THE IMPACT OF A STRENGTH GRADING PROCESS ON SAWMILL PROFITABILITY AND PRODUCT QUALITY

Mattias Brännström

A strength grading process, starting with log grading, was studied with respect to grading yield, impact on quality, and economic efficiency when visual grades according to Nordic grading rules were used for alternate product comparison. Pine (*Pinus sylvestris*) and spruce (*Picea abies*) logs and boards were graded with several varieties of commercial grading and strength-grading equipment. The boards were destructively tested, and the European grade-determining properties strength, stiffness, and density were measured. Models for these were made by partial least squares and validated. A method for the derivation of settings for multiple indicating properties, which increased yield in some cases, was proposed and evaluated. Grading to grade combinations of C40, C30, and C18 was done. The impact of visual override based on deformations was also studied. A simplified economic and sensitivity analysis was done. The outcome was that log grading can be used for strength grading with good economic and quality results. Strength pregrading on logs improves sawmill economy, depending on the species and market situation. Drying quality greatly influences the yield through visual override grading on deformations. Market prices of high grades (>C30) must improve in order to stimulate supply, as it is more economical to produce lower grades.

Keywords: COV; Log grading; Modeling; Multivariate; Picea abies; Pinus sylvestris; Resonance frequency; Sawmill; Strength grading; X-ray; Yield

Contact information: Stora Enso Timber, SE-791 80 Falun, Sweden; Luleå University of Technology, Division of Wood Science and Technology; mattias.brannstrom@storaenso.com

INTRODUCTION

The profitability of the sawmilling process depends to a large extent on how well the available raw material is used, as the single largest cost of the process is the raw material. Traditionally, economy has been achieved by using as much of the incoming log as possible in the final products, *i.e.*, volume yield in boards and planks. This has been enabled by outer shape measurement (3-D scanning) on the log and a focus on the top diameter, which limits the possible sizes to cut from the log. With increasing competition, the focus has turned to value recovery, *i.e.*, to getting the highest payment for the end products aside from the volume yield. Although it has been possible to do this with 3-D scanners (Jäppinen 2000), the quality grading of logs has improved by using x-ray scanning, alone or in combination with 3-D scanners (Oja *et al.* 2004).

Strength grading is one method of adding value to the end product, notwithstanding the fact that the sizes in sawing are optimized for volume recovery. Strength-graded timber is intended for construction purposes, and the European structural timber qualities, C-grades, described in EN338 place requirements on the grade-determining properties (GDPs) of characteristic bending strength, stiffness, and density. The grades are named after the characteristic strength of the grade, so that the fifth percentile of C40 strength is 40 MPa (N/mm^2).

Strength grading can be done visually by manual inspection or using a scanner, with C30 as the highest grade, but machine grading improves the producer's economy through lower costs, higher yields, and greater efficiency. The machines normally estimate one or several of the grade-determining properties by some technology in order to arrive at predictions, indicating properties (IPs). Grading thresholds for the indicating properties are made according to standard EN14081-2, which has requirements on the grading and classification accuracy of the machine. The settings thus achieved are called "machine control" settings and are fixed, contrary to "output control," where settings are gradually altered to account for raw-material variability. After grading, there is a final control, "visual override," so that no features that are not measured by the grading machine will influence strength negatively. The visual override can be done by scanners or manual graders.

Higher strength grades are sold at a higher price than lower grades. There is a balance though, since by using the same raw-material batch and sorting to different grade combinations, the share of low grades increases when higher grades are sorted out. For sawmills using Nordic raw material, it has been simple and profitable to grade only one grade, the European grade C24, as almost all material fulfills the criteria for it. By grading in another combination, such as C40-C30-C18, the C40 price must be balanced with the lower value of the products falling out as a consequence of being "off-grade," meaning either C18 or Reject.

Not all grades are demanded by the market at all times, and especially not in the same dimensions and lengths. Higher grades are normally supplied to a lesser extent, due to the raw-material limitations and need for more advanced and expensive grading equipment, which means that there is a demand for higher grades, while lower grades usually are oversupplied and thus lower priced. For a producer, it would be a great benefit to, prior to sawing, select which grades to produce to fulfill the market demands, while reducing the amount of off-grade material produced. Such early selection of the appropriate raw material for strength-graded products has been studied as implemented by various technologies such as x-ray (Brännström *et al.* 2007; Oja *et al.* 2001) and acoustic methods (Wang *et al.* 2007; Edlund *et al.* 2006). For plantation grown *Pinus radiata*, the financial return from impact-velocity graded logs has been published (Tsehaye *et al.* 2000).

Naturally, such early selection requires profitable products for which the rejected raw material can be used, which is more profitable than the strength-graded off-grade. A rough classification of Nordic sawn goods is made according to "Nordic timber – grading rules…" often called the "Blue book" (Anon. 1997). These grades have been influential guidelines for most commodity grades (which do not include strength grades) in the Nordic countries for a long time, but are today gradually being abandoned by the industry and replaced by customer-adapted grading. Still, the Nordic timber grades represent a large share of the bulk production; consequently, they might serve as a general alternate product.

The timber construction designer is in need of a well-specified material. The material must fulfill the characteristic values, but in addition, the variation in the lowest 5^{th} percentile must not be too large. To account for the material's variation in the resistance to load, various safety factors are used. In reliability-based design, the coefficient of variation (COV) of strength is a key property of the construction material (Anon. 2006). In particular, the lower tail (lowest 10% of the values) is of great importance for the accurate prediction of characteristic strength and the calibration of the material safety factor (γ_M) (Ranta-Maunus *et al.* 2001). If COV can be reduced, both solid timber and engineered wood products can become more competitive from an engineering point of view.

For the future competiveness and credibility of timber as a construction material, a strength-grading process must be developed that allows early steering of raw material on value, volume and yield and in which variation within grades is reduced. This paper is an attempt to determine if that is already possible today with some commercially available grading equipment.

EXPERIMENTAL

This study is based on data gathered in the Finnish research institute VTT's project Combigrade 2 (Hanhijärvi and Ranta-Maunus 2008). The final report gives a comprehensive description of the materials and methods of scanning and laboratory testing. Here follows only a short summary.

Wood Material and Processing

Two different species were used in the study: Norway spruce (*Picea abies (L. karst)*) and Scots pine (*Pinus sylvestris*). Logs were sampled randomly from trucks or railway cars at six different sawmills in Finland. The logs originated from three areas in Finland and two areas in Russia. Five different log classes were used, with top diameters in the range 154–398 mm. Sampling was done such that 44 logs per species, area, and log class were obtained. Sawing was done to the millimeter sizes 38 x 100, 50 x 100, 50 x 150, 44 x 200, and 63 x 200. 44 x 200 mm was sawn as 4 ex log, and all other dimensions were sawn as 2 ex log. Only one board per log was used in the study, but all positions in the sawing pattern were equally represented in the sample. Sawing and drying were done at research facilities under controlled conditions in order to avoid quality flaws due to production.

A comparison of results from different processes depends on the sample at hand, due to statistics in optimum grading and setting derivation. Thus, all specimens that were not measured by all machines, or in laboratory, were left out of the analysis. Finally, 1725 observations remained, 897 on pine and 828 on spruce.

In this study, no consideration of origin, log class (diameter intervals) or sawn dimensions was taken in the final analysis; *i.e.*, the data for each species have been treated as a single entity.

Industrial Scanning and Equipment

The logs were scanned at two different log-grading departments by "Wood-X" log x-ray scanners manufactured by Bintec with four x-ray sources and sensors, giving information on inner features distinguishable by density differences (Anon. 2009a). Data from one mill were mainly used in all analyses, while the other mills' data were used for finding erroneous values. A hand-held device, Fiber-Gen "HM-200" vibration measurement tool, was used when the logs were piled on the log yard to give the impact velocity of the log (Wang *et al.* 2007; Carter *et al.* 2005). The vibration measurement tool gives a confidence value for each measurement. Measurements from the x-ray log scanner and the vibration measurement tool are referred to as "log grading" (LG).

A Finscan "Board Master" visual color scanner was used to get information on shape and defects, such as knots and damage after drying, from dry boards with rough sawn surface (Anon. 2009b). This is accepted as a replacement for manual visual strength grading, but currently not for machine strength grading. In this study, it is referred to as the "dry-grading" equipment (DG).

A Microtec "Golden Eye 706" was used with machine control settings to get a certified grading result for each board (Guidiceandrea 2005). The machine is accepted in EN14081-4 for a wide range of grade combinations and raw material origins. It is referred to as the "machine grading" equipment (MG).

Pretreatment of Industrial Data

The vibration measurement tool was corrected with respect to the temperature differences between the different measurement occasions and their influence on the results. The linear correction was derived based on the assumption that the average velocity values from each occasion should be equal to the average for all of the measurements. This is a reasonable correction suggested by a shift found in earlier studies (Edlund *et al.* 2005; Carter *et al.* 2005). Filtering by the confidence level given for each measurement was done, so that values with confidence lower than 0.9 were excluded. The confidence level was chosen so that a sufficient number of observations would remain after filtering. A search window, based on the same log x-ray model, was used for filtering cases where overtones were detected as the first vibration mode. In both these cases, the modeled stiffness from the log x-ray alone was used instead.

There were no data on the length of the logs, so in order to estimate the dynamic modulus of elasticity of logs, the board length was used. This could have led to some errors for a few observations, since trimming or optimization cuts may have taken place. The effect of these errors cannot be completely disregarded due to single measurements influencing grading settings.

The x-ray log scanner density measurement was corrected for those observations where one of the measurement directions did not work properly. The correction was made entirely based on scanner data. This measurement problem did have a detrimental effect on the results. The visual scanner and the board x-ray scanner in combination with resonance frequency measurement did not need any correction.

Destructive Testing and Optimum Grading

Destructive testing was done in accordance with EN408. Corrections and characteristic values were derived according to EN384. With these standards, the following conditions apply. Destructive testing was done in edgewise four-point bending until failure. Bending strength (f_m) was derived from the highest force applied, and global modulus of elasticity ($E_{m,g}$) was based on 10%–40% of the load-deflection curve. Density (ρ) was measured on a small, knot-free specimen taken close to the fracture. Testing should be done at 12% moisture content (*MC*). If the moisture content differed, then the density and stiffness, but not strength, were corrected to compensate for it. Strength was corrected for size, and characteristic modulus of elasticity was adjusted to pure bending.

The characteristic values were derived as follows: 5th percentile density was derived from the average and standard deviation, assuming a normal distribution, and the 5th percentile bending strength was derived by ranking the destructive values and interpolating if no exact match was found (nonparametric distribution). Correction was made on strength by the factor k_v to account for a lower variability in machine-graded as compared to visually graded material. Instead of applying k_v on the characteristic value of the batch, the requirement on $f_{m,k}$ was altered (Table 1) according to

$$\left.\frac{f_{m,k}}{k_v}\right| \begin{matrix} Grade \le C30, \; k_v = 1.12 \\ > C30, \; k_v = 1.0 \end{matrix} \tag{1}$$

Table 1. C-grade Adjusted Requirements on Grade Determining Properties

Grade	$f_{m,k}/k_v$ MPa	0.95 $E_{m,g}$ MPa	ρ_k kg/m^3
C40	40.0	13300	420
C30	26.8	11400	380
C18	16.1	8550	320

The average modulus of elasticity was derived assuming a normal distribution. Adjustments were made to account for the fact that the weakest section was used in testing by a reduction of the requirement by the factor 0.95 (Table 1) (EN338). The sample average modulus of elasticity was adjusted to pure bending according to EN384,

$$\overline{E} = 1.3 \cdot \left(\sum_{i=1}^{n} \frac{E_i}{n} \right) - 2690 . \tag{2}$$

Optimum grading is a classification based on the destructive values, to achieve what should be the “true” grade of each specimen in a sample. The routine for it is described in EN14081-2. The grade-determining properties for each grade, with corrections, are required to be fulfilled by the optimum graded sample. In addition, there are requirements for cost of misclassification. The more the final classification (the machine-assigned grade) overestimates the grade compared to the optimum, and the greater the distance between optimum and machine-assigned grade, the higher the cost.

The optimum grading (OG) was done according to EN14081-2, with the difference that the cost for a reject was calculated at 0.75 times the grade it was rejected from according to current practice in TC124 TG1 (EN14081-2: Annex A). Optimum grading was done to C24 as a single grade and to the grade combination C40-C30-C18 when that was possible. If no settings could be found for C40, the grade combination C30-C18 was used instead. Optimum grading was done with Matlab (MathWorks 2008).

Modeling

Modeling of moisture-corrected grade-determining properties was done based on nondestructive data from the grading machines, resulting in Indicating Properties for the machines (IPs). The target of the modeling was to achieve models that could be understood and that were stable for all dimensions; *i.e.*, separate models for spruce and pine were made, but no dimension- or log-class-specific models. For the log grading equipment, the models were hierarchic partial least squares (PLS) models, while for the dry-grading equipment, regular PLS models were made. Both have proven stability and good predictive ability (Brännström *et al.* 2007). Models were made with a randomly selected Training Set (TS) consisting of 50% of the observations. Variables were selected based on variable significance analysis and the validation result on the remaining Prediction Set (PS). When the variables were decided, a final model was made with all specimens in the sample. Modeling was done in Simca-P (Umetrics AB 2006).

Derivation of Settings for Strength Grading

Machine control settings were derived for all machines except the certified grading machine as stand-alone strength grading machines. The certified machine was used with certified settings (EN14081-4:2005/A5:2008). No pregrading was applied prior to settings development.

When several indicating property values are being considered, the settings for the grading machines must be derived with some strategy. One strategy is to use the best indicating properties as determined by their R^2 values, but it is not so easy to decide which one to use when there are grade-determining properties, and the correlation might be different in different ranges of the grade-determining properties. For that reason, settings were derived following a procedure of iteratively increasing the setting as little as possible for all indicating properties simultaneously until an acceptable value for the grade-determining properties and cost matrix was found, *i.e.* by using the Smallest Increment Algorithm (SIA) (Fig. 1).

The algorithm finds, by sorting on each grade-determining property, the indicating property value amongst several indicating properties that gives the smallest reduction of the data when it is applied as a setting. This is repeated until the required grade-determining property values are achieved in the remaining data, i.e. the data which are not rejected by applying the preliminary setting. The cost matrix is calculated when all of the requirements on the grade determining properties are met. The iteration continues until the requirement on cost matrix is met. Finally, the result is a vector with settings for different indicating properties. The development of settings can be visualized if the vector with preliminary settings is logged for each iteration.

The log grading was done both with fixed settings, *i.e.* made according to – and fulfilling – the standard, and as pregrading, with a sliding use of the threshold within the indicating property range. As several indicating property values were used also for pregrading, the settings were balanced with the SIA method without using the cost matrix. The setting history from the setting derivation was saved and used for this purpose (preliminary setting, as indicated in fig.1). Derivation of settings was done with Matlab (MathWorks 2008).

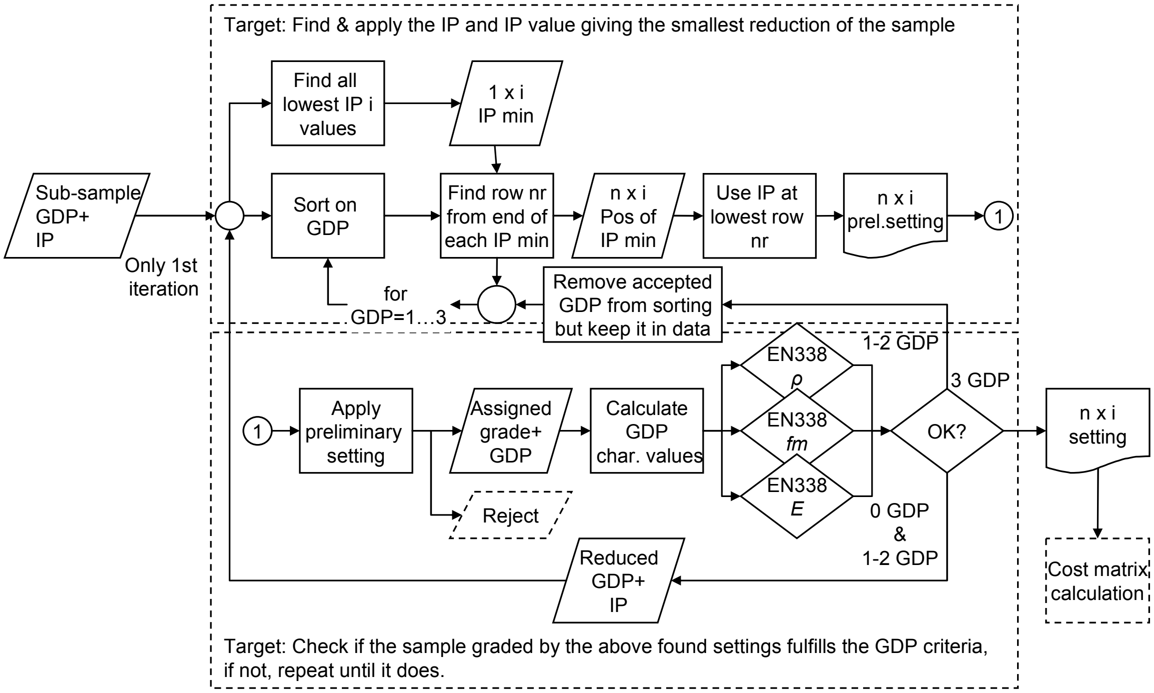

Fig. 1. Description of the setting derivation process according to the Smallest Increment Algorithm (SIA). The full data are fed into the algorithm and are reduced as little as possible by each iteration. Finally, settings fulfilling the criteria are found and can be analyzed by the cost matrix method. If the criteria in the cost matrix are not fulfilled, the iteration continues until they are (not indicated in the figure). IP = Indicating property, GDP = Grade determining property, i = position in a list.

Nordic Timber Quality and Visual Override Grading

For alternative products, the grading result from the visual color scanner and existing factory settings for the visual grades according to Nordic timber grading rules “Blue book” were used (Anon. 1997). For those dimensions where no factory settings for the scanner were available, new ones were developed similar to the existing ones. Consequently, not all settings have been calibrated to the rules in production. This work was done by experts at the machine supplier.

Visual override (VO) was also found by using the visual color scanner and the exact requirement values for deformation as the only criteria; *i.e.*, no fissures or wane were included in the judgment (EN14081-1:2005, Table 1). The machines might not be able to detect other defects, such as abnormal grain deviations and top ruptures. If these defects were included in the sample, the machine settings should account for the uncertainty in grade-determining property prediction introduced by them; thus they were disregarded in the visual override. Although this is not common practice, the effect from these defects on the grading result can be assumed to be small.

The visual override grading was done on dry, but rough-sawn material, which makes deformations larger than after planing. For that reason, the result on C-grading represents the worst case and was not considered in all parts of the analysis. Contrary to C grades, the visual grades were not strictly graded on deformation.

Grading Processes

Different grading processes were studied and compared (Table 2). Two setting combinations were studied, C40-C30-C18 and C30-C18. A sliding scale based on SIA output was used for pregrading. The impact of feedback from dry grading to machine grading (case G is a special case of D) was only studied in one example. Case E was intended to act as a comparison to a pregrading with different characteristics.

Table 2. The Different Grading Processes Studied

Case	Process step 1	Setting type for step 1	Process step 2	Setting type for step 2
A	Log grading	Machine control	-	-
B	Dry grading	Machine control	-	-
C	Machine grading	Machine control	-	-
D	Log grading	Pregrading	Machine grading	Machine control
E	Dry grading	Pregrading	Machine grading	Machine control
F	Log grading	Pregrading	Dry grading	Machine control
G	Log grading	Pregrading	Dry + machine grading	Machine control

Economic Value of Grading

Making accurate calculations of sawmill economics, including different cases, requires a huge effort or support from online systems. For that reason, a rough estimation of profitability was used.

The relative price, compared to net mill price of C30, was used for absolute value studies, assuming that all grades and volumes can be sold—referred to as "full demand." In contrast, a demand-weighted relative value was used for sensitivity analysis of the grading process, to mimic the impact of prices and demand on the value—referred to as "limited demand." There is not always a good demand, or price, for low qualities such as C18 or visual grades below B grade, thus regarded as off-grade (or a "push product") (Table 3). The market prices were based on average net mill prices from sawmills in Finland during the year 2007. For strength-graded products, data came from one sawmill, and for the Nordic timber qualities, data were acquired from three sawmills.

The year 2007 represents, on average, a year in which the demand for wood products was high without being extreme. Strength optimization through defect removal was not allowed in this study, while for visual grades, improving the value by defect removal and module cutting was applied. This reduced the volume in visual qualities. Optimization was done by the machine producer, and the price tables for that are not known.

Process costs were acquired from one Swedish sawmill (Table 4), which are similar to those of Finnish sawmills. A very rough calculation method with cost/m^3 was applied, summing fixed and variable costs and averaging them over the processed volume. The processed dimensions influence production cost, so smaller dimensions increase the production cost/m^3 to some extent; but that was disregarded, and average prices and costs per m^3 were used in order to facilitate analysis. Raw-material cost, which is the largest post, was assumed to be constant and was thus disregarded. Naturally, this is a very rough simplification.

Table 3. Relative Average Net Mill Prices Used for Analysis

C grades	Relative price/m^3		Demand weighted relative price/m^3
C40	108		108
C30	100		100
C18	83		0
REJECT	37		0
Nordic timber qualities	**Spruce**	**Pine**	**Both species**
A	71	79	105
B	67	75	100
C	63	71	0
D	58	67	0
REJECT	37	37	0

Table 4. Relative Production Costs Used for Analysis

Production subprocess	Relative cost/m^3 end product
Log sorting, sawing, packing	7
Drying 12%^{A}	4
Drying 18%^{A}	2
Dry grading^B	5
Planing^B	7
Either of ^{A} and ^{B} marked subprocesses is used in combination.	

The value (V) was found by multiplying volume in a certain grade (vol_{grade}) with the net mill price/m^3 (P_{grade}) and deducting the sum of production costs/m^3 ($C_{process}$) to reach that grade. The Nordic timber (NT) qualities were assumed to be dried to 18% and dry graded (rough sawn surface), while C grades were assumed to be dried to 12% and planed. The log sorting, sawing and final packing were the same for all grades; nonetheless, it was deducted for consistency. For example,

$$V_{Total} = V_{C-grades} + V_{Nordic\ timber\ quality} = \sum_{i=\mathrm{Re}ject}^{C40} vol_{C-grade\ i} \cdot \left(P_{C-grade\ i} - \sum C_{C-grade\ process}\right) + \sum_{i=\mathrm{Re}ject}^{A} vol_{NT\ grade\ i} \cdot \left(P_{NT\ grade\ i} - \sum C_{NT\ process}\right). \quad (3)$$

A special calculation was made for case E, pregrading by dry grading. Although the pregrading was done in the dry-grading department, in terms of cost, it was handled as if it was done in the green-grading department of the sawmill; *i.e.*, the costs were the same as for the pregraded log material. The purpose was to study the general impact of pregrading without involving the process complications caused by different moisture content of different products and the efficiency reduction of such a material flow.

Strength Variation Within Grades

Strength variation within grades was studied through coefficient of variation (COV) and the cumulative strength distribution for some examples. COV was derived for the whole distribution, assuming normal distribution. This simplified analysis makes the results not fully comparable with other studies, where a lognormal distribution is fitted to the lower tail (< 10% of the cumulative), but acts as indication of quality variation. It should be borne in mind that the COV of the whole distribution includes variation to the strong side of the distribution.

RESULTS AND DISCUSSION

For a detailed description of the wood material properties, the project report can be consulted (Hanhijärvi *et al.* 2008). Some differences in the number of specimens and batch properties will be found due to different methods used and due to which part of the data has been used. As settings for machines may depend on the IP value of a single specimen, the differences might influence the result to a lesser extent.

The study covers a large amount of data and a complex process; consequently, extensive amounts of results are made available. Only illustrative examples are shown here to clarify the topics discussed.

Log grading can be done according to different strategies. Models can be created for the weakest- or strongest board in the log, or a model for the average strength of the boards in the log can be made. All depends on the target with the grading, the grading accuracy, and the properties of the graded species. If all boards in the log would have been destructively tested, different models could have been made, compared to the present analysis, where only a random board was selected from each log. It can be compared to grading for average strength of boards in the log. This constitutes an error source when studying potential yield due to in-tree variation and the influence of it on settings. However, it can be assumed that the variation in the sample covers both the weaker and stronger specimens in a log; thus the results are representative.

Models

As the number of models is large, only the performances of the models are presented (Tables 5 and 6).

The modeling results of log x-ray data (Table 5) were similar to the results of the linear models made in Combigrade 2 on the same data (Hanhijärvi *et al.* 2008). The models were hierarchical, such that the density model was included in the $E_{m,g}$ model, and both of those were included in the f_m model. As in earlier research (Brännström *et al.* 2005), the models were stable, based on comparing R^2TS with Q^2TS, R^2PS, and R^2 for the final model. The addition of resonance frequency to the x-ray derived variables improved R^2PS for E models by 6%–9%. In general, the resonance frequency is sensitive to temperature when the wood tissue is raw (Edlund *et al.* 2005; Carter *et al.* 2005), and the measurements were made in wintertime with varying temperature. The applied temperature correction improved the degree of explanation of strength properties.

Table 5. Indicating Property Models for Grade-Determining Properties for Log-Grading Equipment

Species	Modelled property	Technology	R^2 TS %	Q^2 TS %	R^2 PS %	RMSE PS	R^2 all obs %
Pine	f_m	x-ray	56	56	64	8.1 MPa	60
		x-ray + freq.	60	60	66	7.9 MPa	63
	$E_{m,g}$	x-ray	58	57	63	1.3 GPa	60
		x-ray + freq.	68	66	72	1.1 GPa	68
	ρ	x-ray	51	50	54	42 kg/m^3	54
Spruce	f_m	x-ray	43	41	44	8.7 MPa	44
		x-ray + freq.	44	44	46	8.5 MPa	45
	$E_{m,g}$	x-ray	44	42	38	1.4 GPa	41
		x-ray + freq.	54	52	44	1.4 GPa	49
	ρ	x-ray	53	51	31	34 kg/m^3	43

TS = Test set, PS = Prediction set, Q^2 = predictive ability as judged by cross validation on TS, freq. = resonance frequency, RMSE = Root mean square error, f_m = Bending strength, $E_{m,g}$ = Global modulus of elasticity, ρ = Density at 12% MC

The models based on variables from the dry-grading equipment were similar to what can be expected from knot-area ratio models, a bit below for pine and a bit higher for spruce, when compared to manually measured values on the same sample (Hanhijärvi *et al.* 2008) (table 6). It was not possible to model density based on the dry-grading equipment variables.

No data from 3-D log outer shape scanning were available, although some outer shape parameters can be measured by the x-ray log scanner. It has been shown in earlier studies that the shape parameters are important for strength prediction (Brännström *et al.* 2007). It can be assumed that inclusion of outer shape information would improve the models slightly.

Table 6. Strength (f_m) and Stiffness ($E_{m,g}$) Models for the Dry-Grading Equipment

Specie	Property	R^2 TS %	Q^2 TS %	R^2 PS %	RMSE PS	R^2 all obs %
Pine	f_m	37	35	38	9.3 MPa	41
	$E_{m,g}$	39	38	24	1.6 GPa	40
Spruce	f_m	36	34	42	8.9 MPa	39
	$E_{m,g}$	26	25	28	1.5 GPa	27

TS = Test set, PS = Prediction set, Q^2 = predictive ability as judged by cross validation on TS, RMSEE = Root mean square error, f_m = Bending strength, $E_{m,g}$ = Global modulus of elasticity, ρ = Density at 12% MC

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Derivation of Settings and Optimum Grading

The derived settings fulfilled the main requirements in EN14081-2. The reject settings were not studied very carefully; thus the results for reject should be regarded as an indication of what is possible rather than as a fact.

The SIA algorithm did not improve the yield in all cases. One example is given for log grading of pine, to achieve settings for C40 based on the complete sample (only serving as an example, since the ordinary routine according to EN14081 was not followed). For comparison, the best predicting indicating property value, E model (Table 5), was selected as a single indicating property (Fig. 2, left).

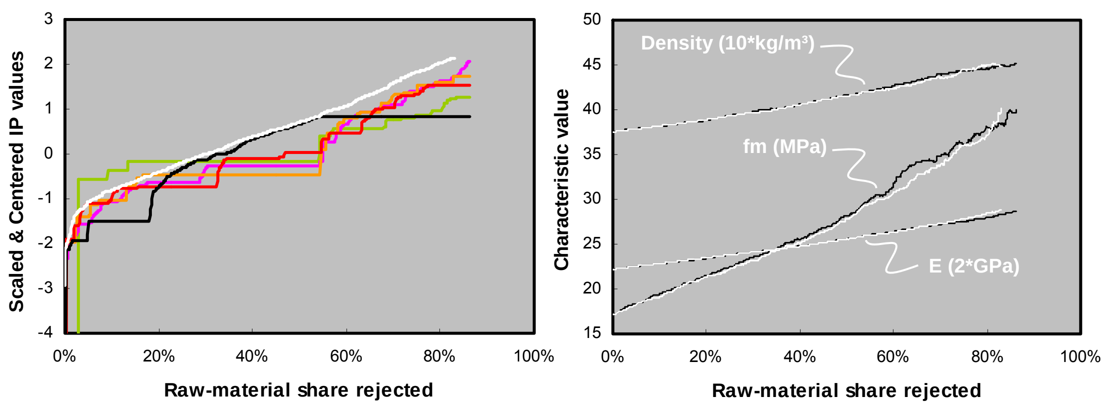

Fig. 2. Example of evolution of settings (left) and grade-determining property values (right) while achieving a setting fulfilling C40 GDP requirements for the complete pine sample by log grading. Left: Settings for five indicating property values combined, compared to the corresponding evolution of a single setting (white), which is based on the same indicating property as the black line. Right: Characteristic values resulting from multiple settings derived by SIA (black) and the corresponding values from a single setting (white). The grade-determining properties are normalized to fit the same plot.

Settings for the grade combination including C40 were not achievable with the dry-grading equipment, due to a too low yield for some subsamples. The log grading equipment could find C40 for both species, but for pine it was not possible to find both C40 and C30 in combination.

The C40 requirements were achieved with higher remaining raw-material share (yield) in the example when using a single indicating property setting, compared to multiple indicating property settings (Fig. 2 left & right). It can be concluded that multiple settings can be beneficial from the point of view of yield, depending on the requirements of the grade and the precision of the competing single indicating property (Fig. 2 right). Figure 3 shows the biggest yield difference at f_m 34 MPa, 6% larger for multiple indicating properties than for a single indicating property.

The main benefit of using multiple settings comes from the ability to grade different grades. C40 settings could not be found for the example data (Fig. 2) by using a single setting (too few assigned specimens in certain subsamples), while it was possible with multiple settings, giving a final yield of 12% (after cost-matrix control and averaging of settings). This agrees with previous research in the field, based on simulations, where it was more common to find settings for high grades by using "combined grading", *i.e.*, settings on several indicating properties (Turk and Ranta-Maunus 2003).

Visual Override

In this study, the visual override grading greatly influenced yield, regardless of whether a grading process was applied or not. A comparison between the optimum and assigned grades from grading all material with a certified grading machine shows only expected differences according to the standard. Comparing the optimum and machine-assigned grades with the assignment including visual override shows the considerable impact of visual override (Tables 7 and 8). C40 and C30 were reduced by 50%, while C18 increased by 100%, and reject increased from 1% to 20%.

Table 7. Yield of Spruce in Optimum Grade (OG) and Machine-Assigned Grade with Visual-Override Grading (MG + VO)

	MG + VO				Sum
OG	**C40**	**C30**	**C18**	**REJ**	**OG**
C40	9%	4%	10%	3%	**26%**
C30	1%	13%	12%	6%	**32%**
C18	0%	6%	24%	11%	**41%**
REJ	0%	0%	0%	0%	**0%**
Sum MG + VO	**10%**	**24%**	**46%**	**20%**	**827 pcs**

Table 8. Yield of Spruce in Machine-Assigned Grade (MG) with and without Visual-Override Grading (VO)

	MG + VO				Sum
MG	**C40**	**C30**	**C18**	**REJ**	**MG**
C40	10%	0%	8%	2%	**21%**
C30	0%	24%	19%	11%	**54%**
C18	0%	0%	18%	6%	**24%**
REJ	0%	0%	0.4%	0.5%	**1%**
Sum MG + VO	**10%**	**24%**	**46%**	**20%**	**827 pcs**

Comparing the machine-assigned grade with additional visual override shows the yield loss due to deformation, as this was the only visual override criterion used in this study. The yield loss could be ascribed to drying quality, since deformation can largely be handled by proper pregrading (spiral-grain-angle grading) and countermeasures in drying operations (counter twist, pressure frames) (Salin *et al.* 2005; Ekevad *et al.* 2006).

The visual color scanner was set to grade exactly on the deformation requirement in EN14081-1, which, compared to the building industry requirements, are too low (Johansson *et al.* 1994). The visual override was based on rough sawn boards, where deformation is larger than after planing; thus these results show a worst case.

By including the visual requirements on deformation in machine control settings, thus regarding them as indicating properties, the effect on yield might be reduced (Table 7). In this study, real strength-influencing parameters did not influence the result of visual override.

Quality Aspects of Grading Process

Pregrading alters the strength distribution toward the safe side, both by an increase in 5th-percentile value of the remaining sample and by a reduction in COV (Fig. 3). The prediction of characteristic value by a normal distribution fitted to the whole sample turned out to be more overestimated with decreasing share of accepted raw material in pregrading; thus the variation does not decrease as much as indicated by COV.

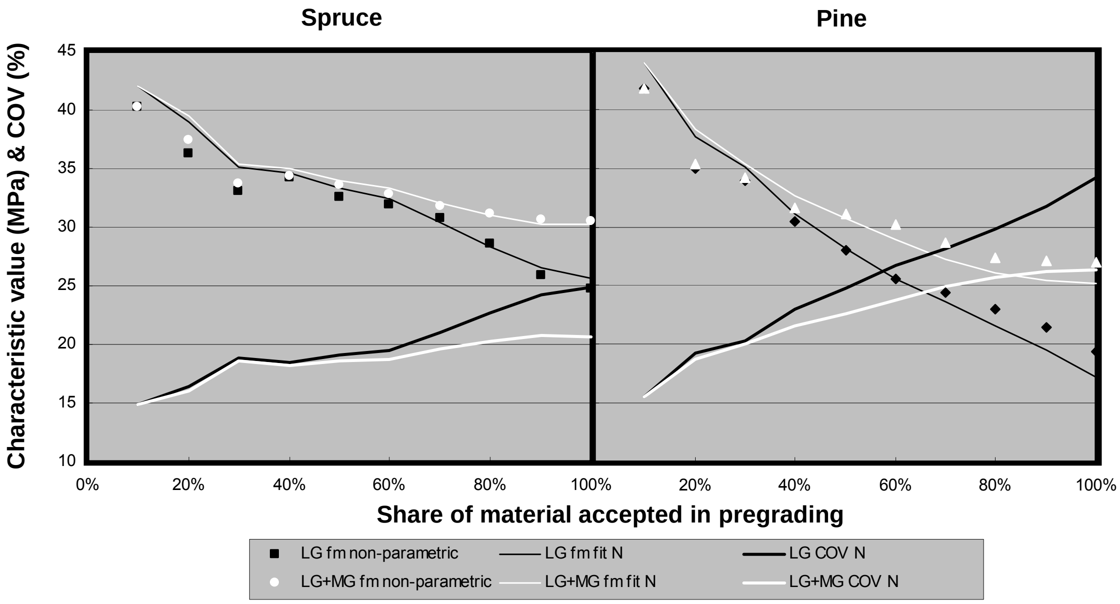

Fig. 3. The influence of pregrading on quality parameters, nonparametric characteristic bending strength and the normal distribution fitted 5th-percentile values. Log grading (LG), without settings (black), is compared to a combination with a grading machine (MG), grading C30 as highest grade. Only the C30 grade is displayed (white series).

To shorten the lower tail of the distribution below the characteristic value, there are two methods available: Improve grading precision or, with maintained precision, increase the requirement value to achieve settings. If special low-COV grades would benefit the customers, a process based on the latter method could be designed for the purpose with tools available today.

For C40 grade, all combinations of grading equipment or visual override resulted in a lower COV and higher characteristic strength when a positive selection was made (compare II, III and V in Table 9 and all combinations in Table 10).

A reduction of COV was not consistent when a negative selection (i.e. grading reject from a previous step in the process) was included in the flow, such as V *vs*. VII, where log-graded reject is graded at the dry grading and the accept from C30 is sent to the grading machine. This shows the risk of negative selection, although when combined with the positive selected material, requirements were fulfilled (V+VII=X). Note that a producer is not allowed to grade rejected specimens a second time, according to the standard.

Table 9. Sample Properties for Spruce Graded with Machine Control Settings by Different Processes.

Process step included	I	II Case A	III Case C	IV	V	VI	VII	VIII	IX = VI + VIII	X Case G
OG C40, C30	I									
LG C40, C30		I								
LG ≥C30					I	I			I	I
LG <C30							I	I	I	I
DG C30							I	I	I	I
MG C40, C30			I	I	I	I	I	I	V	V
VO				I		I		I	I	
Grade	**C40**									
$f_{m,k}$ (MPa)	41.9	40.2	41.9	45.8	43.8	47.2	28.9	16.1	47.2	41.5
$E_{m,g}$ (GPa)	14.7	14.6	14.9	14.9	15.2	15.3	14.3	14.4	15.0	15.0
ρ_k (kg/m³)	422	429	423	419	439	432	416	421	423	427
f_m COV N	13%	15%	15%	13%	14%	12%	17%	18%	14%	15%
Yield	26%	13%	21%	10%	13%	6%	5%	2%	9%	18%
Grade	**C30**									
$f_{m,k}$ (MPa)	32.4	30.4	31.4	31.5	35.4	26.4	33.2	32.4	33.1	33.5
$E_{m,g}$ (GPa)	12.6	13.8	12.2	12.3	12.8	13.0	12.0	12.6	12.7	12.3
ρ_k (kg/m³)	397	415	385	382	408	404	384	389	391	387
f_m COV N	15%	19%	17%	17%	16%	17%	14%	17%	17%	15%
Yield	32%	9%	54%	24%	8%	4%	18%	10%	14%	26%

I indicates the subprocesses in the raw-material flow. V indicates a joining of two material flows in the production process. LG = Log Grading, DG = Dry Grading, MG = Machine Grading, OG = Optimum Grade, VO = Visual Override. Case refers to Table 2. COV N = Coefficient of variation assuming a Normal distribution is followed. LG and MG are made by C40-C30-C18 settings. DG is with C30-C18 settings.

Visual override increased COV and reduced characteristic strength in some cases (VII vs VIII). This result was not consistent (III vs. IV) and needs additional studies of visual override, considering the deformation after planing and other strength-reducing features. It seems as if the machine giving the lowest COV of the machines used in a process will govern the resulting COV (Fig. 4, Table 9).

Nordic timber grades corresponded to strength to a limited extent (Table 11). The reason is mainly that the visual grades depend on knot sizes, which also influence strength. The COV for the best visual grade (A) is comparable to the one achieved by strength grading to C30 as the highest grade (Table 10). However, selecting the amount corresponding to the A-grade yield for pine (10%) with a log strength grading machine gives a characteristic strength close to 45 MPa (Fig. 3), which means that the visual grades do not correspond very well to strength, and thus work well as a complementary product to strength grades. Qualities sold for furniture production or floors, with larger fresh knots, are commonly found in both grade A and grade B (Lycken 2006), which complement high-strength product well due to low strength and high variability (Tables 11 and 12). Surely, many customer-adapted grades complement strength grades even better.

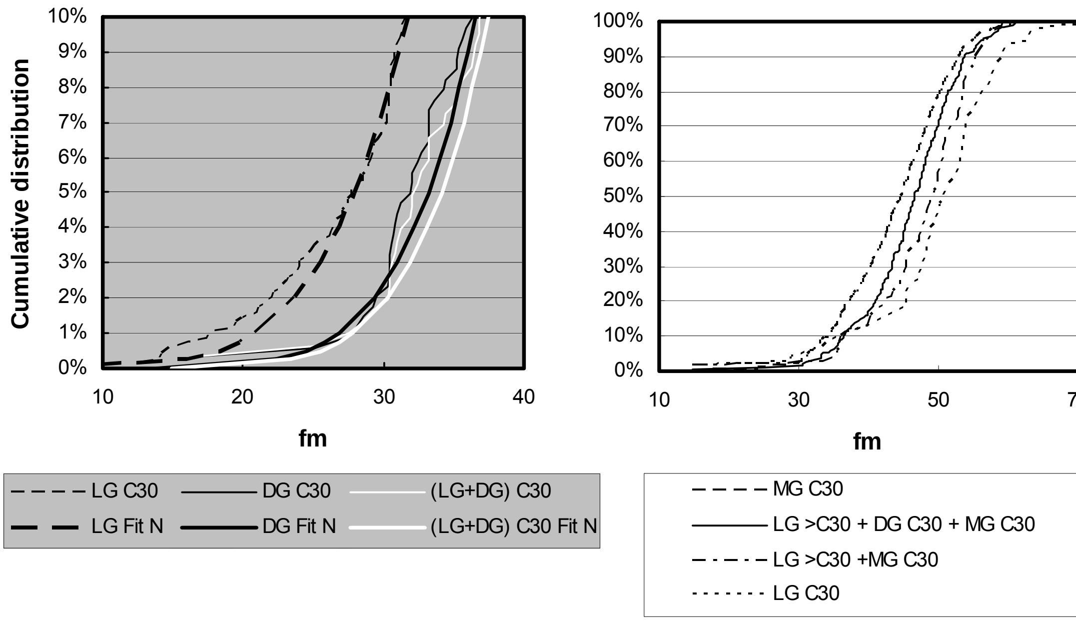

Fig. 4. Cumulative distributions for spruce C30 when C30 was the highest grade. Left: Lower tail from log grading (LG), dry grading (DG) and the combination of both (case A combined with C). Normal distributions fitted to the whole grade. Right: Whole distribution of Case A, Case C combinations of Case A & C, Case A & B & C. The last one corresponds to Table 9, column X.

Table 10. Strength Characteristics and Yield Values Based on Whole Spruce Sample for Different Grades and Combinations of Machine Control Settings

Grade combination	**C40-C30-C18-Reject**					
Process & Grade	**LG C40**	**MG C40**	**LG C40 + MG C40**	**LG C30**	**MG C30**	**LG C30 +MG C30**
$f_{m,k}$ (MPa)	40.2	41.9	45.4	30.4	31.4	33.5
f_m COV N	15%	15%	11%	19%	17%	17%
Yield	13%	21%	10%	9%	54%	5%
Grade combination	**C30-C18-Reject**					
Process & Grade	**LG C30**	**MG C30**	**DG C30**	**LG C30 +MG C30**	**LG C30 +DG C30**	**DG C30 +MG C30**
$f_{m,k}$ (MPa)	27.8	30.5	31.9	31.0	32.3	34.3
f_m COV N	23%	21%	19%	20%	19%	18%
Yield	83%	84%	41%	75%	37%	39%

LG = Log Grading, MG = Machine Grading, DG = Dry Grading. Combinations of equipments are denoted by '+'. COV N = Coefficient of variation assuming a Normal distribution is followed.

Table 11. Yield, Characteristic Strength and COV for Nordic Timber Qualities

	Species	A	B	C	D	Reject
Yield	Spruce	55%	27%	13%	4%	1%
	Pine	10%	37%	42%	11%	0%
Characteristic strength (MPa)	Spruce	30.4	21.7	20.2	19.1	-
	Pine	32.5	19.3	19.1	18.1	-
COV N	Spruce	22%	27%	31%	27%	-
	Pine	20%	32%	36%	38%	-

Table 12. Yield in C grades (MG) and Nordic Timber Qualities for Pine

Pieces	Visual grade				
MG	**A**	**B**	**C**	**D**	**Reject**
C40	36	33	47	17	1
C30	38	85	70	18	0
C18	18	206	242	59	0
Reject	0	8	18	2	0

Economical Value of Grading Processes

For spruce graded to C30, the log-grading machine could compare to the grading machine, but in all other cases, the grading machine was better (comparing case A and C in Table 13). Considering the ability to select the wanted raw material, as well as avoiding unwanted raw material before sawing, the advantage is clear for the log grading equipment. Nevertheless, reject due to visual override must be expected in all cases (Table 9).

Table 13. Grading Yield for Spruce and Pine for Machine Controlled Settings

Spruce	**Case A LG C40**	**Case C MG C40**	**Case A LG C30**	**Case B DG C30**	**Case C MG C30**
C40	13%	21%			
C30	9%	54%	83%	41%	84%
C18	78%	24%	16%	59%	13%
Reject	0%	1%	0%	0%	2%
Pine	**Case A LG C40**	**Case C MG C40**	**Case A LG C30**	**Case B DG C30**	**Case C MG C30**
C40	12%	15%			
C30		23%	54%	40%	71%
C18	88%	58%	29%	57%	10%
Reject	0%	3%	17%	4%	19%

LG = Log grading, DG = Dry grading and MG = Machine grading. The grade in the headers refers to the highest grade in the grade combination.

Although a certifiable result is achieved by the log grading equipment, an identical grading decision will not be achieved by a grading machine later in the process. The pregrading result shows this effect very clearly (Fig. 5). Table 14 shows an example of high agreement between the machines: 81% (Table 14). Different features of the log or board might be considered, or measured differently. For that reason, it is more beneficial to enrich the desired properties by pregrading than to combine two machines with machine control settings, grading the same grade combinations.

Table 14. Grading Result on Spruce by Using Machine Control Settings in both Log Grading (LG) and Grading Machine (MG). (Table 2, combining cases A & C)

Pieces	**LG**		
MG	**C30**	**C18**	**Reject**
C30	623	72	2
C18	61	50	0
Reject	5	14	0

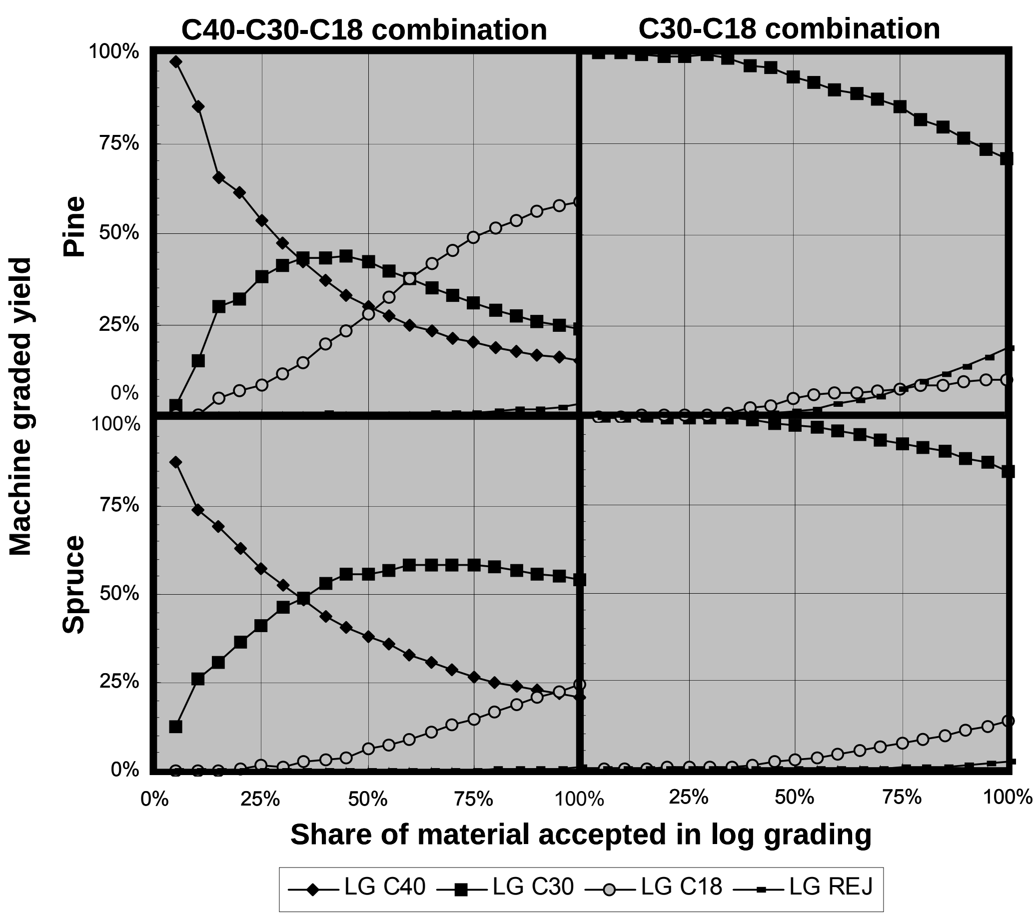

Fig. 5. Machine-graded yield after log pregrading as a share of pieces in each grade. Table 2, Case D.

In this study, the strength-graded products were in most cases better for producer economy in the full demand situation (unweighted, Fig. 6). In the C30-C18 grade combination, a larger share was valued higher in C grades due to higher yields (Fig. 5) and the relatively high price for C30 (Table 3).

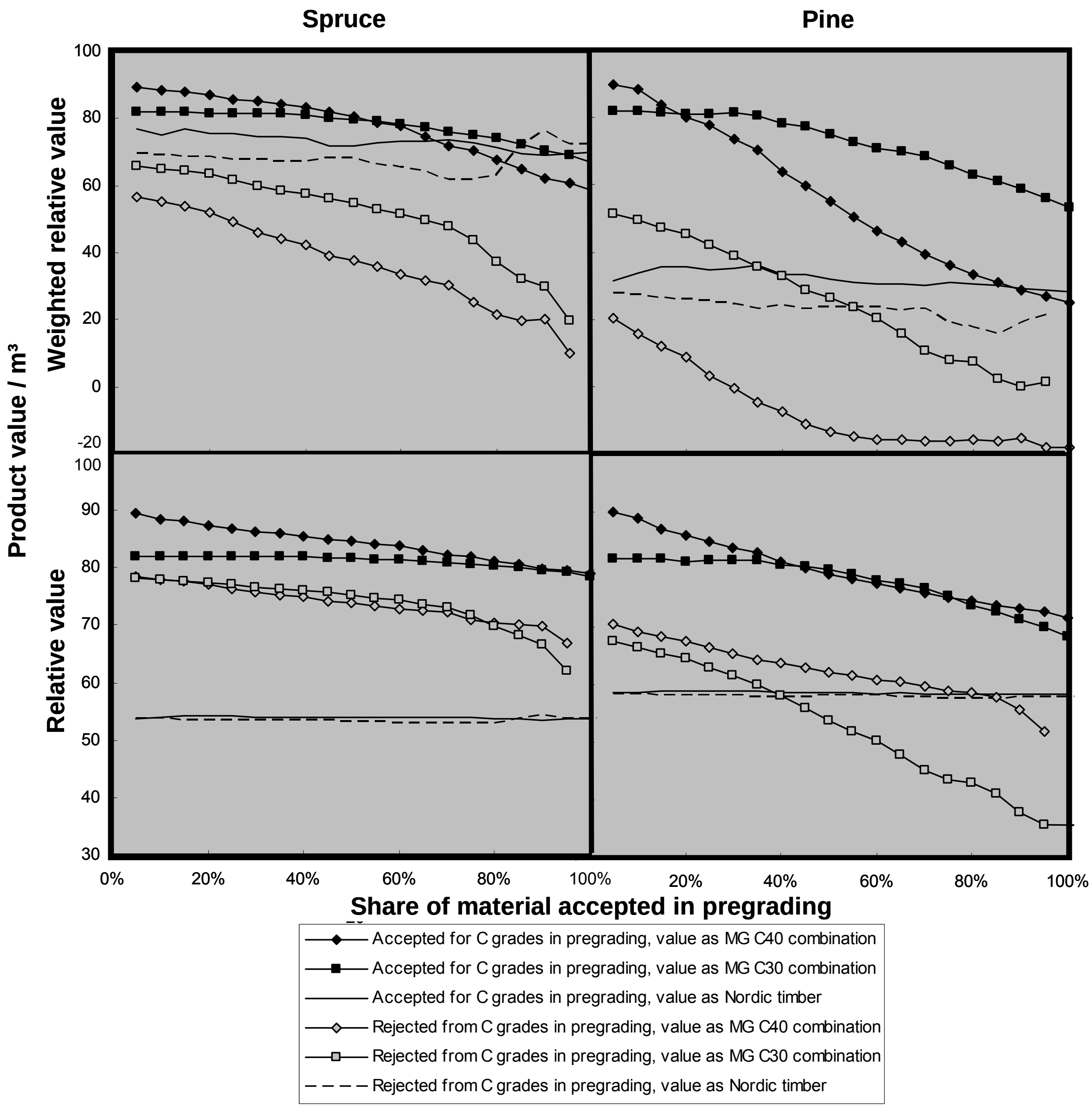

Fig. 6. Batch constituents' average value depending on species, weighted or unweighted grade value, grade combination and share of material accepted in pregrading. Alternate products are Nordic timber visual qualities, also weighted for demand. Accept and reject refer to the log-grading result. The grade refers to the highest grade in the combination, and the value is the sum of values for each grade in that grading. Note the difference in scale between demand-weighted and unweighted plots. Points based on single boards have been removed. 100% share of material accepted in pregrading and "Accepted for C grading" series gives the same value as 0% share of raw material accepted in pregrading and "Rejected from C grading" series.

In general, pine suffered from a lower yield in grades ≥ C30, compared to spruce, which influenced the profitability of the total batch (Fig. 7). On the other hand, the higher value of pine alternate quality (Table 3) caused a higher batch value to be found for stricter pregrading in the full-demand case (<50% accepted in pregrading) compared to spruce at the same level of pregrading and demand. The C-grade value for spruce was so much higher compared to the alternate product that the batch value deteriorated linearly with increased pregrading share for full demand (Fig. 7). In the limited-demand case, value was higher with pregrading than without. In part, the higher yield in the highest alternate grade, A, for spruce compared to pine explains the difference. Another explanation is the low share of C18 and reject for spruce compared to pine (Fig. 5). The consequence was that pregrading influenced all grading processes positively for limited demand of spruce, but not at all for full demand. For pine, a local optimum was found in all cases except C40 grade combinations in full demand, where pregrading was of no benefit.

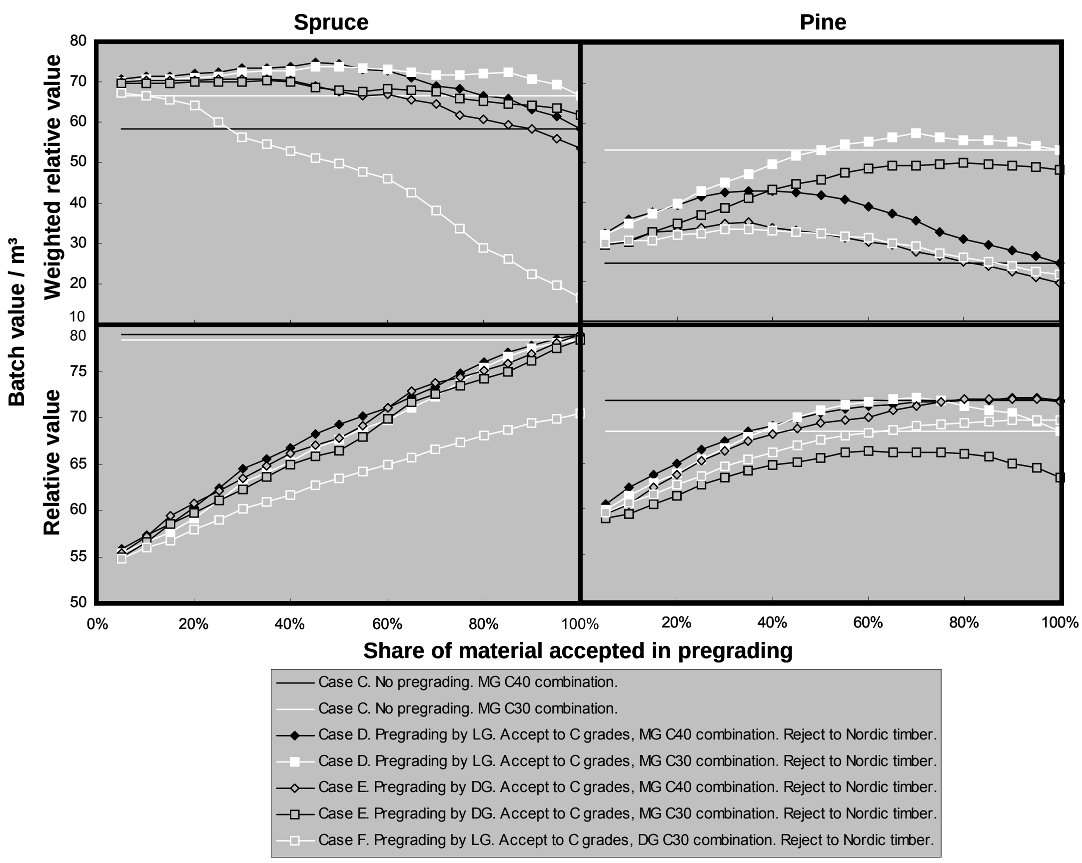

Fig. 7. Batch average value depending on species, weighted or unweighted grade value, grade combination, grading equipment, and share of material accepted in pregrading. The average value when grading accept from log grading to C grades, in different grade combinations, and the reject to Nordic timber. Letters refer to case studied. LG = log grading, DG = dry grading as machine, and MG = machine grading. Note the difference in scale between weighted and unweighted values.

The most favorable grade combination, for machine grading without pregrading, shifted with demand for both pine and spruce (Fig. 7). The grade combination with C40 as highest grade was more competitive with unweighted price levels; the difference was especially large for pine. It can be concluded that the price difference between average net mill price for C40 and C30 was too small to make C40 grading profitable, unless the demand is very high also for lower grades, while anything that can increase the alternate grade price or reduce the share of off-grade is worth all effort. A comparison between final grading by the dry-grading equipment (low R^2) and the grading machine (high R^2) shows that the increased precision always pays off (see Table 2, comparing case F with D and E). This is entirely a consequence of the lower precision (Table 6) in the dry-grading equipment, causing a higher share in C18 to achieve the needed characteristic value for C30.

Pregrading in the dry-grading mill (Table 2, case E) failed as a concept due to reduced flexibility compared to log grading. However, it was beneficial for both species in the limited-demand case, with more selective grading of C40 combination (high share of pregrading reject) compared to no pregrading (Table 2, case C). The total profitability should, in a case where the moisture content is equal for both products, be recalculated due to processing in two departments and changed cost for drying for one of the products (Table 4). The utilization rate of C grades by pregrading, either with high R^2 (log grading) or low (dry-grading equipment), showed expected results: with higher R^2, the off-grades are reduced faster and high grades are kept longer compared to using low R^2 (Fig. 8).

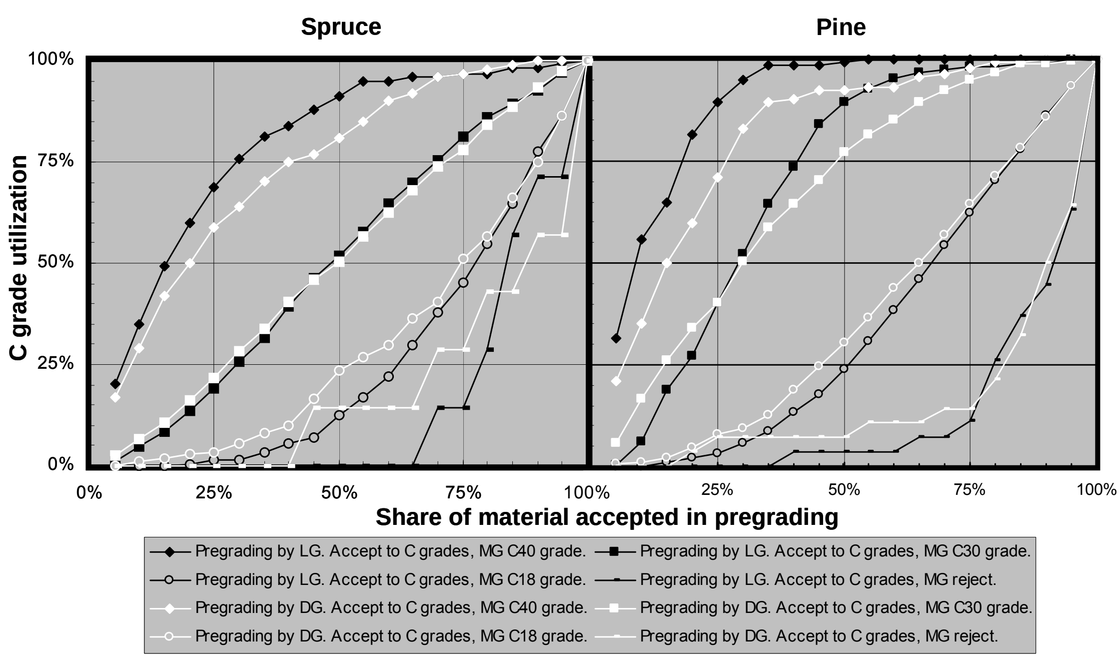

Fig. 8. Utilization of raw material compared to no pregrading, depending on pregrading equipment. LG = log grading, DG = dry grading.

Future Research

The process studied here applied no traceability on the individual level; *i.e.*, no settings were based on several machines combined. Instead, the more short-term realistic system with batch traceability was applied. In practice, logs are graded, gathered into one pile representing the quality for steering the next step in the process, and the grading data are "forgotten." Additional studies on grading processes including individual traceability should be done, as was considered by Flodin *et al.* (2008), and systems for handling the individual data in a safe manner proposed.

It was not studied whether present high-end grades (>C40) could be found more easily with a grading process. To further study such topics, stratified sampling, done by log grading, for example, seems to be needed, as the availability of such high grades is very low in a random sample. The simulation methods used in Turk and Ranta-Maunus (2004) might also be useful in such evaluation. A new classification algorithm, suitable for a grading process, has proven beneficial for yield (Brännström and Westin 2009). Dimension and/or log-class specific models could additionally increase grading precision and thus yield.

A possibility for additional increase in economic value comes by using Output control, in which the settings in the final grading can be adjusted to the distribution of the incoming raw material. It remains to be studied how harmonization of raw-material quality through pregrading of logs impacts the output control process and its profitability. In such a process, green grading should be included, which would be a more natural step in a grading process than to include dry grading.

With the present standard, possible benefits from including the visual override in machine control as a settings should be evaluated; *i.e.* all boards that do not fulfill the visual override would be removed prior to setting derivation, or in a process similar to SIA, in order to base settings only on those specimens that will be sold as structural timber.

To establish machine controlled strength grading done on logs, special attention must be paid to consideration of the effect of seasonal moisture and temperature variation, so that it will not influence the grading result.

CONCLUSIONS

1. Pregrading of structural timber by any means is safe, as long as the best material is selected for continued grading.
2. Pregrading of structural timber increases characteristic values, and coefficient of variation does not increase.
3. It is possible to achieve machine control settings with similar yields with log-grading equipment as with a grading machine for some grade combinations.
4. Log grading can be used efficiently as a strength-grading method, as long as visual override is performed later in the process.
5. Drying process quality has a large impact on the financial result of any strength-grading process through the visual override and should be greatly emphasized for improved economy and quality.

6. C40 as highest grade is only more profitable compared to C30 if there is a full demand for the increased yield in C18 entailed by using it.
7. A grading process for pine is more sensitive to C grade prices and the grading of high grades than is spruce, due to the larger share of material with low grade-determining property values.
8. The visual quality according to Nordic timber is not well related to strength and thus acts well as a complementary grade for C grades.
9. The Smallest Increment Algorithm enabled grading in combinations where it was not possible to develop settings using a single indicating property.
10. The Smallest Increment Algorithm with several indicating properties does not always improve grading or yield compared to using a single indicating property.

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