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FACTORS AFFECTING VOLUME YIELD IN A FORESTRY-WOOD VALUE CHAIN – A SIMULATION STUDY BASED ON CT SCANNING

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Abstract:
The paper presents the results of a simulation study, where log models based on CT scanned logs of Scots pine (Pinus sylvestris L.*) was used as input material to a computer simulation model of a generic value chain involving sawing, drying, crosscutting and finger jointing. The aim was to investigate which factors that affect the volume yield in the value chain, be it forestal, log-, process- or quality-related factors. The results show that factors related to growth conditions and log size have a large impact on the volume yield in the studied value chain, together with quality requirements on knots. Factors such as sawing positioning and log quality had a much smaller impact. It can be concluded that it is possible to model a forestry-wood value chain, while assessing which input variables affect the result in terms of volume yield, using CT scanning of logs and subsequent computer simulation of the production processes.*

Key words: *computer simulation; CT scanning; material efficiency; multivariate statistics.*

INTRODUCTION

The cost of raw material in a forestry-wood value chain takes up a large part of the total costs (Lindholm 2006). Each process step in the value chain affects the material utilization efficiency and therefore the cost efficiency. Wood has high diversity in its inherent features and the different processes must be able to handle this. Every piece of wood is unique and it is challenging to handle the high variability in the input material. In modern production processes, many of the decisions are being made automatically with the aid of computer systems and data obtained from scanning equipment.

Optimization in a production system is usually done at one production unit at a time, optimizing only that particular unit's performance. This leads to sub-optimization since the whole chain from log to an end product is not considered (Perstorper et al. 1995, Usenius et al. 2007). A system based thinking, where the whole chain is considered when optimizing, is more efficient (Beenhakker 1964, Pulkki 2001).

In a long and complex value chain, it is therefore of interest to identify which factors that affect the total material efficiency. Some attempts have been made, based on live tests where the material has been followed through a physical value chain (Broman and Fredriksson 2012). However, there are downsides of doing tests in an industrial environment, i.e. experimenting with the system itself rather than a model. It is usually expensive, time consuming, and, in the case of wood, does not allow for control of variables on a common data set. The reason for this is that wood has inherent properties that are unique for each tree and log, and that many of the production processes involved are irreversible, so the material cannot be restored to its original state. Even though experimenting with the actual system means that there is no need for validation, modelling is advantageous since tests can be done on the same material but with different process parameters.

In some cases, simulation have been used to assess the effect of forest and log features on a product, however these have mainly studied one process at a time, mainly sawing (Pinto et al. 2005, Lundahl and Grönlund 2010, Stängle et al. 2014). Again, this carries with it a risk of sub-optimization and therefore reduced material efficiency, if the value chain contains several sub-processes.

To avoid sub-optimization it is important to study an entire value chain with all included sub-processes, if possible. In addition, simulation models are useful since they reduce the need for expensive and practically unrepeatable test sawing. This study will demonstrate how simulation models can be used to study a value chain involving several sub-processes, thus applying a holistic perspective of the value chain.

When identifying factors that affect yield in a value chain, some sort of statistical model is needed. Partial least squares (PLS) regression is a good prediction method when the predictor variables are correlated to each other and when there can be noise in the data (Wold et al. 2010). This is often the case when wood is studied. For visualising and analysing the structure of observations and variables, principal components analysis (PCA) is useful (Abdi and Williams 2010).

OBJECTIVE

The objective was to investigate which factors affect the volume yield of a production value chain that includes sawing of logs, and subsequent crosscutting and finger jointing of the resulting boards. This was to be done using CT scanned logs, computer simulation tools, and multivariate PCA and PLS regression modelling.

MATERIAL, METHOD, EQUIPMENT

To model a wood value chain with various production processes, a generic product was chosen as study case. The end product was finger-jointed boards of Scots pine (*Pinus sylvestris* L.) with cross-section dimensions of 38×100mm. The studied value chain is described in Fig. 1.

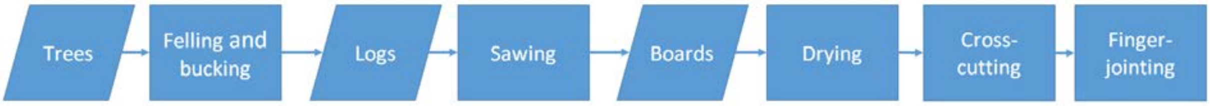

Fig. 1.
The studied value chain and its inherent sub-processes and material.

Roundwood data

This study was based on the Scots pine logs of the Swedish Pine Stem Bank (Grönlund et al. 1995). The stem bank trees, from well-documented sites at different locations in Sweden, have been documented thoroughly regarding tree properties and silvicultural treatments. They were bucked into logs that were scanned with a medical CT scanner (Siemens SOMATOM AR.T) to record internal properties. Knots are described by a parameterized model, which takes into account curvature and the diameter of the knot in two directions, tangential and longitudinal. Each knot is divided into a living and a dead part. Details on the knot model are given by Grönlund et al. (1995) and Nordmark (2005).

Since the aim was to produce boards with dimensions 38×100 mm using a cant sawing pattern, only logs with a top diameter between 130 and 149 mm were used. This means that out of the 628 logs in the Swedish Pine Stem Bank, 118 were used for this study.

Sawing simulation

Sawing simulation was performed using the simulation software Saw2003, developed by Nordmark (2005). The input was log models, based on the CT scanned logs of the stem bank. The log models were constructed by the parameterized knot models and an outer shape description of the log.

Saw2003 models a sawmill that employs cant sawing with two sawing machines, with curve sawing in the second saw, edging and trimming. The latter two are value-optimized according to timber prices and grading criteria. It is also possible to control positioning of the logs during sawing. An example of a log model used in Saw2003 is shown in Fig. 2, with outer shape and knots.

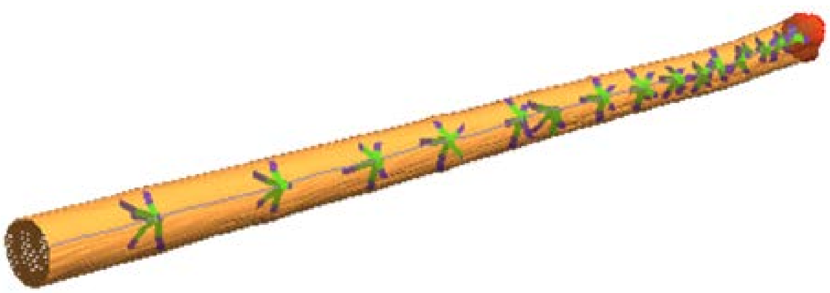

Fig. 2.
Example of log model used in this study.

The sawing simulation results in virtual boards with information about knots, dimensions, quality, value and so forth. Saw2003 has been used extensively in earlier research (Nordmark 2005, Moberg and Nordmark 2006, Lundahl and Grönlund 2010, Berglund et al. 2013, Fredriksson 2014).

All 118 logs were sawn using a cant-sawing pattern, resulting in two centreboards with dimensions 38×100 mm. Only the centreboards were considered in this study. Log rotation and offset was controlled during sawing, rotation was done at ten degrees counter clockwise from horns down, at horns down and at ten degrees clockwise from horns down. At each rotational position, the log was moved in the lateral direction from fully centred to a 10 and 20 mm displacement, respectively. At each position, sawing was made and the resulting virtual boards were saved for further processing. In this way, each log was sawn 3×3 = 9 times. The levels were chosen to achieve a large enough variable span for a visible change in yield, and were based on Berglund et al. (2013) and Fredriksson (2014).

Crosscutting simulation

A crosscutting simulation tool developed and validated by Fredriksson et al. (2015) was used to model crosscutting of the sawn boards that were the result of the sawing simulation. The tool is capable of crosscutting boards, given a product specification with limits on sizes of knots and wane. The outcome is value-optimized, and based on a value of each product set by the user.

Board features are classified as either accepted or rejected depending on a maximum length and width. In case both quality limits for length and width are exceeded, the feature is considered as a defect and is cut away. The rest of the defect-free wood is considered accepted and is subsequently used to value-optimize cutting of products. In this study, only knots and wane were considered since this is the only log feature that is included in the stem bank.

Each board was crosscut with the aim of producing finger-jointed boards, i.e. a variable-length product. The maximum allowed knot size was set at three different levels: 10, 25 and 50 mm. The same thing was true for the minimum and maximum length of the crosscut pieces, the minimum length was set to 130, 170 and 210 mm respectively, and the maximum length to 450, 550 and 650 mm. In this way, each board was crosscut 3^3 = 27 times. Maximum size of wane was set at a constant level of 5 mm maximum length and 2.5 mm maximum width. The levels were chosen based on an industrial case (Broman and Fredriksson 2015, Fredriksson et al. 2015).

Tested variables

20 variables were studied, 18 predictor variables, and two result variables, *Yield* and crosscutting yield (*CCYield*). The variables can also be classified as controllable or non-controllable, since some of them relate to the nature of the biological material. For instance, the growth conditions of the trees and the log shape variables are non-controllable, while the maximum allowed knot size in the product is controllable. The controllable predictor variables are summarized in Table 1, while the non-controllable predictor variables are summarized in Table 2. In addition to the variables in Table 2, a qualitative variable *Log type* describing the log position in the stem was added (butt- middle- or top-log). *Yield* was calculated for each log as the total volume of sawn and crosscut pieces divided by the log volume, while *CCYield* was calculated as the total volume of sawn and crosscut pieces divided by the total volume of sawn and dried timber from each log. Both variables therefore describes volume yield.

Table 1

Controllable variables tested in this study and their variation range

Variable	Saw rotation (deg.)	Saw offset (mm)	Min. length (mm)	Max. length (mm)	Max. knot size (mm)
Abbreviation	Rotation	SawCenter	MinL	MaxL	KnotDia
Process level (Fig. 1)	Sawing	Sawing	Crosscutting	Crosscutting	Crosscutting
Range	-10 to 10	0 to 20	130 to 210	450 to 650	10 to 50
Number of tested values	3	3	3	3	3

Table 2

Non-controllable variables tested in this study and their variation range

Variable	Abbrev-iation	Process level (Fig. 1)	Max value	Min value	Average
Lat-itude (deg.)	Lat	Tree	65	56	62
Height above sea level (m)	HSeaL	Tree	400	100	248
Site index[a]	SI	Tree	28	16	22
Tree length (m)	TLength	Tree	28	18	22
Age (years)	-	Tree	153	70	106
Log quality[b]	VMF_Q	Log	9	1	3
Top diameter (mm)	TDia	Log	149.6	128.8	137.7
Butt diameter (mm)	BDia	Log	233.8	155	180.1
Log vol-ume (m^3)	LogVol	Log	0.144	0.0567	0.0878
Log length (cm)	LogLen	Log	553	329	426
Bow height (mm)	BowH	Log	42	3	15
Taper (mm/m)	Taper	Log	20.4	4.16	10.1

[a]Tree height after 100 years of age
[b]According to the Swedish Timber Measurement Association, VMF

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The number of observations were 118×9×27 = 28674, since there were 118 logs sawn in nine different positions, and the resulting boards were crosscut in 27 different ways.

Statistical analysis

A PCA model was fit to all observations and all variables except crosscutting yield, after scaling of each variable to unit variance and centring on the mean. The PCA model was used to survey which variables were correlated and to give an overview of the collected data. After this, two PLS models were fitted to the same data, but using *Yield* and *Crosscutting yield* as the respective result variables. The PLS model was not intended for prediction of yield, rather to point out important variables in the value chain. The analysis was made using the score- and loading plots of the PCA and the PLS models, together with an analysis of the prediction power and the influencing variables of the PLS model.

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

To ensure as high predictability as possible, and to avoid modelling noise, the model was fit by adding principal components until the Q^2 value stopped increasing.

RESULTS AND DISCUSSION

The R^2 of the PCA model was 0.33, and the Q^2 was 0.19. The model was fit using two principal components. The R^2 and Q^2 values were not very high, but the reason for this was mainly the qualitative variable *Log type*. If this variable was removed, the R^2 rose to 0.48 but the main correlations remained the same. Therefore, we present the model with the log type variable included. The loading scatter plot for the PCA model is presented in Fig. 3.

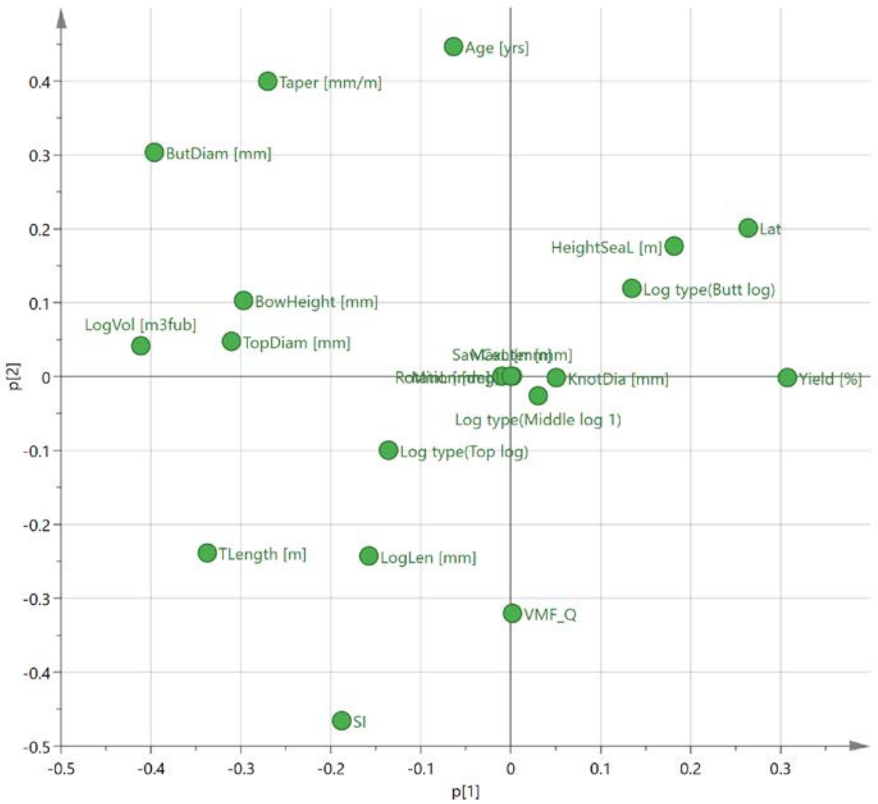

Fig. 3.

Loading scatter plot of the PCA model, showing principal component 1 (horizontal) and 2 (vertical). The overlapping labels close to the origin are* MinL, MaxL, Rotation *and* SawCenter. *For explanations of variable names see Table 1 and Table 2.

As can be seen in Fig. 3, *Yield* is mainly described by the first principal component, and therefore the other variables' correlation with the yield can be seen as their projected value on p[1]. The strongest positive correlations to yield can be found for variables regarding growth conditions, such as latitude, *Lat*, and height above sea level, *HeightSeaL*, suggesting that a slow growing tree is a more favourable source of raw material in this particular case. This is probably an interaction effect between size of knots, distance between knot whorls, allowed knot size, and minimum length. A designed experiment with this in mind would allow further investigation of these effects.

The strongest negative correlations to yield can be found in variables related to log size and shape, such as top diameter (*TopDiam*), bow height and taper. This suggests that the upper limit of the top diameter range chosen for the sawing pattern might have been a bit too large, sawing logs that were oversized. This also means that taper has a negative impact on yield, since the taper only adds log volume while not radically altering the possibilities for sawing. A large bow height means a reduced yield since curved logs are more difficult to saw than straight ones.

Log type affects the yield indirectly, since butt logs usually have smaller knots, and top logs have larger knots. The log quality as judged by the Swedish Timber Measurement Association had little or no correlation to the yield.

The correlation between the controllable variables and yield is rather small, with the largest effect coming from the crosscutting process. This suggests that the range of sawing parameters were chosen a bit too conservatively, even though they were in line with previous studies.

The score scatter plot for the PCA model is presented in Fig. 4. There are distinct groups in Fig. 4, these are individual logs as can be seen when the score plot is coloured according to the log identifier numbers. Therefore, it is to some extent visible how large the optimization space is for each log, i.e. given a certain raw material, a log, the process itself can be adjusted to increase yield.

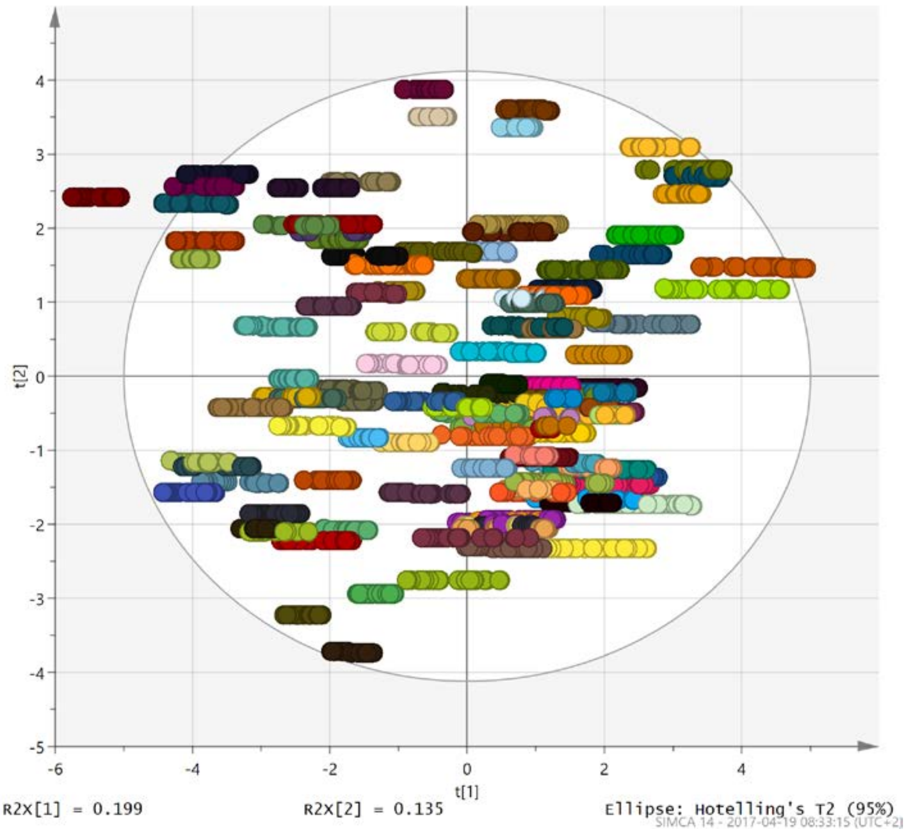

Fig. 4.
Score scatter plot of the PCA model, with the observations colored by log identification number, i.e. each colored group represents one log.

The PLS model using *Yield* as result variable was constructed using three principal components, and had an R^2 and a Q^2 of 0.61. The Root Mean Square Error (RMSE) of the model was 0.067 or 6.7% yield. Fig. 5 shows a scatter plot with the observed and predicted values of yield for the PLS model. This shows a rather well predicted yield with few outliers, even if there is a fairly large spread around the unity line. The shape of the plot also suggests that residuals are evenly distributed and centred on zero.

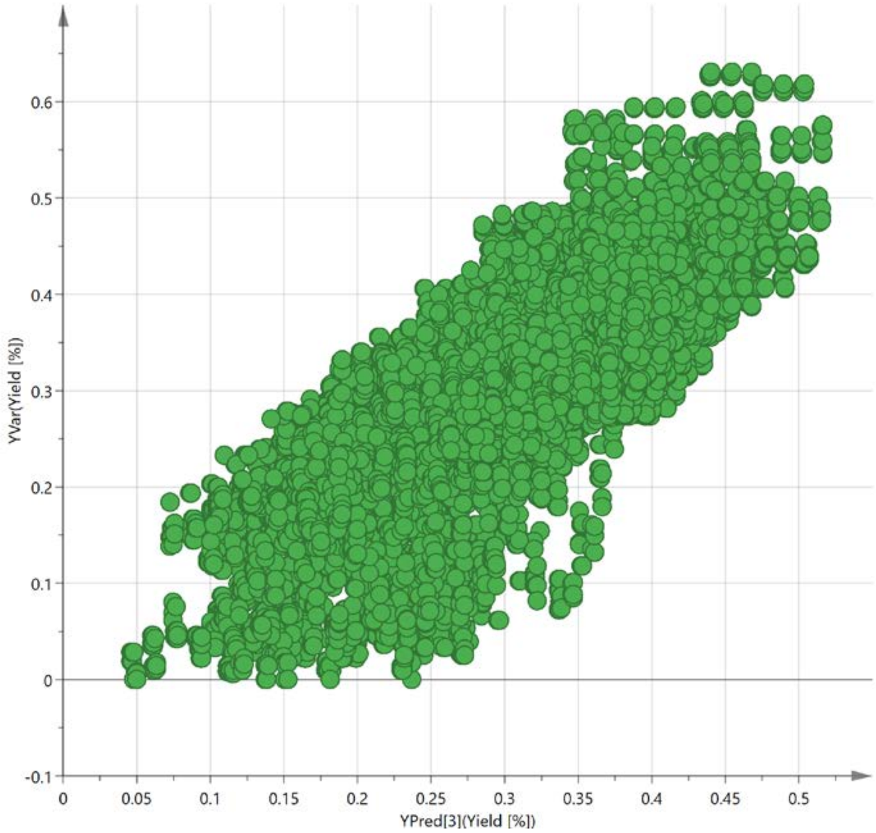

Fig. 5.
Observed (vertical axis) and predicted (horizontal axis) volume yield according to the PLS model.

The coefficients for each of the predictor variables are shown in Fig. 6. The coefficients are scaled and centred to reflect the impact of each variable on the model. The main influencing variable is the maximum allowed knot size. Some of the correlations visible in the PCA model are visible here as well, i.e. variables related to log size, log shape, and tree growth conditions. The minimum allowed length of pieces also has an inverse correlation to yield, since it inhibits the possibilities to optimize crosscutting and fit suitable crosscut pieces between knot whorls.

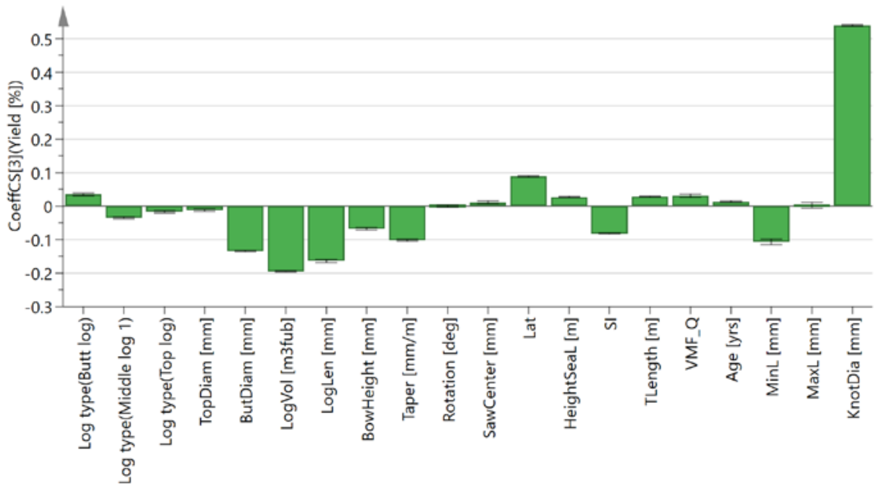

Fig. 6.
Coefficients for the first PLS model, scaled and centred.

The PLS model using *CCYield* as result variable was constructed using two principal components, and had an R^2 and a Q^2 of 0.54. The coefficients for each of the predictor variables are shown in Fig. 7. Many of the effects visible in Fig. 6 can be seen here as well; except that the variables related to the log size and shape have a smaller impact. This is intuitive since *CCYield* only involves the yield in the process of crosscutting boards, so the influencing factors are those related to knots and crosscutting.

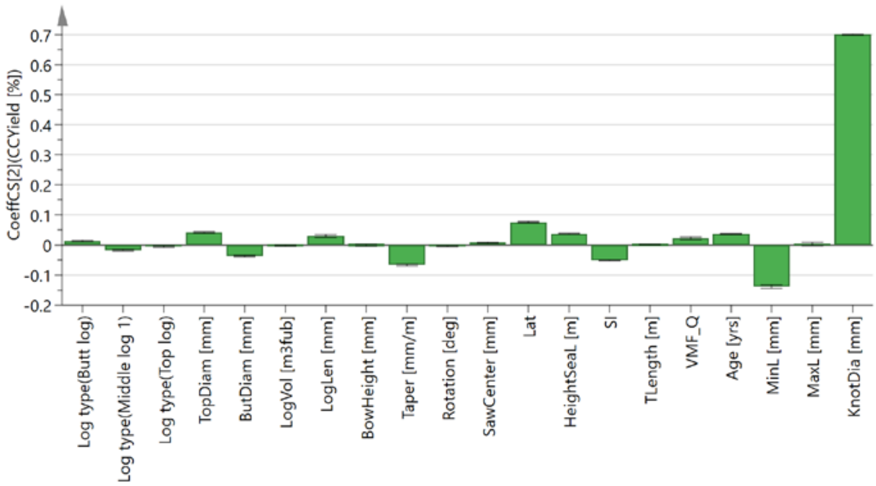

Fig. 7.
Coefficients for the second PLS model, scaled and centred.

CONCLUSIONS

The results show that it is possible to model a forestry-wood value chain, while assessing which input variables affect the result in terms of volume yield. This is enabled by CT scanning of logs together with computer simulation tools and multivariate statistical methods. Future research could be focused on how to use these tools to control processes, finding optimal choices of process variables given a certain raw material for instance.

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