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# Stochastic inversion of fire test data for the T-dependant thermal diffusivity of SA pine

by

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Project(Civil Engineering)458

Final Draft

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October 2021

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### Nomenclature

#### Constants

 $g = 9.81 \,\mathrm{m/s^2}$ 

#### Variables

$\kappa$	Thermal conductivity	 $[W/m\cdot K]$
$\alpha$	Thermal diffusivity	 $[\mathrm{m}^2/\mathrm{s}]$

### Introduction

This chapter will introduce the problem addressed in this project. Previous similar projects as well as the value of this research will also be addressed.

#### 1.1 Background and Motivation

Traditionally the thermal conductivity, otherwise referred to as the  $\kappa$ -value, of timber is based simply off the EN 1995:1-1-2004 or similar standards. This research project will aim to obtain the thermal diffusivity of cross laminated SA-Pine timber by further analysing data obtained by S. van der Westhuyzen for his study of the samples' charring rate.

The thermal diffusivity of timber is a unobservable quantity that cannot be measured directly. Instead, it is related to measurements of temperature and time through differential models. When heat diffusion is calculated using Finite Element methods(TODO:choose which FEM), the process is usually simplified to a linear problem (Fish, 2007). Due to the changes in thermal diffusivity of timber with temperature, as can be seen in EN 1995:1-1-2004(pg number TODO), the diffusivity cannot be linearly modelled. Therefore, the problem lends itself to being analysed by inversion techniques. The aforementioned approach will allow us to obtain information about the diffusivity based on the combination of the information assumed prior to measuring, further referred to as the prior, and the measured data. Using statistical inversion leads to a probability distribution that provides us with a collection of diffusivity estimates and their corresponding probabilities.

Currently the fire rating of specific timber samples are based on fire tests conducted in a furnace. The furnace is kept at increasing temperatures corresponding with the Standard or ISO 834 fire curve as specified in ISO 834 ISO (1999). This process becomes very costly if it has to be repeated every time that timber is used for construction, as timber usage for multiple story construction projects have increased over the past decades. This increase is

partially due to the sustainability of timber as a construction material: not only is it renewable but it also has a small carbon footprint (Salvadori, 2017).

#### 1.2 Aim and objectives

During the course of the project, the student will aim to meet the following objectives:

- 1. Modify a Finite Element Model into an accurate and effective function;
- 2. Compare the model data to the actual acquired data;
- 3. Solve for the thermal diffusivity using Bayes' theorem of inverse problems; and
- 4. Evaluate and explore the posterior probability distribution using the following methods:
  - (a) Maximum a Posteriori
  - (b) Markov-Chain Monte Carlo

#### 1.3 Literature study

Frayssinhes and Collet in their article, Simple Method to Determine the Diffusivity of Green Wood, they determine the global diffusivity of a Douglas fir green log using inverse identification methods. Their experiment was set up by immersing the log with K-type thermocouples into a boiler filled with water at 60°C. These K-type thermocouples were very specifically placed to improve the accuracy of the diffusivity ratio calculation. The finite element model constructed for their calculations used linear interpolation was a four node quadrangle elements. An analytical model was also constructed using the heat propagation equation (TODO? heat diffusion?). The intention of this research was to assist the peeling industry in making the pretreatment process more cost effective. The method proved to be effective at determining the thermal diffusivity of green Douglas fir logs as the  $\kappa$ -values obtained were comparable to those form literature. The methods used by Frayssinhes and Collet (2020) are similar to the methods described later in the report. Yet a crucial difference remains as the temperatures at which these experiments were conducted as well as the final usage of the data differ greatly.

The current  $\kappa$ -values used for the design of timber elements are taken from the EURO code (ref TODO (CEN, 2004)) and are show in figure 1.3.

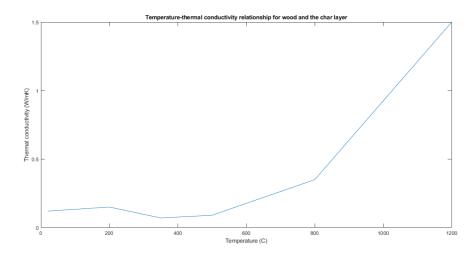


Figure 1.3.1: Standard temperature-thermal conductivity relationship for timber from (CEN, 2004)

### Technical Foundation

#### 2.1 Finite Element Model

Finite element methods (or finite element analysis) is used when the behaviour of an element cannot be accurately depicted by a simple mathematical equation.

#### 2.1.1 History/Origin

#### 2.1.2 method of FEM

A larger element is broken into smaller elements. Assumptions made on the smaller scale have a lesser effect on the final answer than the same assumptions made on a large scale would have had.

#### 2.1.3 heat eq

In its simplest form, the one-dimensional heat diffusion equation is a partial differential equation 2.1.1 dependant on the temperature and thickness of the element. The heat diffusion equation is based on Fourier's Law...(TODO)

$$q = -k\frac{dT}{dx} \tag{2.1.1}$$

#### 2.2 Bayes' theorem of inverse problems

The method of statistical inversion is dependant on a fundamental understanding of the Bayes' theorem of inverse problems. The student obtained this understanding through studying Chapter 3 of statistical and Computational Inverse problems by Kaipio and Somersalo (2005), further referred to merely as Kaipio. There are four principles of Statistical inversion that is essential

to the thorough understanding of these models. Firstly, it is the principle that any variable in the model needs to be modelled as a random variable. This randomness is based on the extent of information that is available. To ensure that the extent of knowledge is accurately portrayed in the model, the extent of knowledge will be coded into the probability distributions assigned to the different variables. Finally, it needs to be understood that the solution of a statistical inversion is a posterior probability distribution. A generalized equation of Bayes' theorem can be seen in 2.2.1 taken from Kaipio.

$$\pi_{\text{post}}(x) = \pi(x|y_{\text{observed}}) = \frac{\pi_{\text{pr}}(x)\pi(y_{\text{observed}}|x)}{\pi(y_{\text{observed}})}$$
(2.2.1)

#### 2.3 Markov Chain Monte Carlo

Markov Chain Monte Carlo (MCMC) is a method of integration. This will be used to determine the mean of the  $\kappa$ -values at specific temperatures. Markov Chain Monte Carlo is a method that was created by combining the concept of Monte Carlo sampling and a Markov Chain. To fully understand MCMC, the methods that it was created from need to be further investigated.

#### 2.3.1 Markov Chains

#### 2.3.2 Monte Carlo Integration

Monte Carlo integration is used to evaluate a probability distributuion. The evaluation is done by drawing a collection of random numbers from the distribution. These numbers are then used as the sample and a sample mean is taken. The arithmetic sample mean can be used to approximate the population mean in accordance with the law of large numbers (Gilks *et al.*, 1996)

### Implementation

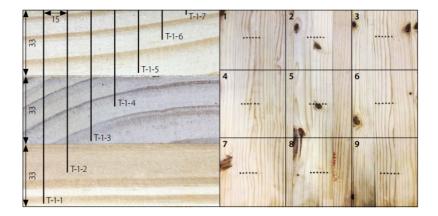
This chapter will elaborate on the test data used as well as the process that was followed to achieve the results in Chapter 4.

#### 3.1 Existing data

The data used was acquired by van der Westhuyzen et al. (2020) for an article assessing the charring rate of both SA-Pine and Eucalyptus. For the purpose of this project, only the data obtained from the SA-Pine test was considered and analysed.

#### 3.1.1 Summary of test

The test was conducted on a sample of 100mm by 0.9m x 0.9m panel of cross-laminated SA-pine. This sample was then divided into nine cubes of 100 mm x 100 mm x 100 mm. Each cube was fitted with seven Type K-thermocouples placed at consecutive 16.5 mm drilled holes, as can be seen in Figure 3.1.1. The test panel was tested in a furnace and was exposed to the standard ISO 834 Fire curve 3.1.2 on one side and room temperature on the other. The panel was exposed to the fire curve for 50 minutes, at which stage near complete de-lamination was observed and the test ended.



**Figure 3.1.1:** Thermocouple layout in test conducted by van der Westhuyzen *et al.* (2020) cross-section (left) and overall layout (right)

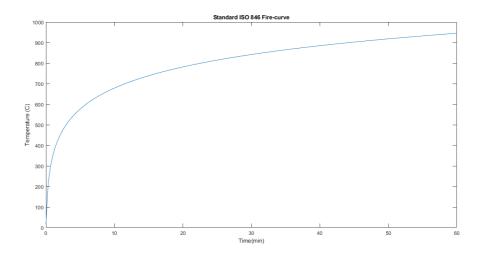


Figure 3.1.2: Standard ISO fire curve TODO

#### 3.1.2 Potential inaccuracies

As with most tests, everything is not always perfect. The potential inaccuracies are discussed below.

In the data, it was observed that two of the thermocouples broke during testing, this resulted in temperature with a magnitude of  $10^{13}$ . That temperature is not possible as the highest ever recorded temperature reached was  $4 \times 10^{12}$  and that only occurred in a atomic explosion. This malfunction required that two of the depth measurements were no longer the average between nine samples but instead the average between eight. Another inaccuracy that could

potentially influence the accuracy of the final result is the accuracy of the depth of the holes in which the thermocouples were placed.

There is also debate about the significance of the contribution of the timber burning to the temperature inside the furnace. For the purposes of this project, it will be assumed that the timber burning does not contribute to the temperature inside the furnace.

#### 3.2 Finite Element Modelling

A one-dimensional finite element model that simulates what we expect to obtain from the fire tests based on the simplified K-values provided in EN 1995:1-2-2004 is modified into a function. This function should provide the temperature of the modelled element based on a specified location and thermal conductivity. The derivation and adaptation of the model are expanded on below.

#### 3.2.1 Derivation

#### 3.2.2 Existing Model

For this project an existing finite element model of heat diffusion by Prof. N de Koker is modified for usage in the Bayes' theorem 2.2.1. This model is used to determine the likelihood function. The current model uses the standard Euro code k-values as well as the specific heat specified in the (CEN, 2004).

The model discretises the wooden element into 32 different elements. For finite element analysis, there are always more elements used to generate the model than usually evaluated. This is done to improve the accuracy of said model. The model is a one dimensional finite element model that takes time differentiation into account.

#### 3.2.3 Adapted Model

The model was changed into a function that takes  $\kappa$ -values and provides a new temperature distribution over the elements for the different  $\kappa$ -values. This function is used in the posterior calculation to determine the likelihood function.

#### 3.3 Inversion method

The basis of the stochastic analysis that was done is the adapted Bayesian equation 3.3.1 below. TODO: further interpret

$$\pi^*(x|T) = \exp\left(-\frac{(\mu - x)^2}{2\sigma_\mu^2}\right) \cdot \exp\left(-\frac{(T - M(x))^2}{2\sigma_{\text{temp}}^2}\right)$$
(3.3.1)

#### 3.3.1 Prior probability

$$\pi(x) = \exp\left(-\frac{(\mu - x)^2}{2\sigma_{\mu}^2}\right) \tag{3.3.2}$$

The prior probability function (Equation 3.3.2) is based on the  $\kappa$ -values assumed prior to any simulation or analysis. The  $\sigma_{\mu}$  in this equation was assumed to be equal to  $0.13W/m\cdot K$ , In this case, the prior values are indicated as  $\mu$  and refer to the vector of  $\kappa$ -values (3.3.3) at specific temperatures ?TODO how to indicate?

$$\mu = \begin{bmatrix} 0.12 \\ 0.12 \\ 0.12 \\ 0.12 \\ 0.15 \\ 0.07 \\ 0.09 \\ 0.35 \\ 1.5 \end{bmatrix}$$

$$(3.3.3)$$

The x (in Equation 3.3.2) refers to a vector of randomised  $\kappa$ -values that correspond with the same temperatures as the values in the  $\mu$  vector. The first iteration of randomised  $\kappa$ -values are generated by creating a random perturbation of the  $\mu$  vector. By multiplying the  $\mu$  vector with  $(0.5+\mathrm{rand}(1,9)\cdot 1.5)$  a half plus a randomised the first values of x are guaranteed to be within an acceptable range of the prior values. The process of obtaining the x vector after the first iteration is discussed later in section 3.3.3.

Initially the program was written to generate completely random new values for the first iteration of x. This later proved to not only be unnecessary but also made the process less accurate as there was a larger burn-in period before the values were anywhere near the actual solution. To increase the accuracy and reduce the number of times the program needed to run to produce a sufficient number of accurate samples the program was changed to the current method. The prior function in this case was relatively easy to generate and incorporate into the program as a well defined list of prior values exist.

#### 3.3.2 Likelihood probability function

$$\pi(T) = \exp\left(-\frac{(T - M(x))^2}{2\sigma_{\text{temp}}^2}\right)$$
(3.3.4)

The likelihood probability was more complex to implement as this required utilisation of the function created from the finite element model, as discussed in section 3.2. This function will output the probability of the modelled values (M(x)) given the measured temperature values (T). As can be seen in Equation 3.3.4 the M(x) vector is written as a function. The function indicated here takes the new randomised x vector and then runs the model to provide a new temperature distribution over time at various nodes. The output of the finite element model was reduced down such that only the nodes at the same depths as the thermocouples are provided to the likelihood function. For the likelihood function the  $\sigma_{\text{temp}}$  value was assumed to be 15°C.

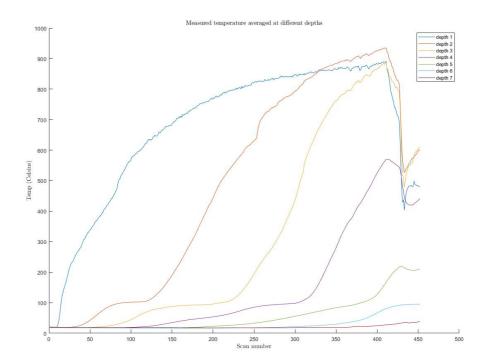
#### 3.3.3 MCMC itegration

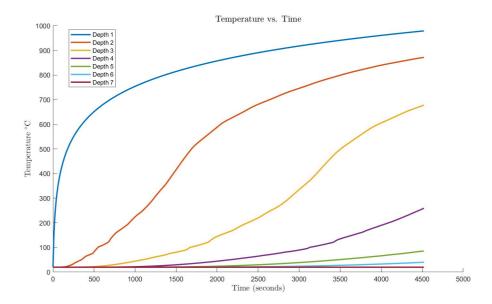
The two main parts of the MCMC integration (as mentioned in section 2) are: how a value is deemed acceptable (Monte Carlo), and how the next random sample is selected after a previous sample is accepted (Markov Chain).

To assist in choosing the next random sample, a step size that indicates how wide the range should be in which the next step will be found was chosen. This concept can be visualized as follows: our accepted point is in the center of a cube. The next possible random point is randomly generate but still within the cube. After this next number is selected the cube moves such that the new point is now the centre and so it continues. The above example simplifies the concept but this understanding can now be expanded. If every coordinate direction in the simple example is seen as a single entry into the x vector, then the example has only three  $\kappa$ -values. But there are 10 values, so the imaginary cube in this situation is now ten-dimensional (don't worry, no attempt at drawing that will be made). Another level of complication can be added if it is taken into account that every point in the cube is no longer equally likely. A distribution within the cube can be chosen, in this case a log-normal distribution was chosen. The shape of the cube then warps into a stranger shape with points closer to the center being more likely choices and the edges being less likely.

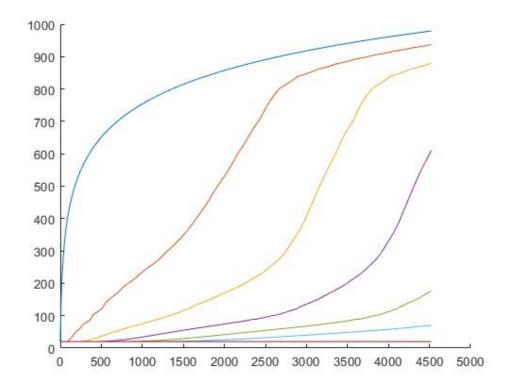
For this project a step size of  $0.05W/m \cdot K$  was chosen.

# Results





**Figure 4.0.1:** Output of finite element model using  $\kappa$ -values as indicated in EN 1995:1-2-2004



Discussion

# Summary and Conclusion

Further development of this concept could lead to simplified methods of calculating the fire rating of specifically SA-Pine as well as other timber samples.

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# Program

# GA outcomes

### Relevant code segments

Below are the relevant code segments taken from the Matlab code that was used to generate the final samples used for analysis.

### Prior function

```
function q_val = prior_pdf(x_values, sigmaMU)

global mu_values
q_val = -0.5*((x_values - mu_values)*(x_values - mu_values)')/(sigmaMU^2);
end
```