constants=
```

Fig. 3. *Header. Variable SawLines defines name of sections with saw line attributes.*

```
[LogSorting]
LengthSpeed=I:130
LogGap=D:1.5
HourCost=I:3300
```

Fig. 4. *Log sorting. LengthSpeed is m · min^{-1}. LogGap is distance between logs in meters. HourCost is SEK · hour^{-1}.*

```
[Saw1]
Name=S:"Band"
Index=I:1
HourCost=I:6289
LogGap=D:0.3
```

Fig. 5. *Saw line attributes. Index is matched with saw line given in sawing pattern file. HourCost is SEK · hour^{-1}. LogGap is default distance between logs in meters. Log gap can be overridden by setting log gaps in the sawing pattern file.*

```
[Trimmer]
HourCost=I:5458
PieceSpeed=M(29,3,I){{19,75,2500},{19
,100,2500},{19,125,2350},{25,75,2550}
,{25,100,2700},{25,125,2400},{25,150,
2300},{25,175,2000},{25,200,1980},{25
,225,1900},{34,112,2800},{34,128,2350
},{38,75,2600},{38,100,2550},{44,100,
```

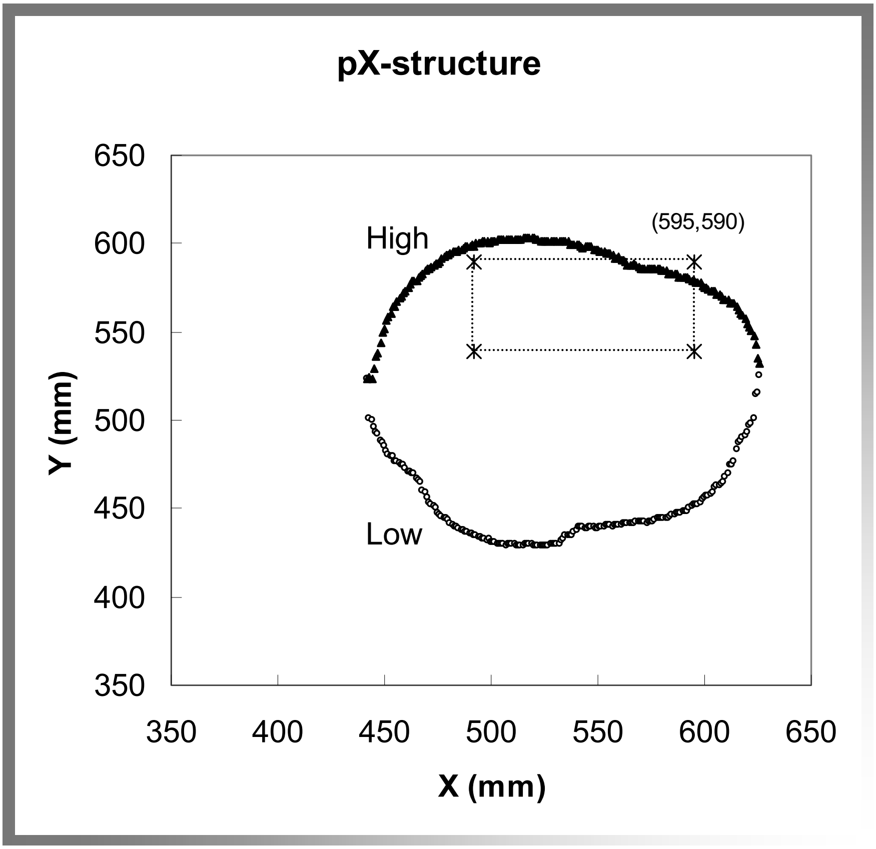
Fig. 6. *Trimmer. HourCost is SEK · hour^{-1}. PieceSpeed is pieces · hour^{-1} with the format (thickness, width, speed).*

```
[Dryer]
ThickMoistCost=M(16,4,D){{19, 18,
43.86, 516.58},{25, 18, 37.84,
448.02},{34, 12, 44.0, 448.92},{38,
9, 43.54, 515.53},{38, 18, 32.51,
365.16},{50, 8, 43.04, 749.20},{50,
9, 42.48, 655.55},{50, 12, 40.81,
780.42},{50, 18, 31.69, 366.79},{63,
```

Fig. 7. *Dryer. ThickMoistCost is cost coefficients when drying boards with a specific thickness to given moisture content. Format is (thickness, moisture content, b_0, b_1). Cost is calculated as ($b0+b1 \cdot length^{-1}$) $\cdot$ volume.*

Appendix C

Saw2003 Kernel



Urban Nordmark
2005-04-05

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INTRODUCTION

This document describes algorithms and calculations internal to the sawmill simulator software Saw2003. The elements that make up the software are presented as they were implemented. Alternative methods are not discussed. The sole purpose of this paper is to aid in understanding why the results come out as they do, and perhaps other researchers or software engineers will find something useful. Fig. 1 provides an overview of the operations involved in processing a log into boards.

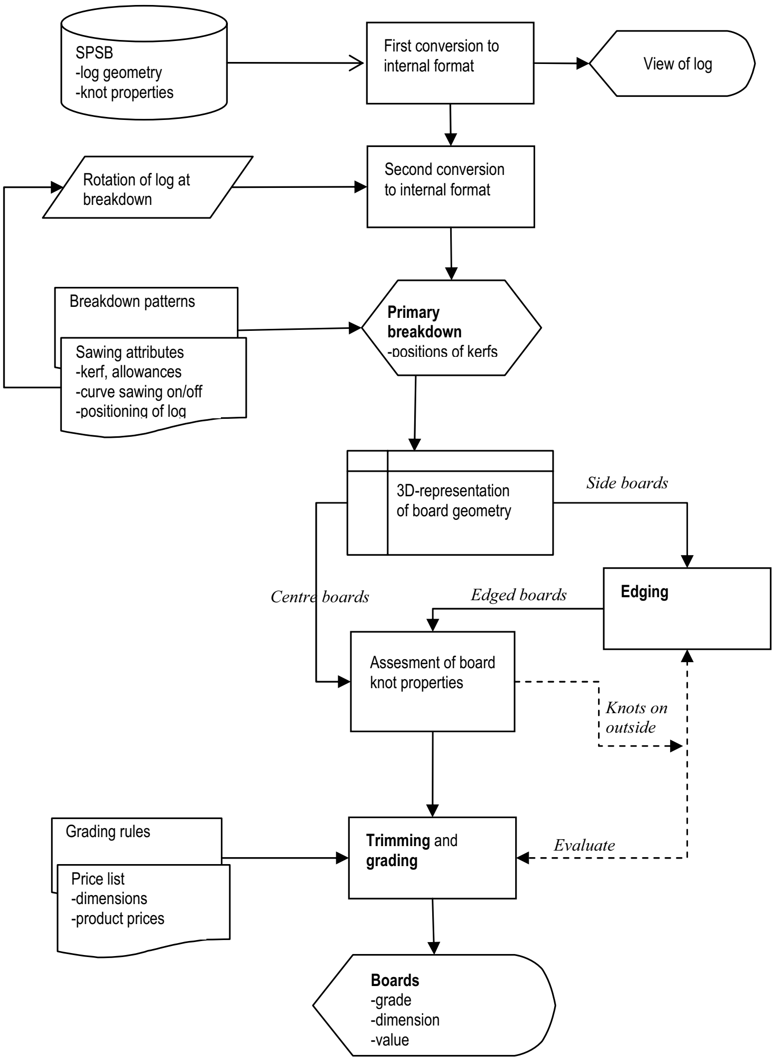


Fig. 1. *Flow of operations in Saw2003 from loading raw log description from Swedish Pine Stem Bank (SPSB) through conversion to final products.*

LOG REPRESENTATION

Descriptions of log and knot geometry following the format of the Swedish Pine Stem Bank (SPSB) can be loaded by the software. As the descriptions are loaded they are converted to an internal format. At the time of sawing a second conversion is performed in order to speed up the performance of the actual breakdown. The second conversion is linked to the rotation of the log. Whenever the log rotation is altered the conversion is recalculated. Internally full 3D representation of log and boards are maintained allowing for realistic graphical views on a computer screen. The dimensions used to describe the geometries are x, y and z were z is the longitudinal direction with butt-end at $z = 0$ and top-end oriented in positive direction with z = log length. Radial extent of log is placed in the first quadrant so that x and y are positive.

Accessing the SPSB

At program start a predefined directory is scanned for log descriptions. The path of the directory is stored in program registry
"HK_CURRENT_USER\Software\SveaskogUrbanNordmark\Ldb_Vsm\Path".
A subdirectory found which name consists of digits is considered to represent a plot (stand) with trees (Fig. 2). The number extracted becomes the plot number. In the next step each plot subdirectory is scanned for log geometry files, that is files with name *"*yt.txt"*. From name of each file found, tree number and log number are extracted from positions T and L in filename *"PPPPTLyt.txt"*. Internal to the software a database of numbers of Plots, Trees and Logs is built. The numbers are used to retrieve the full path to a log geometry file when a log is selected through the interface. When a log geometry file is to be loaded a scan for corresponding knot description file is performed (*PPPPTLkv.txt*) which is loaded if found. Descriptions following the SPSB format can be added or removed from the directory structure and this will be reflected in the program at start up. Aside from the automatic procedure described, any SPSB formatted log description can be loaded through scripts by passing the full path name.

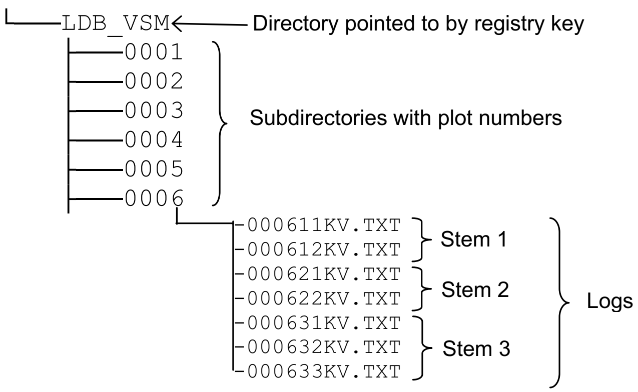


Fig. 2. *Directory structure of SPSB.*

Reading log descriptions

The file format used for storing log geometry descriptions is a variant of the TIFF image standard. The SPSB was originally compiled on a Macintosh computer system. As Motorola processors (Mac) and Intel (PC) have different byte order the program checks whether byte swapping is necessary. Important data in the header are image scale and image length. Image data start at byte 768. There are two images in a file. First image represents heart wood border and second image following immediately after represents log surface. The image width is 364 pixels.

Each row in an image represents a cross-section of the log. First row should be butt-end of log. The longitudinal distance between cross-sections is 10 mm. The 360 first pixels (bytes) of a row give the radius from pith to surface or heart wood border at angles 0-359. Bytes 360 and 361 gives the coordinates of pith (*x, y*). Byte values extracted (0-255) is converted to mm by the scale factor given by (*ImageScale* /256). Image scale varies between 350 mm to 450 mm per 256 pixels. *ImageScale* is stored as a 2 byte integer starting at byte 424 in the header. The polar coordinates are converted to *x*- and *y*- coordinates (Fig. 3). After a complete log has been read the log is repositioned in 3D space so that pith at both log ends is centred at coordinates (500, 500). Fig. 4 give a view of a log-end cross-section.

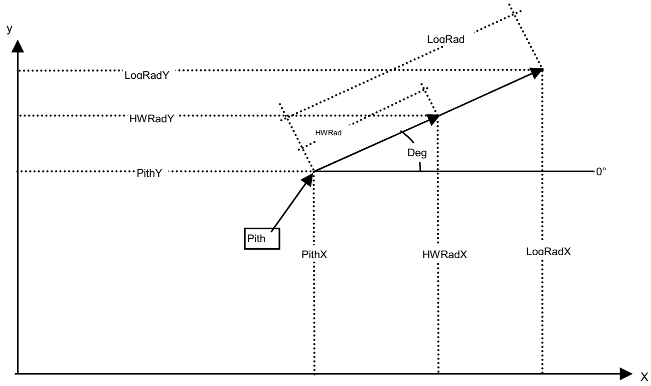


Fig. 3. *Cross-section of log is represented with polar coordinates of heart wood radius (*HWRad*) and surface radius (*LogRad*) originating from pith. Coordinates are converted to rectangular coordinates.*

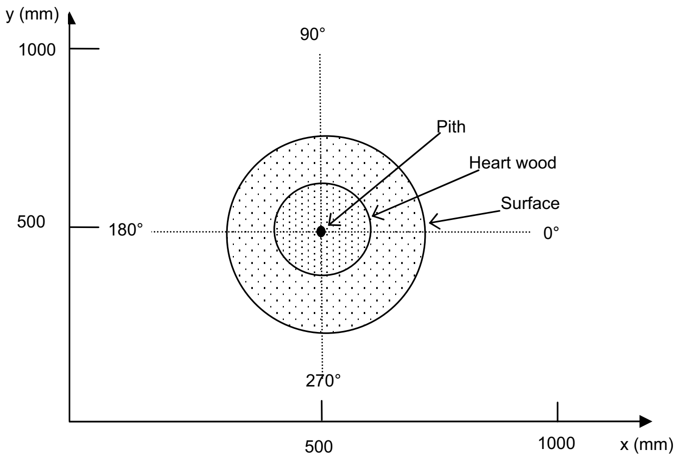


Fig. 4. *Representation of cross-section of log, viewed from top-end towards butt-end. Log is fitted within a 1000 mm x 1000 mm coordinate system and translated so that pith at both log ends is positioned at (500, 500).*

Loading a stem

Logs originating from the same tree can be assembled to a stem. The order logs are connected to each other is given by their log numbers. As each read log is translated so that the pith at each end is located at (500,500) it is simply a matter of adding the cross-sections of every read log to a common array holding the stem.

Cutting a log or a stem

A log can be cut shorter. Cutting is specified by setting a start variable and a stop variable with the positions where the segment is located within the original log. The original log is maintained in memory allowing for elongating or restoring a log that previously has been cut. A cut log is processed further by sawing machines as if the cut-off at each end doesn't exist.

Geometric properties

Area

The area of a cross-section is given by Eq. [1].

$$A = \frac{\pi}{360}\sum_{i=0}^{359} r_i^2 \qquad (1)$$

where:

A = area (mm2)
i = angle
r = radius (mm)

Center of gravity (Cg)

Coordinates of centre of gravity are calculated by Eqs. [2, 3].

$$CgX = \frac{\sum_{i=0}^{359} r_i^2 x_i}{\sum_{i=0}^{359} r_i^2} \qquad (2) \qquad\qquad CgY = \frac{\sum_{i=0}^{359} r_i^2 y_i}{\sum_{i=0}^{359} r_i^2} \qquad (3)$$

where:

CgX = x coordinate of centre of gravity
CgY = x coordinate of centre of gravity
x = x coordinate of radius
y = y coordinate of radius

Diameters

At a cross-section three measures of diameters are derived. *EqDiam* is the diameter of a circle with an area equal to the area of the cross-section. *MinDiam* is the minimum shadow diameter found. *CrossDiam* is the diameter in a given direction. At log level a *SortDiam* is calculated to be used when automatic selection of sawing patterns is enabled.

$$EqDiam = 2 \cdot \sqrt{\frac{A}{\pi}} \qquad (4)$$

The *CrossDiam* is the maximum diameter in a specified direction (*Angle*). The measure corresponds to the shadow diameter in direction *Angle* +90°. An algorithm searches the two opposite sectors specified by *Angle* ±46° and *Angle*+180 ±46°, Fig. 5. The search step is 2°. Diameter is calculated as **max***(d1)*+**max***(d2)* with Eqs. [5-7]

$$d1_i = Cos(v_i) \cdot r_i \qquad (5)$$

$$d2_i = Cos(v_i + 180) \cdot r_{i+180} \qquad (6)$$

$$CrossDiam = \mathbf{max}\, d1_i + \mathbf{max}\, d2_i \qquad (7)$$

where:

$i =$ direction ±46°

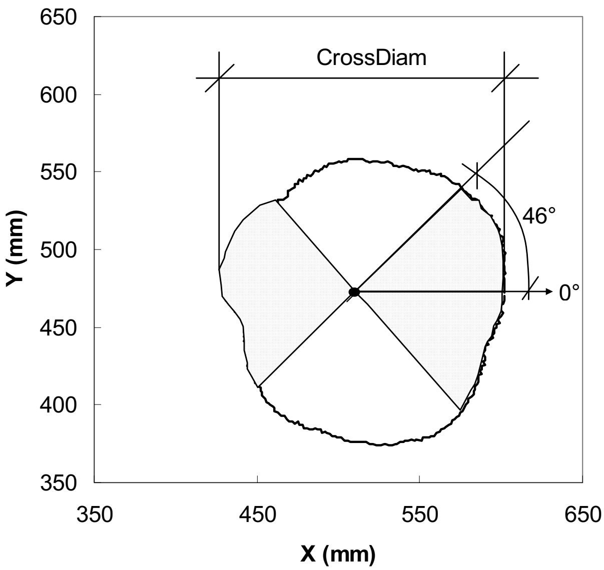


Fig. 5. *Illustration of the CrossDiam measure. Example with search for the maximum extension in direction 0°. Search is done within shadowed areas.*

The *MinDiam* is searched for using the algorithm for *CrossDiam*. Search is performed by passing directions 0°-170° with 10° increment to function *CrossDiam*.

SortDiam is the measure of log small-end diameter used for finding sawing patterns when automatic selection of sawing patterns is enabled. The *SortDiam* is the average *EqDiam* of cross-sections at positions 150mm to 50 mm from log top-end.

Log volume

An array of accumulated log volume is built from butt-end upwards. The increment in volume is given by slice area multiplied with the stem length it represents. With SPSB the stem length increment is 10 mm. The volume of a stem segment anywhere within log butt-end and top-end is then given by Eq. [8].

$$V_{segment} = V_{stop} - V_{start} \qquad (8)$$

where :

$V_{segment}$ = volume of log section
V_{stop} = accumulated volume at top-end of log section
V_{start} = accumulated volume at butt-end of log section

Knot properties in log

In SPSB properties of knots are stored in text files in same directories as their corresponding log geometry descriptions. A knot is described by 11 parameters, (A-K). Figs. 6 and 7 illustrate the notation used in the following equations. The knot angle in radians in tangential direction at the distance r_p pixels from the pith is given by Eq. [9]. Knowing the scale in the original CT images, the diameter of the knot in mm can be calculated. The rotation of the knot axis is given in degrees by Eq. [10], and the longitudinal position within the log is given in cm by Eq. [11]. In the SPSB, parameters *E* and *F* are used to describe the knot diameter in the longitudinal direction. Because the resolution is 10 mm between the CT images, the longitudinal knot diameter is better approximated using Eq. [9] with the assumption that the knot cross-section is circular. Hence, the *E* and *F* parameters are not used here. Parameter *I* is the distance in mm from the pith to the end of the knot. Parameter *J* is the distance in mm from the pith to the dead knot border. Parameter *K* is distance from pith to the outer face of the log at the point where the knot axis intersects the outer face. For a nonoccluded knot, *K* = *I*.

$$\varnothing_P = 2 \cdot \left(A + B(r_P)^{1/4}\right) \qquad (9)$$

$$\Omega_p = C + D \ln(r_p) \qquad (10)$$

$$Z = G + H\sqrt{r_p} \qquad (11)$$

Eq. [9] has been reported with out the coefficient 2 in some papers. Thus giving half the angle $\varnothing_P$.

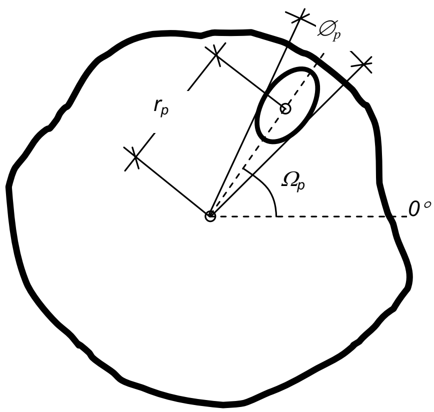


Fig. 6. *Knot geometry notation, projection to a cross-section*

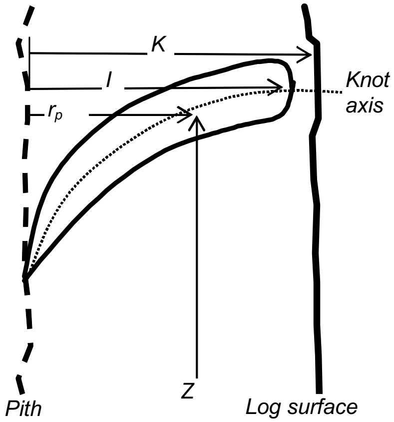


Fig. 7. Knot geometry notation, projection to a radial section.

The functions are converted so they take radial distance in mm instead of pixels. The conversions are given in Eqs. [12-17].

$$a = 2 \cdot A \quad (12)$$

$$b = (2 \cdot B) \cdot Scale^{-\frac{1}{4}} \quad (13)$$

$$c = C - D \cdot \mathbf{ln}(Scale) \quad (14)$$

$$d = D \quad (15)$$

$$g = G \quad (16)$$

$$h = H \cdot Scale^{-\frac{1}{2}} \quad (17)$$

Then the functions become

$$Diam = r_{mm} \cdot \left(a + b \cdot r_{mm}^{\frac{1}{4}} \right) \quad (18)$$

$$Height = 10 \cdot \left(g + h \cdot r_{mm}^{\frac{1}{2}} \right) \quad (19)$$

$$Rotation = c + d \cdot \mathbf{ln}(r_{mm}) \quad (20)$$

As the measures of a knot all originate from the pith, coordinates of pith are stored with every knot. The algorithm for searching if a knot is intersected by a board surface is based on the position of the knot axis. A structure holding the coordinates of knot axis is set at the time of sawing. First the pith is rotated along with the log. Then the rotated coordinates of knot axis at positions 1 mm to knot end (*l*) is calculated.

$$KnotAxis[r_{mm}]\ \begin{array}{l}.x\\ .y\\ .z]\end{array}$$

Log crook

The log crook is of importance when curve sawing is enabled. There are two aspects of the crook handled by the program. First, the direction of the crook, i. e. the radial angle, is used to set the log in rotational position "Crook up". Second, the crook is approximated to a curve function which determines the saw lines in the second saw when curve sawing.

Direction of crook

Direction of crook is measured at the point along the log where the centre of gravity (*Cg*) of cross-sections has its maximum deviation from a straight line through the log. Fix point coordinates of the straight line is calculated as the average *Cg* of a section at the top-end of the log and of a section at butt-end. At the log's top-end the section is 300 mm long and positioned from log small-end and 300 mm towards butt-end. At the log's butt-end the section is 300 mm and positioned between 500 mm to 800 mm from butt-end. Maximum bow height is searched for between the fix points (longitudinal positions 650 mm to (log length-150 mm)). Search is done at positions with an interval of 100 mm. At every position a filtered value of *Cg* is calculated as the average of a 100 mm long section of the log. Deviation of *Cg* from reference line is calculated in both *X*-plane (*dX*) and *Y*-plane (*dY*) respectively. Bow height is calculated as the Euclidian distance of *Cg* to reference line. Fig. 8 provide an example of the search for maximum bow height. At the position of maximum bow-height the direction of the crook is given by the arctangent of *dX*/*dY*.

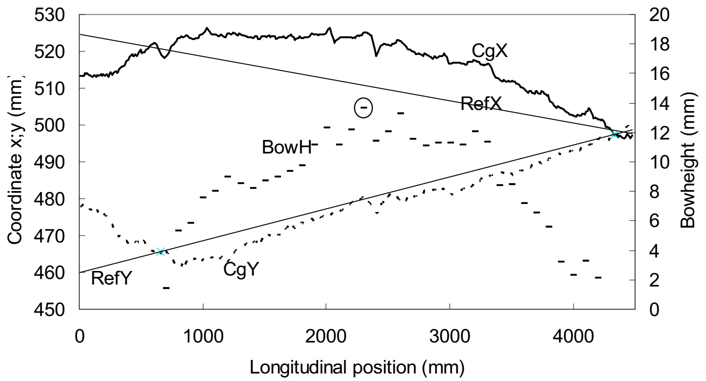


Fig. 8. *Search for maximum (denoted by a circle) bow height (BowH). Bow height is calculated as the Euclidian distance of Center of gravity (CgX and CgY) to the reference line (RefX and RefY). Example with log 1,1,1 from SPSB.*

Curve function

When curve sawing is enabled the saw blades follows a curve given by a second degree polynomial function. Eq. [21] and Fig. 9. The equation is set by the use of multiple regression on the center of gravity of cross-sections along the log. The regression is handled by an underlying matrix class. The interval of positions used for regression follows the *Z-resolution* set on the log (defaults to 100 mm). When sawing the saw blades follow the curve given by the equation but the curve may be displaced by the settings of the log centring units.

$$f(x) = \beta_0 + \beta_1 x + \beta_1 x^2 \qquad (21)$$

where:

$f(x)$ = coordinate
x = longitudinal position (mm)

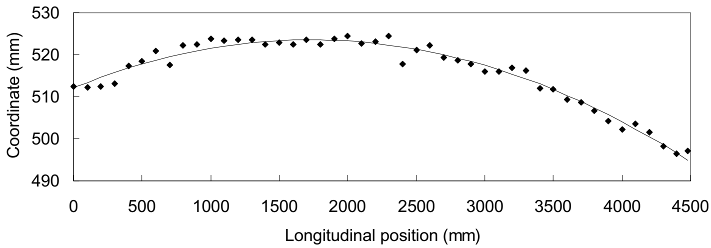


Fig. 9. *Regression line of centre of gravity at longitudinal positions within log. Example with log 1,1,1 from SPSB and rotated crook upwards.*

SAWING

Primary breakdown is controlled individually at first saw and second saw. Settings that affect the geometric aspects of the results are breakdown pattern, saw allowance, shrinkage allowance, kerf and log positioning. Furthermore the log can be either straight sawn or curve sawn in second saw.

Positioning of log

Log is positioned prior to sawing. The positioning determines where the kerfs are placed through the log. Positioning is controlled by centring units, two at first saw and two at second saw. A centring unit is placed at a given distance from the top-end of the log. With two centering units at different distances a straight line equation through the log is derived, Fig. 10. The centre of the current sawing pattern then follows this line.

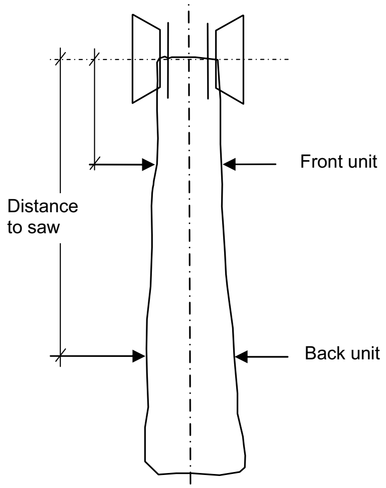


Fig. 10. *Geometry of log centring setup. Log is individually centered at first saw and second saw respectively.*

When a centring unit is set to 0 (zero) the saw line centre passes the centre of the log at the longitudinal position where the unit is placed. Offset at a unit is given in mm. By setting both units to same value the log can be parallel displaced while keeping the front unit setting fixed the log butt-end can be skewed by changing the back unit settings. The centred position at a unit is measured at the one log cross-section closest to the unit. Centre is the coordinate in the mid of minimum and maximum extension of cross-section in the considered dimension (*X* or *Y*), Fig. 11.

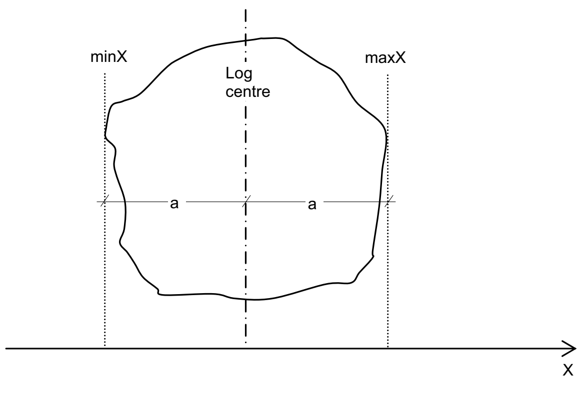


Fig. 11. *Principle of determining the centre position of a log cross-section at first saw.*

Internally in the software the log is fixed and the sawing centre line is fitted to the coordinates of the log. When straight sawing in second saw, the principle of centring is the same as in first saw. When curve sawing the log in second saw, the curved sawing centre line passes centring units at offsets given by the settings at each unit, Fig. 12.

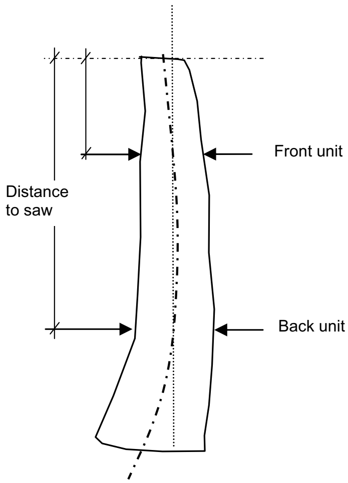


Fig. 12. *Principle of curve sawing at second saw. The curve crosses the straight log centre line at centering units when the offset is set to 0.*

Secondary conversion of log representation

Prior to breakdown the log data are converted to a rotated representation of the log. This conversion is recomputed whenever log rotation has changed or the log otherwise has been altered. The new data are stored in two structures *pX* and *pY*. *pX[zPos]* references a processed cross-section at *zPos* mm. These cross-sections hold the following data:

.Pos[]	array of high/low values
.Height	height of cross-section within log (mm)
.Cg	coordinates of centre of gravity (mm)
.start	first index of high/low array
.stop	last index of high/low array

The *.Pos[xPos]* array gives the lower and upper y-coordinates of log surface at position *xPos* from *xPos = start* to *xPos = stop*.

In Fig. 13 examples of values contained in *.Pos[]* are shown together with a board. The wane at the corner outside log can be calculated as with Eqs. [22, 23]

$$Wane_{depth} = 590 - pX[zPos].Pos[595].high \qquad (22)$$

$$Wane_{width} = 595 - pY[zPos].Pos[590].high \qquad (23)$$

With the example wane depth is 11.6 mm and wane width is 32.0 mm. Such calculations are very fast as they require few computer operations. The example shown is the essence of the break down calculations used. In order to avoid testing for all possible combinations of interrelations between board coordinates and log structure some heuristics are used.

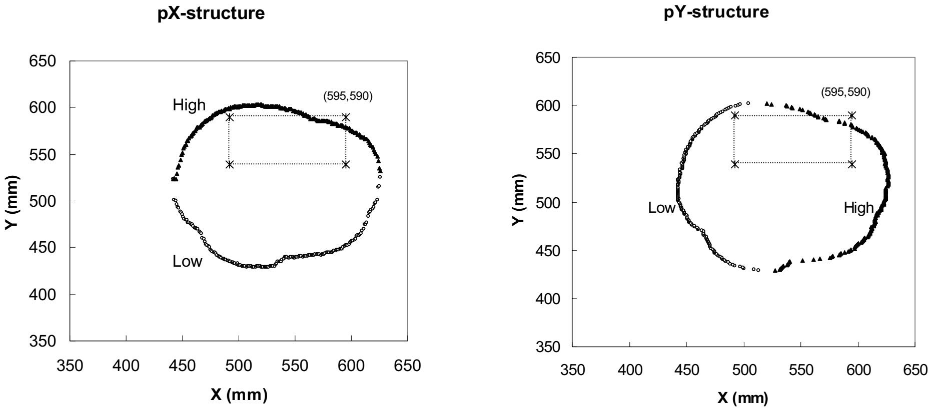


Fig. 13. *Representation of cross-section by structures pX (left) and pY (right) after rotation and conversion. Referencing pX by an x-position the lower (low) and upper (high) extension of log is given in y-coordinates. pY works in analogy, referencing by y-positions gives extension of log in x. Example with cross-section no. 62 of log 1,1,1 from SPSB. The position of a 50x100 centre board is also shown.*

Breakdown

The actual breakdown proceeds after the second conversion of log geometry previously described. Conceptually the process is a sequence of operations. At first saw the log is divided into side boards and a cant. The cant is then rotated 90° and passed to the second saw where the cant is divided into side boards and centre boards. Side boards from first and second saw are edged. Finally all boards are trimmed.

First saw (CantSaw) and second saw (DealSaw)

A sawing pattern chosen for break down of a log specifies the nominal widths of the cuts at the saw. The actual cutting dimensions are calculated using variables *SawAllowance* and *ShrinkAllowance*, Eq. [24]. The kerf width is given by the variable *SawBladeWidth*.

$$CW_{raw} = Sa + Sh \cdot CW_{nom} \qquad (24)$$

where:

CW_{nom} = nominal cut width (mm)
CW_{raw} = raw cut width (mm)
Sa = saw allowance (mm)
Sh = shrink allowance

Following the procedure of log centring, the positions of cutting lines at each cross-section are calculated. At first saw a cutting line through a cross-section is defined by an x-coordinate while at second saw a cutting line is defined by a y-coordinate. Faces produced by the cuts are stored in a *BoardSide* structure. Variables of the *BoardSide* are:

.*Width*	nominal width of face, on side boards this is set when edging (mm)
.*RawWidth*	green target size (mm)
Normal	orientation of face in 3D (x,y,z)
.*SideProfile*[]	array of 1D-profiles

The *Normal* in *BoardSide* gives the key on which dimension in space is considered in the *SideProfile* structure. The data within *SideProfile* define start and stop coordinates in mm for different features. Start corresponds to left point when viewed from top-end and with face upwards.

.height	zPosition within log
.cutPos	position of face,
.target_start	targeted start position
.target_stop	targeted end position
.wane_start	start position the board (left)
.wane_stop	end position board (right)
.face_start	start position of sawn surface (left)
.face_stop	stop position of sawn surface (right)

In Fig. 14 is illustrated how the array of *.SideProfile[]* builds the outside face of an edged side board. In Fig. 15 the relation of a single *SideProfile* to the log is illustrated

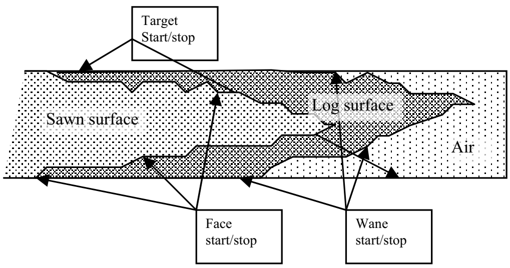


Fig. 14.*. Representation board side. Board side is built up by an array of 1D-profiles which define start and stop coordinates of sawn surface, log surface and targets.*

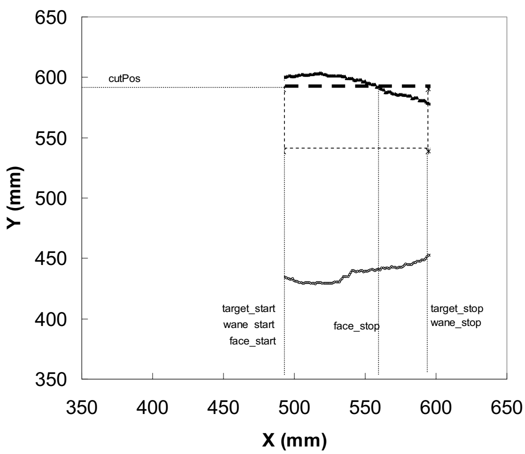


Fig. 15. *Cutting line at y = 590 on cant at cross-section no. 62, log 1,1,1 from the SPSB. The* SideProfile *of the outlined board's outside is shown. Normal (x,y,z) of board side is (0,1,0).*

The process of sawing at first and second saw is accomplished by grouping four board sides together to form a board and setting the values on their *SideProfiles*. Side boards have incomplete data until they have been edged.

Setting knots on board

The algorithm used for detecting if a knot in the log is intersected by the cutting plane of a board side is based on the 3D coordinates of the knot axis and the *SideProfiles* of the board's four sides. At the outermost loop the algorithms iterates over the knots of the log. For a given log knot the algorithm iterates over the knot's radial distance (r_{mm}) from 1 mm to knot end (I) retrieving 3D-coordinates (x,y,z) of the knot axis. Next step is to iterate over the boards' four sides retrieving the *SideProfile* given by z. The Normal of board side is used to determine which dimension of knot axis is to be used to check whether there might be an intersection. If $Normal.y \neq 0$ then *KnotAxis.y* is compared to *cutPos* of *SideProfile* and if y is within 3 mm from the cutting plane we might have an intersection. Next step is to check if *KnotAxis.x* ± *knot diameter/2* is within *face_start* and *face_stop* and if so we have a knot on the board face. At the point of intersection the knot is assumed cylindrical with diameter given by Eq. [18] (D_{knot}) and oriented in the direction of knot axis, Fig. 16. With notations as in Fig. 17, Eqs. [25-30] are used to set the properties of a board knot. The value of r at the intersection in relation to knot parameter J determines if the knot is marked as sound or dead.

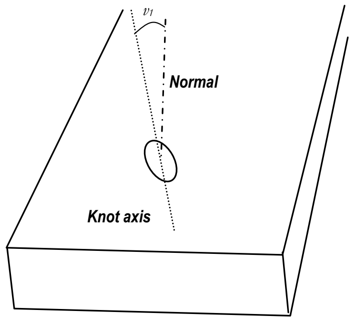


Fig. 16. *Cylindrical diameter of knot at point of intersection is projected to board face.*

$$v_1 = \frac{\pi}{2} - \left|\mathbf{arctan}\left(\frac{dx}{xz}\right)\right| \qquad (25)$$

where:

v_1 = angle of knot axis to *Normal* of board side
dx = difference of x_{r-1} and x_{r+1} at intersection
xz = Euclidian distance of dx and dz

$$v_2 = \frac{\pi}{2} + \mathbf{arctan}\left(\frac{dz}{dx}\right) \qquad (26)$$

where:

v_2 = rotational angle of knot axis
dz = difference of z_{r-1} and z_{r+1} at intersection

$$D_{long} = D_{knot}\left(1 + \frac{|\cos(v_2)|}{\cos(v_1)} - |\cos(v_2)|\right) \qquad (27)$$

$$D_{tang} = D_{knot}\left(1 + \frac{|\sin(v_2)|}{\cos(v_1)} - |\sin(v_2)|\right) \qquad (28)$$

$$D_{minor} = D_{knot} \qquad (29)$$

$$D_{major} = \frac{D_{knot}}{\cos(v_1)} \qquad (30)$$

where:

D_{knot} = diameter of knot in log from Eq. [18]
D_{long} = diameter in longitudinal direction
D_{tang} = diameter in tangential direction
D_{minor} = minor axis of ellipse
D_{major} = major axis of ellipse

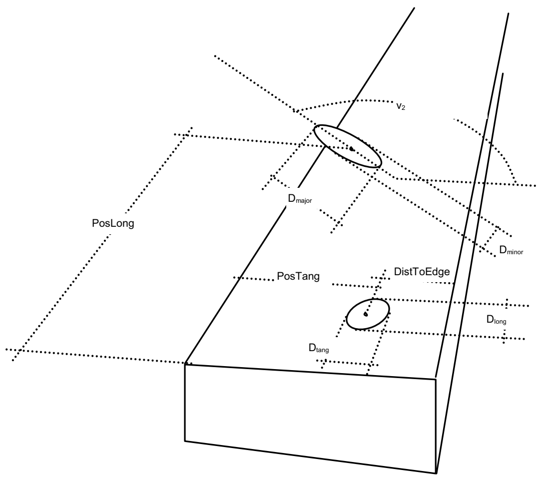


Fig. 17. *Notations used when calculating knot diameters.*

Afterwards the knot type is classified following the Nordic Timber Grading rules and the diameter used for grading is set (Table 1).

Table 1. *Knot types and corresponding diameters.*

Index	Type	Criteria	Diam
1	Round	Default	$(D_{minor} + D_{major})/2$
2	Spike	$D_{major}/D_{minor} \geq 3$	$(D_{minor} + D_{major})/6$
3	Splay	Knot axis outside of sawn surface	$(D_{minor} + D_{major})/3$
4	Edge	Knot on edge side	D_{tang}

The calculated diameter is finally reduced with the part of the knot that is outside the sawn surface (Splay and Edge knots).

Edging

Edging of side boards is value optimized. It is not truly optimizing but evaluates a number of edging solutions and selects the one giving the highest value. The edging patterns are built upon a straight line through a butt-end point and a top-end point on the board's outer face. These points are located at each end of the longest continuous sawn surface area but not closer to butt-end than 200 mm and not closer to top-end than 1000 mm. The points are positioned at the centre of the tangential profiles' sawn surface. At the outermost loop, the position of the top-end point is varied sideways between -*MaxOffset* mm to +*MaxOffset* mm with *Step* mm increments. An inside loop varies the butt-end position in analogy. At each combination of end points an inner loop is evaluating possible cut widths centred by the end points. Each width cut is evaluated by a combined trimming and grading module. At the module wane and knots on the outer face are considered while knots on the prospective edges are not as these are considered hidden until the actual edging. The resulting values from all positions and widths are compared and the setting predicting the highest value is chosen. Finally the edged board is passed to the trimming and grading stations and this time knots on all sides are considered. Thus, the final length and grade may deviate from the predictions made when evaluating edging patterns. In Table 2 edging patterns are evaluated on a side board with *MaxOffset* = 10 mm and *Step* = 10 mm. In Fig. 18 the profile of the board is shown together with the best solution.

Table 2*. Evaluation of edging patterns on a side board. Best solution is indicated by bold text.*

Offset top (mm)	Offset butt (mm)	Width (mm)	Length (mm)	Value (SEK)	Grade
-10	-10	75	2100	8.98	A
-10	-10	100	0	0.00	OffG
-10	0	75	2100	8.98	A
-10	0	100	0	0.00	OffG
-10	10	75	2100	8.98	A
-10	10	100	0	0.00	OffG
0	-10	75	2400	10.26	A
0	-10	100	0	0.00	OffG
0	0	75	2700	11.54	A
0	0	100	0	0.00	OffG
0	**10**	**75**	**3600**	**15.39**	**A**
0	10	100	0	0.00	OffG
10	-10	75	2700	11.54	A
10	-10	100	1800	4.79	B
10	0	75	2700	11.54	A
10	0	100	0	0.00	OffG
10	10	75	1800	7.70	A
10	10	100	0	0.00	OffG

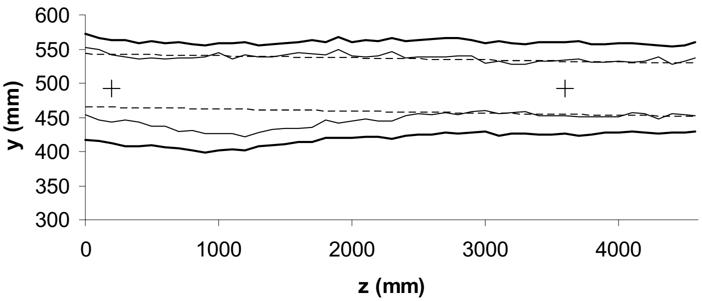


Fig. 18. *Outer face as made up of the array of* SideProfile. *Thick solid lines are* wane_start *and* wane_stop *Thin solid lines are* face_start *and* face_stop. *Dashed lines are the best edging solution from table 2. Plus signs are the end-points from which possible edging patterns are built.*

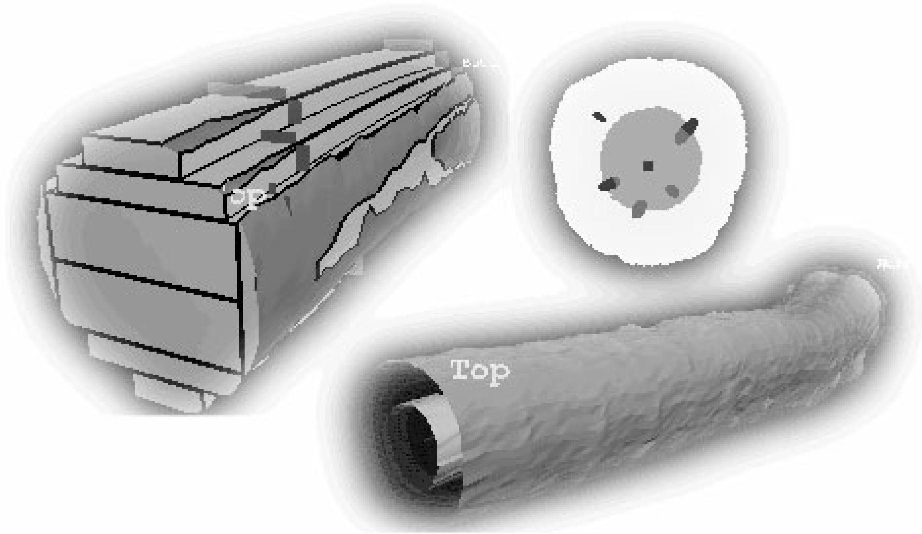
Trimming

The trimming and grading of boards is value optimized. At each end of board there is a minimum trimming. Between these points the algorithm finds the product specified by thickness, width, length and grade that yields the highest value. There is a *Step* parameter (default 10 mm) controlling the discretation of possible cuts investigated. The first step is to pre-process the quality features into bitfields for fast searching of the best alternative. A quality feature at a given longitudinal position is defined by a 32 bit integer (*Q*). A set bit in *Q* indicates the quality the board holds at that longitudinal position and the position of the set bit gives the quality index corresponding to the quality definition file. E.g. board holds quality 2 and 3 at a specific position.

Then the *Q* becomes $2^2 + 2^3 = 12$ and binary 0100 **OR** 1100 = 1100. *Q* = 30 indicates that qualities 1-4 are applicable. The used system limits the maximum number of qualities to 32.

For each board side, an array of *knotSizeQ* is set for knot size and an array of *waneSizeQ* is set for wane size. Next procedure is an **AND** operation at every longitudinal position on *knotSizeQ* and *waneSizeQ* with all board sides into a common *boardQ*. Along with this *boardQ* array, an array is set holding the longitudinal distance where the board has same quality. The other features considered are knot sum and wane length. Knot sum is knot diameters summed over 1000 mm board length. First an array of accumulated knot sums is prepared from butt-end to top-end of board on all sides. From this an array of *knotSumQ* is built on every board side starting at butt-end +1000 mm and ending at top-end. The arrays of the four sided then are **AND**:ed together into an array giving *knotSumQ* of the board at different positions. The wane length is preprocessed into an array of accumulated lengths. If wane at a given longitudinal position is larger than 3 mm then a length equal to the *Step* is added. Finally the best cutting alternative is searched for by evaluating all possible cuts defined by board lengths given by price list. The search starts at the stage from butt-end given by minimum board length found in price list + minimum trimming. Stage is incremented in steps defined by *Step* parameter. At a stage possible products with the current board's thickness and width are evaluated. Products are laid out from stage towards butt-end. If quality of a product is consistent with the quality of the board segment the value is calculated. At evaluation knot sum and wane length are also considered. The cut giving the product with highest value is finally chosen for trimming. Is should also be noted that the Nordic Timber Grading rules allow the inside face to be one grade worse than the other sides. This is accounted for by a one bit right shift of *Q* at inside prior to the **AND** operations building the *boardQ*.

Appendix D



Urban Nordmark

2004-10-25

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INTRODUCTION

The sawmill simulation software Saw2003 hosts a VBS-engine (Visual Basic Script) which means that any VB-script can be loaded to and run by Saw2003. Furthermore, the software in it self exposes a lot of its functionality to VBS. Taken together, any user can compile a script for automating sawing simulations, without having to recompile the actual C++ source code, and run it through the software.
A complete manual for VBS standard functionality can be downloaded from Microsoft. Search for **scrdoc56en.exe**. Additionally, the Windows script components must be installed on the computer, file **scripten.exe**. However, this file is installed as an integrated part of Internet Explorer. It is also very helpful to have the script debugging facilities installed, **ie401dbg.exe**. All files can be found at
http://msdn.microsoft.com/library/default.asp?url=/downloads/list/webdev.asp for download.

CLASS DESCRIPTIONS

Properties, methods and functions of all classes are listed in alphabetical order. Note that the class name can differ from the name of an instance.

Properties

Properties are described by its type and assignment. Types are *int* for integer, *double* for floating point variables, *string* for text and *obj* for objects (classes). Assignment is either R, or L and R. R means that the property can be on the Right side of an assignment, i. e. the variable can be read. L means that the property can be on the Left side of an assignment, i. e. the variable can be set.

Methods

A method performs some action but do not return a value. The methods can take arguments. In the listing arguments are prefixed with *int_*, *dbl_* or *str_* indicating the type. Where there are ambiguities on the scale, arguments are postfixed with the units e.g. *_mm* for millimetre. Arguments in a method is never enclosed with parentheses, e. g. `SawMill.Log.CutLog 0, 3550`.

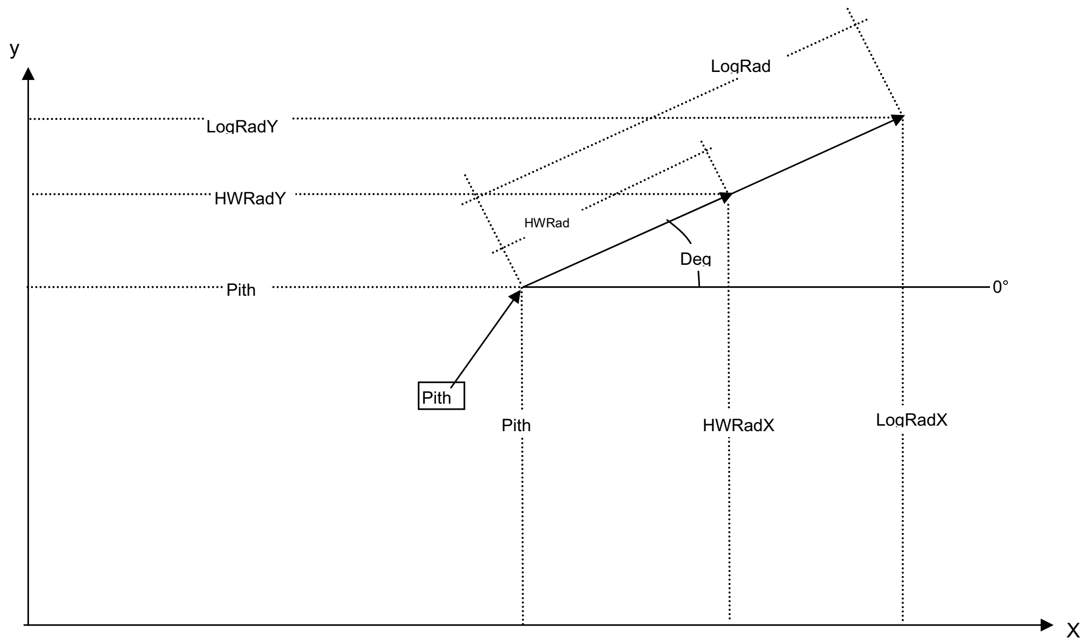
Functions

Function are similar to methods but returns a value. The arguments of a function must be enclosed within parentheses whenever the returned value is used. Whenever the return value is not used the function acts as a method and should not have parentheses, e.g.

`SawMill.Log.Load 3, 1, 2`	Load log but do not check return value
`If SawMill.Log.Load(3, 1, 2) Then` …	Load log and check return value

Angle

A slice is described of 360 Angles. Each *Angle* holds the extension of the log in the given direction and with the pith as origin.



Instances `SawMill.Log.Slice().Angle()`

Angle

Properties	**Type**	**Assign.**	**Description**	**Example**
`Deg`	*int*	R	Degrees	
`HWRad`	*double*	R	Radius in mm of heart wood	
`HWRadX`	*double*	R	X-coordinate of heart wood	
`HWRadY`	*double*	R	Y-coordinate of heart wood	
`LogRad`	*double*	R	Radius in mm of log surface	
`LogRadX`	*double*	R	X-coordinate of log surface	
`LogRadY`	*double*	R	Y-coordinate of log surface	

Board

A *Board* resulting from sawing a log.

Instances `SawMill.Products.CantBoard()`
`SawMill.Products.DealBoard()`

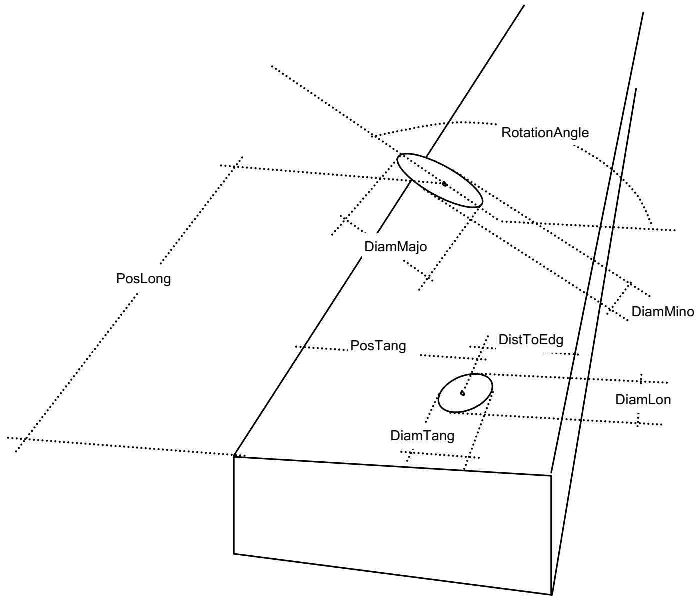
Board **Properties**	**Type**	**Assign.**	**Description**	**Example**
`InSide`	*obj BoardSide*	R	Pith side of board	`set boardSide = Products.CantBoard(0).InSide` boardSide now references pith side of first board from first saw
`LeftEdge`	*obj BoardSide*	R	Left edge when viewed from top end and with sap wood side facing up	`nProfiles = Board.LeftEdge.ProfileCount` Get the number of profiles (geometry) of boards left edge
`Length`	*double*	R	Length prior to trimming (mm)	`cutOff = Board.Length – Board.TrimmedLength` Total length trimmed off
`MC`	*int*	L,R	Moisture content of board. Defaults to 18%. To be used with cost assessments	`Board.MC = 12` Moisture content of board now set to 12%
`OutSide`	*obj BoardSide*	R	Sap wood side of board	
`RawThickness`	*double*	R	Thickness raw measure (mm)	
`RawWidth`	*double*	R	Width raw measure (mm)	

`RawVolume`	*double*	R	Volume raw	
`RightEdge`	*obj BoardSide*	R	Right edge when viewed from top end and with sap wood side facing up	
`SheetName`	*string*	R	Name of price sheet (product name)	`qual = Board.SheetName` qual now holds the product name of the board
`Thickness`	*double*	R	Board thickness (mm)	`thick = Board.Thickness`
`TrimmedLength`	*int*	R	Length of trimmed board (mm)	`txt = txt & "Length=" & Board.TrimmedLength` Add board length to string txt
`Type`	*string*	R	Board type. "s" if side board, "c" if centre board	`If brd.Type == "s" Then Edger.Edge brd` If board is a side board then edge it
`Value`	*double*	R	Board value (SEK)	`totValue = totValue + brd.Value` Add board value to totValue
`Width`	*double*	R	Board width (mm)	`txt = "Width=" & Board.Width` Write width to string txt
`Volume`	*double*	R	Board volume (m^3)	`txt = txt & "Volume=" & Board.Volume` Add board volume to string txt

BoardKnot

BoardKnot is the description of a knot on a BoardSide.

Instances `.OutSide.Knot()`
`.InSide.Knot()`
`.LeftEdge.Knot()`
`.RightEdge.Knot()`



BoardKnot

Properties	Type	Assign.	Description	Example
Diam	*double*	R	Knot diameter as used for grading	
DiamLong	*double*	R	Knot size in longitudinal direction	
DiamMajor	*double*	R	Major axis in mm	
DiamMinor	*double*	R	Minor axis in mm	
DistToEdge	*double*	R	Knot pith's distance to nearest edge	
DiamTang	*double*	R	Knot size in tangential direction	
PlaneAngle	*double*	R	Inclination of knot axis to board plane	
PosLong	*double*	R	Position in longitudinal direction. Butt end = 0.	
PosTang	*double*	R	Position in tangential direction. Left start of face = 0.	
PosX	*double*	R	Coordinate of knot pith in 3D space	
PosY	*double*	R	Coordinate of knot pith in 3D space	
PosZ	*double*	R	Coordinate of knot pith in 3D space	
RotationAngle	*double*	R	Orientation of major knot axis	
Sound	*Boolean*		Boolean. True if sound knot.	
Type	*int*	R	Type of knot 0 = not defined 1 = round 2 = spike 3 = splay 4 = arris	

BoardSide

Side of a board, can be *OutSide*, *InSide* or *LeftEdge*, *RightEdge*.

Instances

```
SawMill.Products.CantBoard()/.Products.DealBoard()
.OutSide
.InSide
.LeftEdge
.RightEdge
```

BoardSide **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Knot(int_index)`	*obj BoardKnot*	R	Get a BoardKnot	`kn = Knot(0)` Get the first BoardKnot on side
`KnotCount`	*int*	R	Number of knots on board side	`knNr = KnotCount` knNr is the number of knots on board side
`Name`	*string*	R	Name of board side	`name = Board.InSide.Name` name is now "InSide"

`Profile(index)`	*obj SideProfile*	R	Get a SideProfile	`set sp =`
				`  Board.InSide.Profile(1)`
				Gets the 2:nd SideProfile

`ProfileCount`	*int*	R	Number of SideProfiles	`For spNr = 0 To Board.LeftEdge`
				`  .ProfileCount-1`
				` sp=Board.LeftEdge`
				` .Profile(spNr)`
				`Next`
				Iterate through all SideProfiles of LeftEdge

BuckLog

The *BuckLog* class represents logs resulting from simulated bucking of a stem by a harvester.

Instances `BuckStation.BuckLog()`

Class Properties	Type	Assign.	Description	Example
`DiamButt`	*int*	R	Butt end diameter (mm)	
`DiamClass`	*int*	R	The diameter class in the log price list matching the log	
`DiamMid`	*int*	R	Diameter of log at middle position (mm)	
`DiamTop`	*int*	R	Diameter of log at top position (mm)	
`Length`	*int*	R	Length of log (mm)	
`LengthClass`	*int*	R	The length class in the log price list matching the log	
`Sort`	*string*	R	Name of the assortment as given in log price list	
`SumValue`	*double*	R	Value sum of all logs up to and including this	
`TopPos`	*int*	R	Position of top end within stem	
`TopVolume`	*double*	R	Volume by top measure if basis for pricing ($m^3$to)	
`Volume`	double	R	Solid volume of log (m3fub)	

BuckStation

The *BuckStation* class simulates bucking by a harvester. That is: Bucking rules are defined by a log price list following the StanForD description for Apt-files, Stem is considered 2-Dimensional (diameters and length).

Instances `BuckStation`

BuckStation

Properties	Type	Assign.	Description	Example
`BuckLog(int_index)`	*obj BuckLog*	R	Retrieve a BuckLog object	
`BuckLogsCount`	*int*	R	Gets number of BuckLogs resulting from a call to Buck(stem)	
`Discretation`	*int*	L,R	Resolution of cut positions (mm)	
`OK`	*Boolean*	R	Boolean. True if a StanForD apt-file is loaded	
`SDev`	*double*	L,R	The standard deviation of random errors on stem's diameter	
Methods				
`Buck(obj_stem)`			Bucks the given stem	
Functions	**Return type**			
`LoadStanForD(str_path)`	*Boolean*	R	Loads an apt-file	

Bump

The *Bump* class holds the proportion of a log's bumpiness in the current interval.

Instances `SawMill.Log.Bumps.Bump()`

Bump **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Name`	*string*	L,R	Name of the instance formatted as Bu0-5	`PutInfo SawMill.Log.Bumps.Bump(1) .Name` Writes the name of 2:nd bump object
`Proportion`	double	R	Proportion of log with bumpiness in the interval of the object	

Bumps

The *Bumps* class is a placeholder for the distribution of bumps on a log. In order to work, bumpiness data files must be present in the stem bank file directories. Bumpiness grouping is enabled by a setting `Log.ProcessBumps=true`.

Instances `SawMill.Log.Bumps`

Bumps

Properties	**Type**	**Assign.**	**Description**	**Example**
`Bump(int_index)`	*obj Bump*	R	Gets Bump object with index	`prop05=Bumps(0).Proportion` Get the proportion of log with bumpiness (0-5). Actual interval is set up with Init.
`Count`	*int*	R	Number of Bump objects	`nBumps=Bumps.Count`
Methods				
`Init(str_init)`			Initialize bump intervals	`Bumps.Init("0-5,5-10,10-20,20-50")`

CantSaw

The *CantSaw* object is the first saw. The saw cuts a block which can be further processed by the *DealSaw*. To access properties and methods of the *CantSaw*, add *SawMill.CantSaw.* to the code examples below. Several class attributes are common in both *CantSaw* and *DealSaw* and thus presented after the *DealSaw* class.

Instances `SawMill.CantSaw`

CantSaw

Properties	Type	Assign.	Description	Example
`AutoHornsDown`	*Boolean*	L,R	True if AutoHornsDown is enabled	`AutoHornsDown = False` Log will now be sawn with current rotation
`Rotation`	*int*	L,R	Rotation of the log	`Rotation = 15` Sets the log rotation to 15 degrees
Methods				
`HornsDown`			Rotate the log horns down (crook up)	`HornsDown` Log is now rotated horns down

CantSaw/DealSaw

These attributes exists in both saws. Note that they can be set independently in each class

Instances `SawMill.CantSaw`
`SawMill.DealSaw`

CantSaw/DealSaw

Properties	Type	Assign.	Description	Example
`AutoCenter`	*Boolean*	L,R	True if automatic centring of log/block is enabled	`bAC = AutoCenter` bAC is now False if AutoCenter is disabled
`Back`	*obj CentrationUnit*	R	The rear centring unit	`Back.DistToSaw = 3000` Distance set to 3000 mm
`Front`	*obj CentrationUnit*	R	The front centring unit	`Front.DistToSaw = 1000` Distance set to 1000 mm
`Knots`	*Boolean*	L,R	If False, no knots will set on boards	`Knots = False` Turn off knots descriptions
`SawBladeWidth`	*double*	L,R	Saw kerf	`sbw = SawBladeWidth` Gets the thickness of the saw blade
`SawAllowance`	*double*	L,R	Adds to the nominal width or thickness of boards (mm)	`SawAllowance = 1.0` Boards will be cut 1.0 mm thicker or wider than calculated from shrink allowance.
`ShrinkAllowance`	*double*	L,R	Factor for calculating raw board	`ShrinkAllowence = 1.025`

			dimensions	A block with 100 mm nominal width will be cut to 102.5 mm raw + SawAllowance.
Methods				
`SetLogPos( int_Parallell_mm, int_Skew_mm)`			Sets the log position relative to the centred position	`SetLogPos(-10, 0)` Log is parallel displaced -10 mm

CentrationUnit

Each saw has two units responsible for positioning of the log/cant. Using the same offset in both units the log is parallel displaced. With different offsets the log is skewed.

Instances	`SawMill.CantSaw/SawMill.DealSaw`
	`.Front`
	`.Back`

CentrationUnit **Properties**	**Type**	**Assign.**	**Description**	**Example**
`DistToSaw`	*double*	L,R	Distance to saw centre (mm)	
`Offset`	*double*	L,R	Offset of log at CentrationUnit where 0 is the centred position (mm)	

Cost

Costs are calculated on log level. A valid cost file must be loaded and the post list must have sawing speeds(m/min) and log gaps(mm). Cost are calculated when SumCost is explicitly called.

Instances `SawMill.Cost`

Cost **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Drying`	*double*	R	Cost of drying	
`FileName`	*string*	R	Path of cost file	
`LogSorting`	*double*	R	Cost of log sorting	
`OK`	*Boolean*	R	Boolean. True if cost file is loaded	
`Sawing`	*double*	R	Cost of sawing operation including raw sorting and edging	
`Trimming`	*double*	R	Cost of trimming	
Functions	**Return type**			
`Load(str_path)`	*Boolean*			
`SumCost( obj_post, obj_log, obj_prod)`	*double*	R	Calculates costs. Must be called prior to accessing any properties	`sumCost=SawMill.Cost.SumCost( SawMill.Post, SawMill.Log, SawMill.Products)` All cost properties have been calculated and the sum is stored in sumCost

Crook

The *Crook* class holds a description of the log's crook properties.

Instances `SawMill.Log.Crook`

Crook **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Angle`	*int*	R	Direction of crook (deg)	
`Bow`	*int*	R	Maximum bow height (mm)	
`Position`	*int*	R	Position of maximum bow, butt end = 0 (mm)	

DealSaw

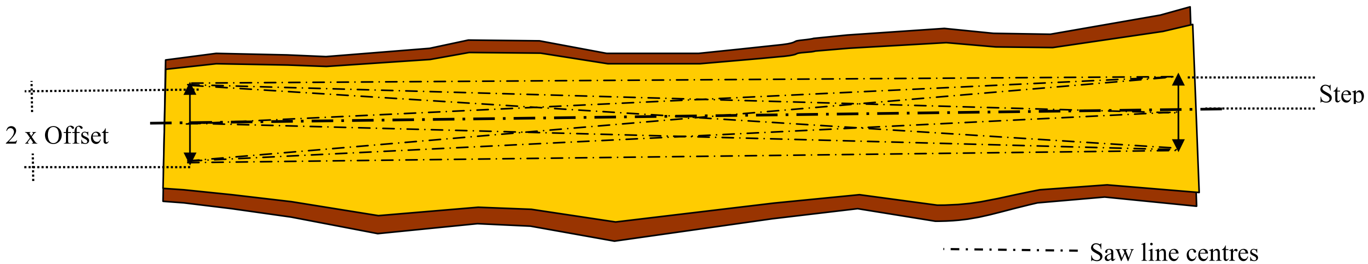
The *DealSaw* is the second sawing machine which cuts the block (cant) into boards. Several class attributes are common in both *CantSaw* and *DealSaw* and thus presented after the *DealSaw* class.

Instances `SawMill.DealSaw`

DealSaw **Properties**	**Type**	**Assign.**	**Description**	**Example**
`CurveSaw`	*Boolean*	L,R	True if curve sawing is enabled	`CurveSaw = False` Block will not be curve sawn

Edger

The *Edger* object performs the edging of sideboards by searching for the optimal value. During optimization the centre of the saw line is moved to different positions at the top end and butt end of the face independently. The maximum offset from the mid position is specified by the Offset property and the line is moved in steps given by the Step property. At each positions all possible widths of the board is evaluated.



Instances `SawMill.Edger`

Edger

Properties	**Type**	**Assign.**	**Description**	**Example**
`MaxOffset`	*int*	L,R	The limits of the centre line when searching for the optimal edging of the boards	`MaxOffset = 10` Max offset is set to 10 mm
`Step`	*int*	L,R	The discretation when positioning the centre line	`Step = 10` The centre line will be moved in steps of 10 mm

Methods

`Edge(obj_board)`			Edges a board	`Edge brd` Edges board brd

Knot

The *Knot* class holds properties for a single knot as given by the *StemBank*. Must not be confused with *BoardKnot*.

Instances `SawMill.Log.Knot()`

Knot **Properties**	**Type**	**Assign.**	**Description**	**Example**
`A`	*double*	L,R	Knot parameter A	
`B`	*double*	L,R	Knot parameter B	
`C`	*double*	L,R	Knot parameter C	
`D`	*double*	L,R	Knot parameter D	
`E`	*double*	L,R	Knot parameter E	
`F`	*double*	L,R	Knot parameter F	
`G`	*double*	L,R	Knot parameter G	
`H`	*double*	L,R	Knot parameter H	
`I`	*double*	L,R	Knot parameter I	
`J`	*double*	L,R	Knot parameterJ	
`K`	*double*	L,R	Knot parameter K	
`Scale`	*double*	L,R	Scale of knot parameters (mm/pixel)	

Methods			
`PostCreate`			If any of the knot parameters have been altered, call post create to execute some internal recalculations.
Functions	**Return type**		
`Diam(dbl_r_mm)`	*double*	R	Get knot diameter at postion r mm from pith (mm)
`End`	*double*	R	Get the end of knot in mm from pith
`Height(dbl_r_mm)`	*double*	R	Get height position in tree at r mm from pith
`Rotation(dbl_r_mm)`	*double*	R	Get rotational angle at postion r mm from pith
`SoundEnd`	*double*	R	Get the position where knot becomes dry, in mm from pith
`TanAngle(dbl_r_mm)`	*double*	R	Get knot diameter in radians at postion r mm from pith

LdbLog

This class is to reference log files in the SPSB. Must not be confused with the Log class that is used for loading and holding actual log data.

Instances `SawMill.StemBank.Plot().Tree()`
`.Log()`
`.LogNr()`

LdbLog

Properties	Type	Assign.	Description	Example
`Name`	*string*	R	The full path to the log geometry file	`path = SawMill.StemBank .PlotNr(51) .TreeNr(1) .LogNr(2).Name` The path to log 2 from tree 1 on plot 51
`Nr`	int	R	Log nr as extracted from file name	

Log

The *Log* object holds the currently loaded log. It is capable of reading log descriptions from files as well as complete stems.

Instances `SawMill.Log`

Log Properties	Type	Assign.	Description	Example
`Bumps`	*obj Bumps*	R	Bumpiness of log. Prerequisites are 1) ProcessBumps = true before loading log. 2) Bumpiness data available in the StemBank	`Bumps.Init "0-10,10-20,20-100"` Bumps will be distributed among these three intervals.
`Crook`	*obj Crook*	R	Holds the log's crook attributes	`Log.Crook.Bow` Gets the log's bow height
`FirstSliceNr`	*int*	R	The index of the first slice of a cut log	`sliceNr = FirstSlice`
`Knot(int_index)`	*obj Knot*	R	Retrieve Knot by nr.	`set k = Log.Knot(47)` k now references the 48:th knot of log
`KnotCount`	*int*	R	Number of knots in log	`For k = 0 To Log.KnotCount-1`

				Iterate through all knots
`LastSliceNr`	*int*	R	The index of the last slice of a cut log	`sliceNr = LastSliceNr`
`Length`	*int*	R	Length of (cut) log in mm	`length = Log.Length / 10` length is now log length in cm
`LogNr`	*int*	R	Log number in SPSB	
`OK`	*Boolean*	R	Boolean. False when no log is loaded	`if(Log.OK)` Is a log loaded?
`PlotNr`	*int*	R	Logs plot origin in SPSB	`str = Log.PlotNr` str now has the plot number
`Rotation`	*int*	L,R	Log rotation	`Log.Rotation = 25` Set log rotation to 25 degrees
`ScaleFactor`	*double*	R	Scale factor of the log geometry source file (mm/pixel)	`sf = Log.ScaleFactor`
`Slice(int_index)`	*obj Slice*	R	Retrieve Slice nr. First slice is indexed 0.	`set slice = Log.Slice(10)` slice now references the 11:th slice
`SortDiam`	*double*	R	Diameter of log used for automatic selection of breakdown pattern when enabled	`sd = SortDiam` sd now is the average Eq-diameter of log in the 150 to 50 mm from topend.
`StartHeight`	*int*	R	Log cutting position	`sh = Log.StartHeight` butt position of cut log in the tree/log
`StopHeight`	*int*	R	Log cutting position	`sh = Log.StopHeight` top position of cut log in the tree/log
`TreeNr`	*int*	R	Tree number in SPSB	`str = Log.PlotNr &Log.TreeNr &Log.LogNr`

				str now contains complete ID of log.
`Volume`	*double*	R	Log volume in m^3fub	`vol = 1000 * Log.Volume` Get log volume in litres
Methods				

`CutLog(`
`int_startPos_mm`
`,`
`int_stopPos_mm)`
			Cut log/tree	`CutLog(1000, 4400)`
				A 3400 mm long log is cut from the loaded log/tree

Functions	**Return type**			

`CrossDiam(`
`int_pos_mm,`
`int_angle_deg,`
`int_relativeTo)`
	double	R	Diameter of the log, in the specified direction, at pos from end (relativeTo, 1= top end, 2=butt end)	`diam = Log.CrossDiam(100,`
				`90, 1)`
				Gets diameter 100 mm from top of log in the vertical direction

`EqDiam(int_pos,` `int_relativeTo)`	*double*	R	Diameter of log derived from the cross-section's area (relativeTo, 1= top end, 2=butt end)	`diam = Log.EqDiam(100, 1)` Gets the equivalent diameter 100 mm from top end of the log

`Load(int_plot,`
`int_tree,`
`int_log)`
	Boolean	R	Load a log from SPSB. Returns True if successful	`bSuccess = Load(51,1,1)`
				Load log 1 from tree 1 on plot 51

`LoadGeometryFile(`
`str_path)`
	Boolean	R	Load any log geometry file. Returns True if successful	`bSuccess =`
				`loadGeometryFile("c:\`
				`data\logs\mylog1.txt")`
				Load geometry file mylog1.txt

`LoadKnotFile(`
`str_path)`
	Boolean	R	Load any knot parameter file. Returns True if successful	`bSuccess =`
				`loadKnotFile("c:\data`
				`\logs\myknots1.txt")`

				Load knot file myknots1.txt
`LoadTree(plot, tree)`	*Boolean*	R	Loads a tree. Merges logs belonging to same tree. Returns True if successful.	`bSuccess = LoadTree(1, 2)` Loads tree 2 on plot 1
`MinDiam(int_pos_mm, int_relativeTo)`	*double*	R	Minimum diameter of log at pos mm from end (relativeTo, 1= top end, 2=butt end)	`minD = Log.MinDiam(100,1)`

OrderBook

The *OrderBook* is used for production control. By defining desired share of specified products in an order file the OrderBook tries to meet the demand by adjusting prices on the targeted products.

Instances `SawMill.OrderBook`

OrderBook **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Active`	*Boolean*	L,R	Boolean. Turn on/off production control	`OrderBook.Active=True` Enable production control
`DefaultPriceCoefficient`	*double*	L,R	Initial price coefficient	`OrderBook.DefaultPriceCoefficient=120` Start with prices 20% higher than given by price list
`FileName`	*string*	R	Loaded OrderBook file path.	`PutInfo OrderBook.FileName` Writes file name to InfoView
`Lambda`	*double*	L,R	Step control parameter	`OrderBook.Lambda = 0.1` Sets the step control to 0.1
`MaxPriceDeviation`	*double*	L,R	Maximum allowed deviation from price given by price list	`OrderBook.MaxPriceDeviation=30` Prices can differ ± 30% from price given by price list
`Prod(int_index)`	*obj OrderProd*	R	Access to OrderProd objects (products controlled)	`OrderBook.Prod(0).ProdVolShare` Currently produced volume share of product 0

`ProdCount`	*int*	R	No of products controlled	`For i=0 To SawMill.OrderBook.ProdCount-1` Iterate over the controlled products
`Volume`	*double*	R	Total volume produced	
Methods				
`AddDistProducts(obj_QualDist)`			Add production of distributed products	`OrderBook.AddDistProducts(SawMill.QualDist)` Adds fraction of products as given by QualDist
`AddProducts(obj_Prod)`			Add production	`OrderBook.AddProducts(SawMill.Products)` Adds products from last sawing operation
`UpdateCoefficients`			Adjust price coefficients	`OrderBook.UpdateCoefficients` New price coefficients will be calculated based on development of order book since last update
Functions	**Return type**			
`Load(str_Path)`	*Boolean*	R	Load an order book file	`SawMill.OrderBook.Load "MyOrderBook.txt"`

OrderProd

OrderProd is the product under production control. Product is either controlled by number of boards or by volume share. Never both at the same time. It is recommended to control by volume share since this is well tested.

Instances `SawMill.OrderBook.Prod()`

OrderProd Properties	Type	Assign.	Description	Example
`Coefficient`	*double*	L,R	Price coefficient in percent of the price given by price list	
`Length`	*double*	R	Length of product	`OrderBook.Prod(1).Length=4200` Change the length of the product under control
`OrdNo`	*double*	L,R	Ordered number of boards	
`OrdVolShare`	*double*	L,R	Ordered volume share of product (‰)	`OrderBook.Prod(1).OrdVolShare=10` Change ordered volume share to 10 per mille
`ProdNames`	*string*	R	Allowed products in group	`str=OrderBook.Prod(1).ProdNames` Product names matching price lists
`ProdNo`	*double*	R	Produced number of boards	
`ProdVolShare`	*double*	R	Produced volume share (‰)	
`Thickness`	*double*	L,R	Thickness of product (mm)	`thick=OrderBook.Prod(0).Thick`

				Get the thickness of the 1:st product
`Width`	*double*	L,R	Width of product (mm)	`width=OrderBook.Prod(0).Width`
`VolCtrl`	*Boolean*	L,R	Boolean. True of volume is controlled. False if number of boards are targeted	
`Volume`	*double*	L,R		

Plot

The *Plot* class gives a structured access to the files in the SPSB.

Instances `StemBank.Plot()`
`StemBank.PlotNr()`

Plot **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Name`	*string*	R	The file directory	
`Nr`	*int*	R	The Plot nr as extracted from directory name in SPSB	
`Tree(int_index)`	*obj Tree*	R	Gets Tree by index (ordinal)	`set tree = StemBank.Plot(0).Tree(0)` tree now references the first tree on the first plot in the stem bank
`TreeCount`	*int*	R	Number of Trees on plot	`nTrees = Plot.TreeCount` Gets the total number of trees on the Plot

`TreeNr(int_nr)`	obj Tree	R	Gets Tree by its number	set tree = SawMill.StemBank.PlotNr(51) .TreeNr(1) tree now references the tree with the given identity 1 on plot 51

Post

The *Post* class holds a break down pattern with associated data.

Instances

```
SawMill.Post
SawMill.PostList.Post()
SawMill.PostList.PostDiam()
```

Post

Properties	Type	Assign.	Description	Example
`CantCut(int_index)`	*obj PostCut*	R	Retrive a PostCut object. Zero based index.	`Post.CantCut(0).Thick` Thickness of first cut in CantSaw
`CantCutCount`	*int*	R	Nr of cuts in CantSaw	`nr = CantCutCount`
`DealCut(int_index)`	*obj PostCut*	R	Retrive a PostCut object. Zero based index.	`Post.DealCut(2).Type` Type of board of 3:d cut in DealSaw ('s'=sideboard or 'c'=centreboard)
`DealCutCount`	*int*	R	Nr of cuts in DealSaw	`nr = DealCutCount`
`ID`	*int*	R	ID nr as given in the postlist file	`idnr = SawMill.Post.ID`
`LogGap`	*int*	L,R	Log gap in mm. To be used together with cost assessments.	`Post.LogGap = 550` Log gap now is 550 mm
`MaxDiam`	*int*	L,R	Max diameter of logs to be cut with the Post	`If SawMill.Log.EqDiam(100, 1) <= SawMill.Post.MaxDiam`

				Check if log diameter is less than the given max diam
`MinDiam`	*int*	L,R	Min diameter of logs to be cut with the Post (mm)	`minD = Post.MinDiam` Get the minimum log diameter for the Post
`Name`	*string*	L,R	The name given in the postlist file	`Post.Name = "MyPost"` Sets the name of the post to MyPost
`Nr`	*int*	L,R	A running index of Posts	`nr = Post.Nr` Gets the ordinal of Post in the PostList
`SawLine`	*int*	L,R	An index which can be used to process logs with different setups based on Post selected	`SelectSawLine Post.SawLine` Run user defined subroutine to set up saw based on saw line given in post.
`SawSpeed`	*int*	L,R	Processing speed of saw with that pattern (m/min)	
`SumCantWidth`	*int*	R	Sum of all cuts in the CantSaw (nominal mm)	`width = Post.SumCantWidth` Get the total width.
SumDealWidth	int	R	Sum of all cuts in the DealSaw (nominal mm)	`width = Post.SumDealWidth` `Get the total width.`

PostCut

The PostCut holds the thickness and boardtype of one cut in a Post.

Instances `SawMill.Post/SawMill.PostList.Post()/SawMill.PostList.PostDiam()`
`.CantCut()`
`.DealCut()`

PostCut

Properties	Type	Assign.	Description	Example
`Thick`	*int*	L,R	Thickness of cut (mm)	`If Post.CantCut(0).Thick = 19 Then …` Special processing for boards with thickness 19 mm.
Type	string	L,R	Board type (“s”=side board, “c”=centre board, “b”=block)	`Post.DealCut(2).Type` `Type of of 3:d board cut in DealSaw`

PostList

The *PostList* holds a list of sawing patterns.

Instances `SawMill.PostList`

PostList

Properties	Type	Assign.	Description	Example
`Count`	*int*	R	Number of posts in list	`nr =PostList.Count` Gets the number of posts in list
`FileName`	*string*	R	Path of loaded file	`name = PostList.FileName` Get the path of the loaded file
`OK`	*Boolean*	R	Boolean. True if a list is loaded	`if PostList.OK` Is a post list is loaded
`Post(int_index)`	*obj Post*	R	Gets the Post specified by the zero-based index	`post = PostList.Post(0)` Sets a reference to the first post
`PostDiam(int_index)`	*obj Post*	R	Gets a Post from array filled with posts selected after a call to PostDiamCount	`PostList.PostDiamCount(155)` `post = PostList.PostDiam(0)`

				Gets the first post where log diam 155 mm is within min/max limits
Functions	**Return type**			
`Load(str_filename )`	*Boolean*	R	Loads a post list file. Returns True if successful.	`PostList.Load "MyPostList.txt"` Loads the post list file "MyPostList.txt"
`PostDiamCount( dbl_diam_mm)`	*int*	R	Gets the number of posts where diam is within min/max limits and fills the array PostDiam	`nPosts = PostList.PostDiamCount(155)` Get the number of posts applicable for a log with diameter 155 mm

PriceList

The *PriceList* gives the individual value of all feasible combinations of width, length and thickness. The prices are organized in price sheets, one sheet per product.

Instances `SawMill.PriceList`

PriceList **Properties**	**Type**	**Assign.**	**Description**	**Example**
`ChipPrice`	*double*	L,R	Price of by-products per solid m3	`PriceList.ChipPrice = 215` Sets the chip price to 215/m3
`FileName`	*string*	R	Name of loaded file	`name = PriceList.FileName` Get the path of the loaded file
`OK`	*Boolean*	R	Boolean. False if no list is loaded	`isOK = PriceList.OK` if isOK = True, a price list is loaded

`PriceSheet(int_index)`	*obj PriceSheet*	R	Gets the PriceSheet specified by the zero-based index	`set ps = PriceList.PriceSheet(1)` Sets a reference to 2:nd price sheet
`PriceSheetByName(str_name)`	*obj PriceSheet*	R	Gets PriceSheet by its name	`set ps = PriceSheetByName("A-s")` Sets a reference to the price sheet with name A-s
`SheetCount`	*int*	R	Number of price sheets	`count = PriceList.SheetCount`
Functions	**Return type**			
`Load(filename)`	*Boolean*	R	Loads a price list file. Returns True if successful.	`PriceList.Load "Prices August 03.txt"` Loads the price list file "Prices August 03.txt"

PriceSheet

The *PriceSheet* gives the individual value of all feasible combinations of width, length and thickness for a certain quality.

Instances `SawMill`
`.PriceList.PriceSheet()`
`.PriceList.PriceSheetByName()`

PriceSheet **Properties**	**Type**	**Assign.**	**Description**	**Example**
`BasePrice`	*double*	L,R	The base price of the quality (SEK/m^3)	`bp = PriceList.PriceSheet(0).BasePrice`

				Get the base price of the first sheet
`Index`	*int*	R	The feasible qualities as given by the quality definition. The Index is or:ed 2^qindex.	`index = Index` If index now is 6 than qualities 1 and 2 are allowed (2^1 + 2^2)
`Name`	*string*	L,R	Name of price sheet	`PriceSheet.Name = "Box"` The name is now Box

Methods

Functions	**Return type**			
`Price(int_thick_mm, int_width_mm, int_length_mm)`	*double*	R	Get the price of a board with the specified dimensions	`value = GetPrice(50, 100, 4200)` Gets the value of a board with the given dimensions. If the board is not found, value will be 0.

Products

The *Products* class holds the resulting boards after sawing a log.

Instances `SawMill.Products`

Products Properties	Type	Assign.	Description	Example
`BoardValue`	*double*	R	Total value of all boards having a grade (SEK)	
`CantBoard(int_index)`	*obj Board*	R	Gets a board sawn in first saw	`thick = CantBoard(0).Thickness` Gets the thickness of first board
`CantBoardCount`	*int*	R	Number of boards from first saw. Number includes the block	`nBoards = SawMill.Products .CantBoardCount` Get the number of boards from first saw
`ChipValue`	*double*	R	Value of chips (SEK)	`val = val + Products.ChipValue` Add chip value to val
`ChipVolume`	*double*	R	Volume of chips (m3)	`vol = ChipVolume` Get chip volume
`DealBoard(int_index)`	*obj Board*	R	Gets a board sawn in second saw	`value = DealBoard(1).Value` Get value of 2:nd board from second saw
`DealBoardCount`	*int*	R	Number of boards from second saw	`nBoards = DealBoardCount` Get the number of boards from first saw
`Value`	*double*	R	Total value of log (SEK)	`If Value <> Boardvalue + ChipValue` Should be equal, something is wrong

`Yield`	*double*	R	Volume yield from sawing log in %	`str = "Yield " & FormatNumber(Products.Yield,1)` Writes yield to string with one decimal digit
Methods				
`SetSums`			Sums up board values and calculates yield and chip properties. Necessary if boards have been altered after a DoSaw operation	

QualBoard

A *QualBoard* is a board that has been trimmed with a pre-set knot quality. However, wane properties may be determining a lower quality of the board.

Instances `SawMill.QualDist.Quality().Board()`

QualBoard **Properties**	**Type**	**Assign.**	**Description**	**Example**
`SheetName`	*string*	R	Name of price sheet that the board was priced by.	
`Thickness`	*double*	R	Thickness of board (mm)	
`TrimmedLength`	*double*	R	Final length of board (mm)	
`Value`	*double*	R	Value of board (SEK)	
`Width`	*double*	R	Width of board (mm)	
`Volume`	*double*	R	Volume of board (m^3)	

QualDist

The *QualDist* object holds distribution of qualities. Set the proportion of each grade in the Quality array before calling DoSaw. In the sawing operation of a log each centreboard is trimmed with all qualities in the Quality array. The summed value of centreboards is calculated.

Instances `SawMill.QualDist`

QualDist **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Active`	*Boolean*	L,R	Boolean. Turn on/off assessment of boards with grades given by QualProp objects	
`Quality(int_quality)`	*obj QualProp*	R	Access a QualProp object by quality index	`SawMill.QualDist.Quality(1).Proportion=0.2` Sets the proportion of grade 1 to 0.2
`Value`	*double*	R	Summed value of centre boards	
`Volume`	*double*	R	Summed volume of centre boards	

QualProp

QualProp holds resulting centre boards trimmed and graded with the current knot quality.

Instances `SawMill.QualDist.Quality()`

QualProp Properties	Type	Assign.	Description	Example
`Board(int_index)`	*obj QualBoard*	R	Access a QualBoard object.	
`BoardCount`	*int*	R	Number of QualBoard	`nCB=SawMill.QualDist.Quality(1).BoardCount` Gets the number of centre boards that yielded a positive value when knot properties were set to quality 1
`Index`	*int*	R	Quality index as given in the quality definition file	
`Proportion`	*double*	L,R	Proportion of log with this quality on the centre boards	`prop=SawMill.QualDist.Quality(1).Proportion` Get the proportion of quality 1

Saw2003

The sawmill simulator has an object oriented approach. The top level object is Saw2003 and this object does not have to be explicitly given in the script. It holds the super object *SawMill*. Most other classes must be accessed through the *SawMill* object.

Instances `Saw2003` `Document`

Saw2003/Document

Properties	Type	Assign.	Description	Example
`BuckStation`	*obj BuckStation*	R	Object for simulating bucking by a harvester	`BuckStation.Buck(SawMill.Log)` Bucks a stem
`Com`	*obj SockWnd*	R	Sockets communication over the internet, (under development)	`Com.Listen(4711)` Enables communication on port 4711
`SawMill`	*obj SawMill*	R	The actual sawmill simulation engine	`Set sm = Saw2003.SawMill` Sets a reference to the SawMill object
Methods				
`ClearInfo`			Clears the InfoView	
`PutInfo(str_text)`			Write text to InfoView	`PutInfo(SawMill.Post.Name)` Outputs Name of the selected pos
`ShowMsg(str_message)`			Shows a message in a pop-up messagebox	`ShowMsg(SawMill.Post.Name)` Outputs Name of the selected post
`UpdateViews`			Refreshes the screen. May slow down the processing of large scripts	`SawMill.DoSaw` `UpdateViews` Make sure results are reflected in the interface

Functions	**Return type**			

`CreatePriceList`	*obj PriceList*	R	Creates a second pricelist which can be set to sawmill for fast switching without having to reload file	`set pl2=CreatePriceList`
				`pl2.Load "MyPL.txt"`
				`set pl1=SawMill.PriceList`
				`SawMill.PriceList=pl2`
				Change pricelist on the fly

`Test`	*string*	R	Writes "Script Test" to InfoView and returns "Script Test"	`s = Test` s now contains "Script Test"

SawMill

The *SawMill* is the placeholder for all simulated machinery as well as the *PriceList* and *PostList*. The *SawMill* also holds the *StemBank* object which contains the parametric descriptions of the virtual logs in the SwedishPineStemBank (SPSB).

Instances `SawMill`

SawMill

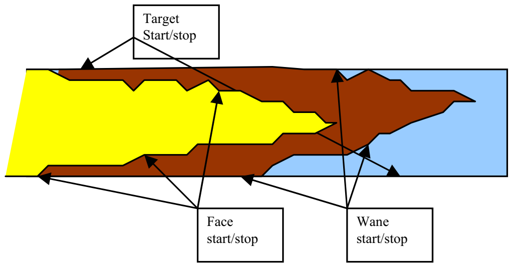
Properties	Type	Assign.	Description	Example
`AutoPost`	*Boolean*	L,R	True if AutoPost is enabled	`AutoPost = False` Turning off AutoPost
`CantSaw`	*obj CantSaw*	R	First sawing machine	`SawMill.CantSaw. SawBladeWidth = 4.5` Set the saw kerf of the first saw to 4.5 mm
`Cost`	*obj Cost*	R	Object for calculating costs of sawmill operations	`SawMill.Cost.Load "CostFile.txt"` Load a cost-formatted text file.
`DealSaw`	*obj DealSaw*	R	Second sawing machine	`kerf=SawMill.DealSaw. SawBladeWidth` Get the saw kerf of the second saw
`Edger`	*obj Edger*	R	Edging machine	`SawMill.Edger.Edge brd` Edges board brd
`Log`	*obj Log*	R	Log loaded in sawmill	`SawMill.Log.Volume` Gets the volume of the current log
`OrderBook`	*obj OrderBook*	R	Order book for production control	`OrderBook.Active = false`

				Turns off production control
`Post`	*obj Post*	R	Sawing pattern selected	`SawMill.Post.MinDiam` Gets minimum diameter limit of current post
`PostList`	*obj PostList*	R	The list of available posts	`postsNr = SawMill.PostList.Count` Gets the total number of posts
`PriceList`	*obj PriceList*	L,R	Price list of the boards	`SawMill.PriceList.ChipPrice = 210` Sets the chip price
`Products`	*obj Products*	R	Resulting boards after sawing a log	`cv = SawMill.Products. ChipVolume` Gets the volume of chips
`QualDist`	*obj QualDist*	R	Object for assessment of volume and value when a log yields a distribution of grades (e.g. A= 0.1 B=0.25 C=0.65)	`QualDist.Quality(1).Proportions = 0.1` Set the proportion of grade 1 of log to 0.1
`StemBank`	*obj StemBank*	R	Pine Stem Bank	`SawMill.StemBank. GetFileName(1,2,3)` Gets the path to plot 1, tree 2, log 3
`Trimmer`	*obj Trimmer*	R	Trimming machine	`SawMill.Trimmer.Step = 50` Sets the discretation in the optimization to 50 mm
`ZResolution`	*int*	L,R	The distance between cross section profiles used in sawing	`SawMill.ZResolution = 50` With the SPSB logs every 5:th cross-section is now used for describing board geometry

Functions	Return type			
`DoAutoPost`	*Boolean*	R	Selects the first post where current log falls within min max limits	`bOK = SawMill.DoAutoPost` if bOK = True post is now selected
`DoSaw`	*Boolean*	R	Saw current log	`bOK = SawMill.DoSaw` if bOK = True log was successfully sawn

SideProfile

The *SideProfile* gives a 1-dimensional view of the board side. Start positions can be higher than stop positions depending on orientation of board side in 3D-space.



Instances	`.OutSide.Profile()`
	`.InSide.Profile()`
	`.LeftEdge.Profile()`
	`.RightEdge.Profile()`

SideProfile

Properties	**Type**	**Assign.**	**Description**	**Example**
`CutPos`	*double*	R	The plane position of face in space (mm)	
`FaceStart`	*double*	R	Start position where sawblade has touched the board (mm)	
`FaceStop`	*double*	R	Stop position where sawblade has touched the board (mm)	
`Height`	*double*	R	Position in log (z) (mm)	
`TargetStart`	*double*	R	Ideal start position (mm)	
`TargetStop`	*double*	R	Ideal stop position (mm)	
`WaneStart`	*double*	R	Actual start of profile (mm)	
`WaneStop`	double	R	Actual stop of profile (mm)	

Slice

Slice is the cross-section of a log.

Instances `SawMill.Log.Slice()`

Slice

Properties	Type	Assign.	Description	Example
`Angle(int_index)`	*obj Angle*	R	Get an Angle object, index	
`AngleCount`	*int*	R	Number of Angles in slice. Should be 360	
`Area`	*double*	R	Area in mm^2 of cross section	
`CgX`	*double*	R	Center of gravity, X- coordinate (mm)	
`CgY`	*double*	R	Center of gravity, Y- coordinate (mm)	
`EqDiam`	*double*	R	Equivalent diameter derived from area (mm)	
`Height`	*double*	R	Height in mm of cross-section in log. Butt end = 0	
`MinDiam`	*double*	R	Minimum diameter of slice	
`Nr`	*int*	R	Slice number, ordinal	
`PithX`	*double*	R	X-coordinate of pith in slice	
`PithY`	*double*	R	Y-coordinate of pith in slice	
Functions				
`CrossDiam(int_angle)`	*double*	R	Get diameter in direction given by angle	

SockWnd

The *SockWnd* class is under development and is intended for communication with other applications across a computer network. Applications such as a log scanner or an order system for instance.

Instances `Com`

SockWnd **Properties**	**Type**	**Assign.**	**Description**	**Example**
Methods				
`Listen(int_portNr )`			Start listen for TCP/IP connections on a port	`Com.Listen(4711)`
Functions				

StemBank

The *StemBank* class gives a structured access to the files in the SPSB.

Instances `SawMill.StemBank`

StemBank **Properties**	**Type**	**Assign.**	**Description**	**Example**
`Plot(int_index)`	*obj Plot*	R	Gets plot by index (ordinal)	`set plot = StemBank.Plot(0)` plot now references the first plot in the stem bank
`PlotCount`	*int*	R	Number of plots	`nPlots = StemBank.PlotCount` Gets the total number of plots in the stem bank

`PlotNr(int_nr)`	*obj Plot*	R	Gets plot by its number	`set plot = SawMill.`
				`StemBank.PlotNr(51)`
				plot now references the plot with the given identity 51

Functions	**Return type**			

`GetFileName(`
`int_plotNr,`
`int_treeNr,`
`int_logNr)`
	string	R	Get the path to a log geometry file	`fn = GetFileName(1,2,3)`
				fn now holds the path to log 3 from tree 2 on plot 1

Tree

The *Tree* class gives a structured access to the files in the SPSB.

Instances `SawMill.StemBank.Plot()`
`.Tree()`
`.TreeNr()`

Tree Properties	Type	Assign.	Description	Example
`Log(int_index)`	*obj LdbLog*	R	Gets Log by index (order)	`set log = StemBank.Plot(0).Tree(0).Log(0)` tree now references the first log in first tree on the first plot in the stem bank
`LogCount`	*int*	R	Number of Trees on plot	`nLogs = Tree.LogCount` Gets the total number of logs in Tree
`LogNr(int_nr)`	*obj LdbLog*	R	Gets Log by its number	`set log = SawMill.StemBank.PlotNr(51).TreeNr(1).LogNr(2)` log now references the log with the given identity 2 from tree 1 on plot 51
`Name`	*string*	R	Tree name as extracted from filename	
`Nr`	*int*	R	Tree Nr as extracted from filename	

Trimmer

The trimming machine. Responsible for grading of boards as well.

Instances `SawMill.Trimmer`

Trimmer **Properties**	**Type**	**Assign.**	**Description**	**Example**
`MinTrimButt`	*int*	L,R	Minimum trimming length at butt end (mm)	`Trimmer.MinTrimButt = 40` Now at least 40 mm will be cut off from butt end
`MinTrimTop`	*int*	L,R	Minimum trimming length at top end (mm)	`trimTop = Trimmer.MinTrimTop` Gets the minimum trimming length at top end
`Step`	*int*	L,R	The discretation in trimming optimisation (mm)	`Trimmer.Step = 100` Trimming alternatives will be evaluated at positions with the interval 100 mm starting from butt end.
Methods				
`TrimBoard(obj_board)`			Trims a board, including grading.	`set board = Products.CantBoard(0)` `Trimmer.TrimBoard(board)` Trim first board from first saw