Cost optimized
Timber Machine Strength Grading

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motivation

development of efficient grading models requires
cost and reliability considerations

- incorporate all types of uncertainties (aleatory, epistemic)
- utilize all available information efficiently (grading machine measurements)
- optimize combination of strength grades according to material properties of ungraded input material
- react on different material qualities within the timber material supply (flexible settings)
- fit into the overall production process seamlessly
overview

maximum benefit

sufficient reliability

derivation of settings

efficiency

predictive distribution of GDP

compliance with constraints

assessments of characteristic values

customer's demands

overview

grading process

observations of indicating property

derivation of settings

predictive distribution of GDP

compliance with constraints

assessments of characteristic values
sampling | grading | testing
---|---|---
non-destructive indicating property (IP) | destructive grade determining property (GDP) | RELATIONSHIP

existing data – sampling and testing

regression equation

\[
tension\ strength = \beta_1 + \beta_2 \cdot IP + \epsilon
\]

with

- \( \beta_1 \sim N(\mu_{\beta_1}, \sigma_{\beta_1}) \) \hspace{1cm} 1st regression coefficient
- \( \beta_2 \sim N(\mu_{\beta_2}, \sigma_{\beta_2}) \) \hspace{1cm} 2nd regression coefficient
- \( \epsilon \sim N(\mu_{\epsilon} = 0, \sigma_{\epsilon}) \) \hspace{1cm} error term
- \( \sigma_{\epsilon} \sim N(\mu_{\sigma_{\epsilon}}, \sigma_{\sigma_{\epsilon}}) \) \hspace{1cm} standard dev. of error term
existing data – description of material properties

assessment of prior probability density functions

overview

existing data

- prior timber material properties
- Bayesian regression analysis

grading process

- observations of indicating property

computations

- derivation of settings
- predictive distribution of GDP
- compliance with constrains

optimization routine

assessment of characteristic values
grading process

various information – monitoring of grading machine data

- GoldenEye (MiCROTEC)
- Sylvatest (CBS-CBT)
- Timbergrader (Brookhuis)

monitoring of indicating property

- real-time measurements of the grading device for every graded board
- no additional costs arise since boards are graded anyway
- utilization of the gathered information for description of input material quality
- until now this information is not used for the grading concepts...
grading process

monitoring of indicating property

![Graph showing the grading process](image)

1. control of output
   - additional testing
   - actualization of grading model
   - adjustment of grading machine settings

   combination of strength grades remains constant

2. analysis of the input timber material quality
   - real-time assessment of prior probability distribution of IP
   - predictive benefit
   - optimized grade combination for maximized benefit

optimization of strength grade combination

PROBLEM: varying input material qualities — what to do?
INPUT (what has to be known?)

- market values of strength classes, costs of grading machine, maintenance, personnel
- constrains = requirements of EN 338
- observations of the indicating property belonging to the current sub-sample (prior probability distribution)
- relationship between IP and GDP

OUTPUT (what is desired?)

- optimized acceptance criteria = grading machine settings
  (sufficient reliability, maximum benefit, efficiency)
definition of objective function

\[ B_T(\sigma_C, A_C, GP) = V^T \times C_{\text{grade}} \]

benefit of graded timber
acceptance criteria (settings)
volumes in particular grades

prior probability distribution of input timber material
particular grading procedure
monetary benefit (market values)

optimization of the grading machine settings

\[ \max_{A_C} B_T(\sigma_C, A_C, GP) \]
subject to: \( N_{\text{req}}, C_{\text{grade}} \)

constraints (requirements EN 338)
grading costs
optimization of the grading procedure

comparison of different grading machines or grading strategies (mechanical, visual, ...)

\[
\max_{GP} \max_{A_c} B_T \left( f \sigma_C(s), A_C, GP \right) \geq C_G(GP)
\]

subject to: \( N_{req}, C_{grade} \)

maximized benefit

costs for
- machine
- maintenance
- personnel
...

simplex algorithm

- algorithm for numerically solving of linear programming problems
- minimization of negative values objective function
1st example

1. example – simulated data

<table>
<thead>
<tr>
<th>relative market values</th>
<th>C40</th>
<th>C35</th>
<th>C30</th>
<th>C24</th>
<th>C18</th>
<th>reject</th>
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<tbody>
<tr>
<td></td>
<td>2</td>
<td>1.66</td>
<td>1.33</td>
<td>1</td>
<td>0.5</td>
<td>0.2</td>
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</table>

strength classes according to EN 338
1. example – simulated data

**varying mean value**

coefficient of variation = 0.33 and coefficient of correlation = 0.70

![Graph showing varying mean value with lower and higher grade bounding boxes and benefit.](image1)

**varying coefficient of variation**

mean value = 45 MPa and coefficient of correlation = 0.70

![Graph showing varying coefficient of variation with lower and higher grade bounding boxes and benefit.](image2)
1. example – simulated data

**varying coefficient of correlation**

Mean value = 45 MPa and coefficient of variation = 0.33

Coefficient of correlation between IP and bending strength [MPa]

2nd example
2. example – real data

- **GoldenEye 706 dataset:**
  - Norway spruce, Central Europe
  - tested in tension
  - n=1162; 8 sub-samples (A-H)
- assessment of prior distributions at total sample (n=1162)
- Bayesian regression analysis at total sample (n=1162)
- observations of indicating properties at individual sub-samples (A-H)
- given market values for the strength grades
- predictive calculation of optimized grading machine settings for each sub-sample

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2. example – real data

**assessment of prior probability density functions**

- **tension strength**
  - Probability density function
  - Cumulative distribution function
- **indicating property**
  - Probability density function
  - Cumulative distribution function
2. example – real data

Bayesian regression analysis between
tension strength and indicating property

*transformation of IP and GDP values into logarithm*

\[ \text{tension strength} = \beta_1 + \beta_2 \cdot \text{IP} + \epsilon \]

<table>
<thead>
<tr>
<th>normal distributed random variables</th>
<th>correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1 )</td>
<td>( \beta_2 )</td>
</tr>
<tr>
<td>( \mu_\beta_1 = 0.1187 )</td>
<td>( \mu_\beta_2 = 0.9542 )</td>
</tr>
<tr>
<td>( \sigma_{\beta_1} = 0.1980 )</td>
<td>( \sigma_{\beta_2} = 0.0600 )</td>
</tr>
</tbody>
</table>

\( n=500 \)
Bayesian regression analysis between tension strength and indicating property

2. example – real data

<table>
<thead>
<tr>
<th>sample</th>
<th>n  [-]</th>
<th>mean [MPa]</th>
<th>CoV [-]</th>
<th>CoC [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>1162</td>
<td>27.6</td>
<td>0.42</td>
<td>0.804</td>
</tr>
<tr>
<td>A</td>
<td>112</td>
<td>26.7</td>
<td>0.32</td>
<td>0.739</td>
</tr>
<tr>
<td>B</td>
<td>137</td>
<td>29.7</td>
<td>0.41</td>
<td>0.833</td>
</tr>
<tr>
<td>C</td>
<td>125</td>
<td>29.8</td>
<td>0.44</td>
<td>0.801</td>
</tr>
<tr>
<td>D</td>
<td>110</td>
<td>25.0</td>
<td>0.40</td>
<td>0.769</td>
</tr>
<tr>
<td>E</td>
<td>117</td>
<td>26.8</td>
<td>0.47</td>
<td>0.783</td>
</tr>
<tr>
<td>F</td>
<td>125</td>
<td>26.2</td>
<td>0.42</td>
<td>0.844</td>
</tr>
<tr>
<td>G</td>
<td>104</td>
<td>24.5</td>
<td>0.31</td>
<td>0.776</td>
</tr>
<tr>
<td>H</td>
<td>103</td>
<td>32.7</td>
<td>0.35</td>
<td>0.806</td>
</tr>
</tbody>
</table>

sample characteristics of bending strength and interrelation with indicating property (CoC)
### 2. example – real data

<table>
<thead>
<tr>
<th>sample</th>
<th>higher grade [-]</th>
<th>lower grade [-]</th>
<th>predicted benefit [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>C40</td>
<td>C30</td>
<td>1.004</td>
</tr>
<tr>
<td>A</td>
<td>C35</td>
<td>C24</td>
<td>1.132</td>
</tr>
<tr>
<td>B</td>
<td>C40</td>
<td>C30</td>
<td>1.134</td>
</tr>
<tr>
<td>C</td>
<td>C40</td>
<td>C30</td>
<td>1.169</td>
</tr>
<tr>
<td>D</td>
<td>C40</td>
<td>C24</td>
<td>1.026</td>
</tr>
<tr>
<td>E</td>
<td>C40</td>
<td>C30</td>
<td>1.042</td>
</tr>
<tr>
<td>F</td>
<td>C40</td>
<td>C30</td>
<td>0.915</td>
</tr>
<tr>
<td>G</td>
<td>C35</td>
<td>C24</td>
<td>0.988</td>
</tr>
<tr>
<td>H</td>
<td>C40</td>
<td>C30</td>
<td>1.304</td>
</tr>
</tbody>
</table>

average benefit of sub-samples: 1.083

### conclusions

- real-time assessment of input timber material quality by continuous monitoring of indicating property
- predictive computation of grading output with given settings, market values and constrains
- maximization of grading benefit by optimization of strength grade combinations
- sufficient reliability, high efficiency

- future investigations
  - model extension also to MOE and density
  - implementation into overall grading concept
obrigado!

 Contributions by Mi.CROTEC (Brixen, Italy) are acknowledged for allowing us to publish the results of machine grading by the grading device GoldenEye700.

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grading process

grade determining property (GDP) vs. indicating property (IP)

grade 1
grade 2
grade 3

IP 1
IP 2
regression model