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MAXIMIZING INFORMATION OBTAINED FROM STANDARDIZED FIRE TESTS USING A BAYESIAN FRAMEWORK

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Abstract. Current practice is mostly focused on prescriptive design approaches where the performance of the structure in case of fire is assessed based on its performance in standardized fire tests. Those tests indicate whether the structural member can withstand standardized ISO 834 fire exposure for a certain code specified time. This method however does not provide an explicit safety level. This issue is enlarged even more by the fact that the ISO 834 fire exposure does not represent a natural fire exposure, but a pseudo-worst-case exposure, making the correlation between the standardized fire test results and real-life behaviour of structural members exposed to fire questionable. However, there has been a century-old tradition of standardized fire tests with a lot of experience and infrastructure based on it. For that reason, here, a methodology is presented to obtain more information on the behaviour of structural members exposed to a natural fire from the standardized fire test results by using a Bayesian framework. As an example structure, a simply supported concrete slab is considered. Its failure during the standardized fire test is modelled and the parameters affecting the time when it fails (i.e., parameters affecting the nominal fire resistance time) are determined. The model is then used in a Markov chain Monte Carlo procedure to update parameter distributions based on the measured fire resistance time. Using these updated distributions, a full probabilistic calculation of the performance of the slab considering a natural fire exposure is then conducted to assess the failure probability.

Keywords: Bayesian analysis, concrete, fire, safety level, uncertainty.

1. Introduction

Structural stability of a building in case of fire is of utmost importance both for the safety of its occupants as well as for other fire safety objectives such as property protection. Therefore, it is essential to provide a building design with an adequate safety level. In the structural sense, it is important to mitigate the risk of a collapse due to the fire effects.

A common way of representing a structure's performance in the case of fire is through its fire-resistance rating. The fire-resistance rating represents how long a structural member can withstand a furnace test before collapsing. During the furnace test, the structural member is exposed to a standardized fire exposure, a universal temperature-time curve that in its essence should represent a conservative worst-case fire scenario.

This approach has a lot of benefits: it is standardized, it provides the same temperature exposure for a range of different materials and structural members, and therefore can be used to compare different solutions. However, it also has a few shortcomings. First of all, the standardized temperature-time curve does not represent any real fire scenario. This temperature-time curve is monotonically increasing and therefore does not include the cooling phase of the fire. Secondly, even though it should represent an envelope case for multiple possible fire scenarios, there are cases where this approach is not conservative [1].

Despite these shortcomings, the standardized approach is highly popular. There is an abundance of data and research focused on the material and structural behaviour of members exposed to the standard temperature-time curve. Unfortunately, the test does not provide any direct information about how the structure will behave in a real fire situation. All it provides is a time of failure for a structural member exposed to a fire scenario that, as mentioned earlier, might be conservative, but does not represent a real fire. This problem is even enhanced by the fact that a lot of current building codes allow the use of this value as proof of safety by prescribing the minimal fire resistance rating a member must achieve in the standardized test.

In order to overcome this issue, in this paper, a Bayesian updating procedure is applied. The Bayesian framework in fire safety engineering has been successfully used in the past in a variety of fire safety problems. For example, Wang and Zabaras [2] used them in order to determine the magnitude of a heat source from the temperature data, Guo et al. [3] used a zone

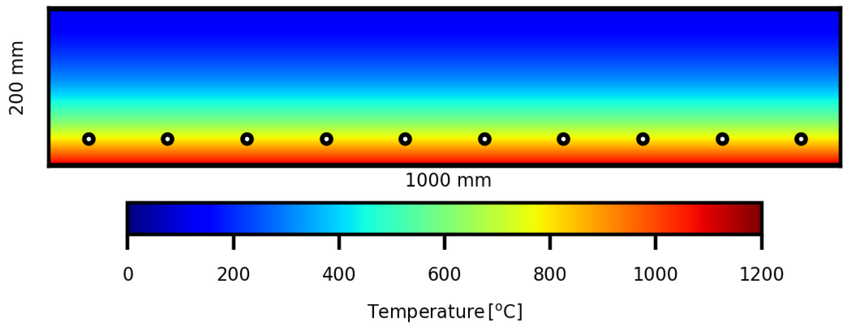

Figure 1. Temperature field of a 20 cm thick concrete slab with the concrete cover of 35 mm after 120 min of standardized fire exposure.

model as a forward model for a Bayesian inversion to obtain the fire size and its origin within a multi-compartment structure based on the measured gas temperature. Overholt and Ezekoye [4] managed to invert the fire's heat release rate based on the measured temperature data from room-scale experiments.

The Bayesian updating is used to predict the behaviour in a more realistic fire for the case of a simply supported concrete slab, considering the fire resistance as measured in the standardized test. Using numerical heat transfer analysis, a Bayesian framework and full probabilistic calculation, the failure time determined during the furnace test is used to compute the failure probability in case of a natural fire.

2. Methodology

2.1. Overview

The procedure presented in this paper consists of two main parts. First, the prior distributions of the material properties of the slab are updated considering the measured fire resistance time. Second, these posterior distributions are used to determine the failure probability of the slab in case of the natural fire. For the updating procedure, a model that calculates the failure time during the furnace test must be created. That is done by calculating the time instant when the capacity of the slab is lower than the loads applied. Afterwards, this model is used in the Bayesian framework to update the material properties based on the test failure time.

Using the updated material properties based on the test failure time the failure probability is calculated for the slab exposed to a natural fire. A Monte Carlo calculation is conducted taking into account uncertainties in the fire exposure, loads, geometry and updated material properties. Finally, the failure probability is calculated for different values of test failure times and compared.

2.2. Thermal calculation

In order to determine the capacity of the concrete slab in the case of fire, the first step is to determine the temperate distribution inside of it. This requires the solution of a heat transfer problem which is commonly solved using the finite difference method. In this study, a 20 cm thick reinforced concrete slab exposed to the heating from the bottom side is considered. A fine mesh with the size of 0.1 mm and a time step of 0.1 s is used. The boundary condition on the bottom (heated) side is defined using a gas temperature-time curve and heat transfer through convection (convective heat coefficient $h_{conv} = 25\,\mathrm{W/(m^2.K)}$ and radiation (emissivity $\varepsilon = 0.7$). On the top (cold) side, an ambient temperature of $T_{amb} = 20°\mathrm{C}$ is imposed. The density of concrete in the function of temperature is defined by EN 1992-1-2 [5] with a moisture value of 3 %. A common approach of calculating for a concrete only section and assuming that the reinforcement temperature is equal to the concrete at the same position is employed. Figure 1 shows the temperature distribution of the slab after 120 min of ISO 834 fire exposure.

The uncertainty associated with the parameters in the heat transfer problem is the focus of this paper. Thus, probabilistic models for the thermal properties, thermal conductivity k and specific heat c_p of concrete, are used. The models' origin and details are presented in [6] and the main characteristics are summarized here. The main assumptions are that each of these properties is a continuous function of temperature, and at each temperature the values are distributed according to the Gamma distribution. In order to obtain a random curve, the same quantile is used for all temperatures. For example, if the specific heat has a 5 % quantile value at 20 °C, it will also have a 5 % quantile value at 100 °C, 200 °C and so on. This way it is possible to define one continuous function for a thermal property at any temperature based only on the quantile value considered. This enables a quite easy implementation in numerical models and its use is presented in the following paragraph.

First, a quantile value for each of the thermal properties is chosen independently, next mean and standard deviation at each needed temperature are calculated using the following formula (temperature T in °C),

Parameter	Symbol	Unit	Distribution	Mean	Standard deviation	Ref.
Thermal conductivity	k	[W/(m.K)]	Gamma	Temperature dependent	Temperature dependent	[6]
Specific heat	c_p	[kJ/(kg.K)]	Gamma	Temperature dependent	Temperature dependent	[6]
Reinforcement yield strength	f_y	[MPa]	Lognormal	560	30	[7]

TABLE 1. Prior distribution for the parameters used in the Bayesian framework.

valid in the range 20 – 1200 °C [6]:

$$\begin{gathered} k_{mean}\,[\mathrm{W/(m.K)}] = \\ 6.627\cdot 10^{-7}\cdot T^2 - 1.458\cdot 10^{-3}\cdot T + 1.772 \\ \\ c_{p,mean}\,[\mathrm{kJ/(kg\cdot K]} = \\ -2.953\cdot 10^{-7}\cdot T^2 + 6.498\cdot 10^{-4}\cdot T + 0.872 \\ \\ k_{std}\,[\mathrm{W/(m\cdot K)}] = \\ 3.19\cdot 10^{-7}\cdot T^2 - 0.691\cdot 10^{-3}\cdot T + 0.434 \\ \\ c_{p,\,std}\,[\mathrm{kJ/(kg\cdot K)}] = \\ -3.500\cdot 10^{-7}\cdot T^2 + 7.700\cdot 10^{-4}\cdot T + 0.042 \end{gathered} \tag{1}$$

Afterwards, using these values and given quantile, well-known equations defining the Gamma distribution are used to calculate both thermal properties for each needed temperature. Finally, the same moisture peak should be added to the specific heat curve as defined in EN 1992-1-2 [5].

2.3. Bending capacity and failure time

Once the temperature inside the slab is calculated, its bending capacity can be calculated using the following formula [11]:

$$\begin{gathered} M_R = A_s\cdot k_{fy}(T)\cdot f_y\cdot\left(h - c - \frac{\phi}{2}\right) - \\ \frac{\left(A_s\cdot k_f y(T)\cdot f_y\right)^2}{2\cdot b\cdot k_{fc}(T)\cdot f_c} \end{gathered} \tag{2}$$

where A_s is the reinforcement area, $k_{fy}(T)$ is the temperature-dependent strength retention coefficient for the yield strength of steel, f_y is the yield strength of steel in normal design conditions, h is the slab height, c is the concrete cover, ϕ is the reinforcement diameter, b is the width of the slab, $k_{fc}(T)$ is temperature-dependent strength retention coefficient for the compressive strength of concrete and f_c is the compressive strength of concrete in normal design conditions.

In order to calculate when the slab would fail during the furnace fire resistance test, first the temperature distribution needs to be calculated for each point in time of the test. That is done using the described numerical heat transfer model and the ISO 834 fire curve as boundary temperature-time curve. Then, using Equation 2 the slab's capacity can be calculated for each point in time and from it consecutively the failure time can be calculated by determining the point in time when the capacity is lower than the applied loads. The loads during the test are assumed to be equal to 50 % of the slab's capacity in normal conditions, (i.e., 50 % utilization in normal design conditions).

This process is computationally expensive for later probabilistic calculations. Hence, for 10 000 different combinations of the stochastic variables (Table 1), a failure time is calculated and a polynomial regression model is fitted on the results (with the coefficient of determination being $R^2 = 0.99$). All the other parameters in Equation 2 have been regarded as constants instead of variables.

2.4. Updating of uncertain parameters based on standardized fire test

The updating procedure is a standard Bayesian procedure using Markov Chain Monte Carlo simulations. The parameters that are updated are the quantiles of the thermal properties' models and the yield strength of the reinforcement. All the priors are presented in Table 1.

The likelihood is defined under the assumption that the failure time error is normally distributed with a mean of 0 and standard deviation σ_{err} and is presented in Equation 3:

$$L\left(y|\boldsymbol{X}\right) = \frac{1}{\sigma}\,\exp\left(-\frac{1}{2}\,\frac{\left(y - M(\boldsymbol{X})\right)^2}{\sigma_{err}^2}\right) \tag{3}$$

where y is the measured failure time, $M(\boldsymbol{X})$ a model output for the input parameters $\boldsymbol{X} = (k, c_p, f_y)$. The measurement uncertainty σ_{err} is modelled by a normal distribution with a mean of 2 min and a standard deviation of 1 min, these values are chosen based on the model error and measurement precision during the furnace test.

2.5. Natural fire exposure

The end goal is to obtain the probability of failure in the case of a real fire using the measured test failure time. For that, the thermal gradient for a natural fire exposure also has to be calculated. A parametric

Parameter	Symbol	Unit	Distribution	Mean	Standard deviation	Ref
Fuel load	q_f	$[\mathrm{MJ/m^2}]$	Gumbel	780	234	[8]
Concrete cover	c	[mm]	Beta $[\mu \pm 3\sigma]$	40	5	[9]
Dead load	G	[kNm]	Normal	27	2.7	[10]
Live Load ($Q_k = 16$)	Q	[kNm]	Gamma	3.2	3.04	[10]
Load model uncertainty	K_E	[−]	Lognormal	1	0.1	[10]
Resistance model uncertainty	K_R	[−]	Lognormal	1	0.15	[10]

TABLE 2. Distributions of the parameters used to calculate the failure probability.

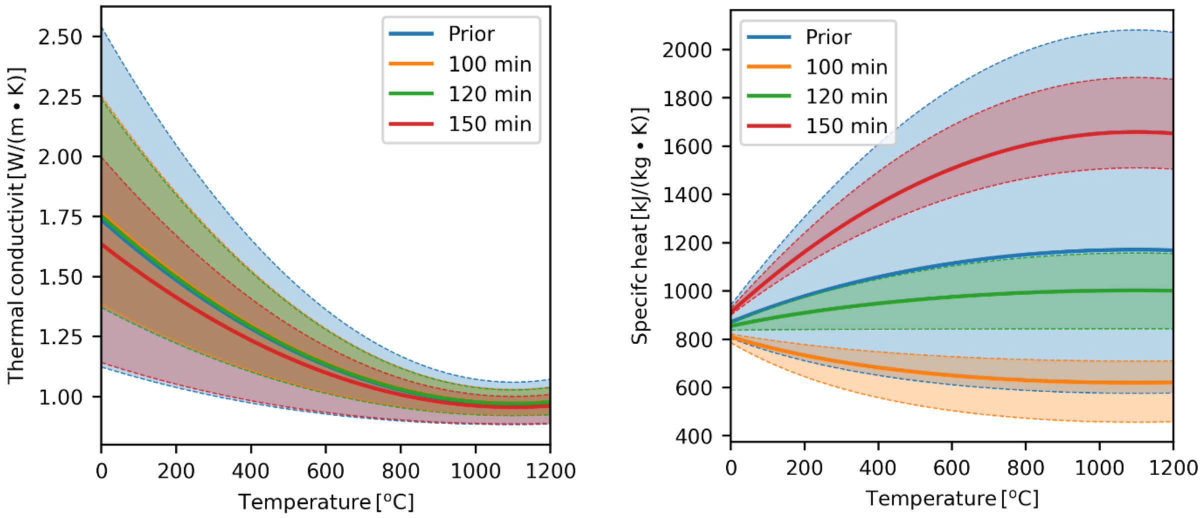

FIGURE 2. Posterior distributions for thermal conductivity (left) and specific heat of concrete (right) at different temperatures for different values of failure time with the shaded 90 % Highest Density Intervals (HDI).

fire curve from EN 1991-1-2 [8] is used to represent a natural fire exposure. In order to use it, some parameters defining the compartment where the slab is located must be defined. In this study, a compartment with dimensions of 10 m × 10 m × 3 m, opening factor $O = 0.05m^{1/2}$ and wall linings with thermal inertia of 1450 $\mathrm{J/(m^2KS^{1/2})}$ is considered. These parameters can be considered as easily determined and constant. However, to define the parametric fire curve, the fuel load in the compartment also needs to be defined. There is a lot of uncertainty on this parameter and therefore it will be considered stochastically (see Table 2).

Similarly, as with the analysis of the furnace test, a heat transfer calculation is needed to determine the temperature gradient and the slab's bending capacity. Again, polynomial regression is used as there is a need for a large number of calculations. For 1000 different combinations of the thermal conductivity quantile, the specific heat quantile and the compartment fuel load, the temperature gradient is calculated and that data is used for the regression.

The final step is the calculation of the conditional failure probability given a structurally significant fire. This is done using the updated material properties' distributions and additional stochastic parameters (presented in Table 2). The failure probability is calculated using Equation 4 which describes the limit state Z.

$$Z = K_R \cdot M_R - K_E \cdot (G + Q) \tag{4}$$

3. Results and discussion

The Bayesian updating was performed multiple times for different assumed values of the failure time during the test. Updated posterior probability density functions of both thermal conductivity and specific heat at different temperatures for a few failure times are presented in Figure 2. From these results, it is observed that the failure time is not particularly sensitive to the value of the thermal conductivity and the updating procedure results in only small changes to the prior distribution. For example, at ambient temperature, the standard deviation reduces from 0.42 to approximately 0.29 W/(m.K). However, the failure time is highly dependent on the value of the specific heat. The standard deviation at ambient temperature reduces from 0.57 for the prior to roughly 0.13 kJ/(kg.K) for the posterior. Furthermore, an almost linear relation between the posterior mean value of the specific heat and the failure time can be seen, as shown in Figure 3 (left).

Using the first Bayesian method (MCMC) the yield strength of reinforcement steel was also updated, how-

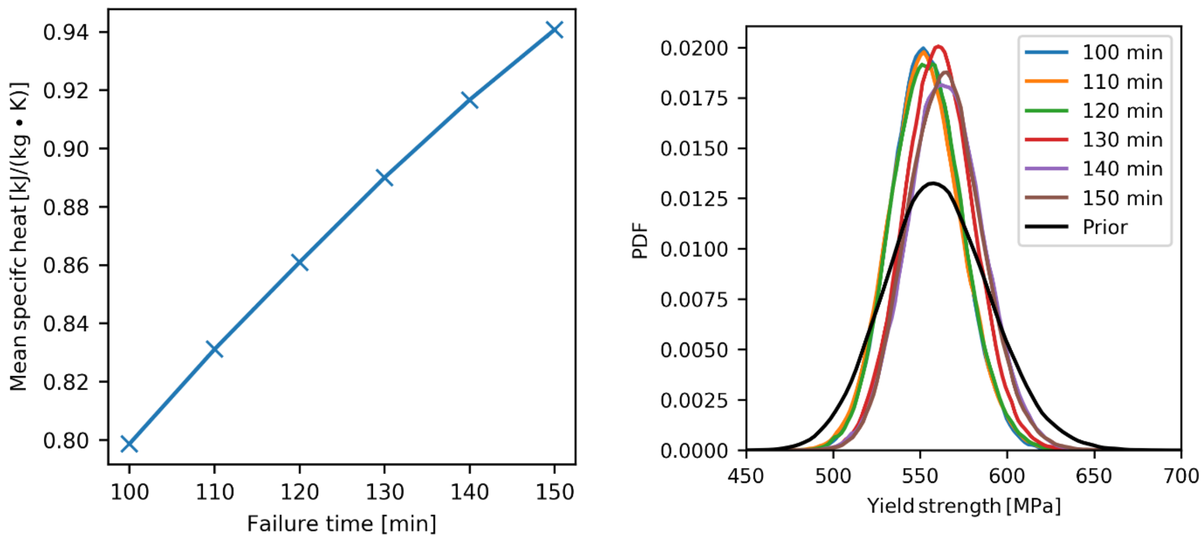

Figure 3. Posterior mean value of the specific heat of concrete at ambient temperature in function of the failure time (left); posterior distributions of the reinforcement steel yield strength at ambient temperature for different values of the failure time (right).

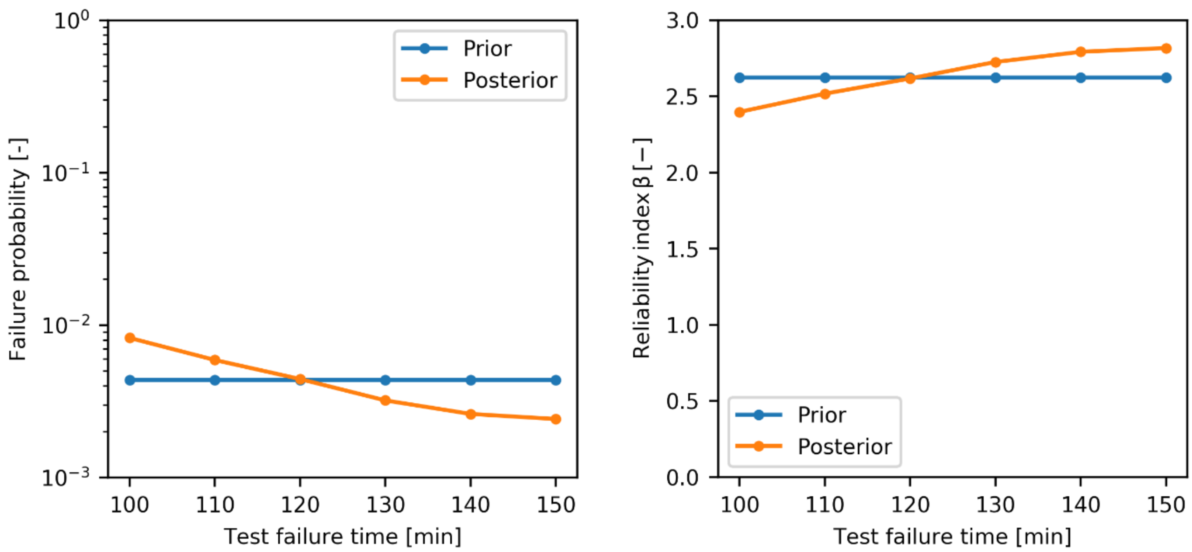

Figure 4. Failure probability (left) and reliability index (right) in the function of the failure time.

ever, according to the results in Figure 3 (right), it is evident that the failure time sensitivity to this parameter is relatively low.

It must be mentioned that the MCMC sampling method might produce unrealistically low posterior uncertainty as in theory the update would only be specifically valid for the tested slab and not account for the possible variations between similar slabs that are going to be used for the same structure (which are not tested). In the case where more than one test is used, a procedure similar to the one presented in [12] should be used where the mechanical properties of reinforcement are not updated in order to focus on the thermal properties.

To determine how much the failure probability changes with the updated posteriors, the failure probability is first determined based on the prior distributions. This is calculated using 10^6 Monte Carlo realizations and the obtained value is equal to $4.4 \cdot 10^{-3}$. . The probability of failure is then also calculated using the posterior distributions using the posteriors for thermal conductivity and specific heat instead of their respective priors. The results are presented in Figure 4 in the function of the failure time. In order to demonstrate how different test failure times affect the probability of failure in the case of the real fire, the failure probability has been calculated for the range of test failure times from 110 to 150 min and it ranges from $8.35 - 2.03 \cdot 10^{-3}$.

As expected, a higher value of the failure time leads to a lower value of the failure probability. However, what is interesting is that for failure times lower than

120 min, the failure probability is higher than the one calculated using the prior distributions. When analysing the distributions of the moment capacity of the slab, it is observed that the reduction of the variability compared to using prior distributions is almost negligible. This can be attributed to the fact that the uncertainty on the resistance of the slab is mainly governed by the uncertainty on the fuel load. However, the posteriors of the thermal properties still have an effect, as it is observed that the mean value of the capacity changes for different measured failure times.

4. Conclusions

A procedure to obtain a more precise failure probability of a structural member in case of fire using Bayesian updating based on the standard furnace test result was presented. This procedure focuses on maximizing information from the highly used furnace test in relation to the performance-based assessment of the structural capacity under a real fire condition. As the furnace test provides the failure time in case of standardized fire exposure, a clearer connection from its results to the structure's behaviour in real fire is explored. The procedure is demonstrated on the case of a reinforced concrete slab.

A standard Markov Chain Monte Carlo simulation approach was used and showed that the failure time during the test is most sensitive to the variation of the specific heat. For example, the updating procedure resulted in a reduction of the standard deviation of specific heat at ambient temperature from the prior value of 0.57 to a posterior value of approximately 0.13 kJ/(kg.K).

This also has an effect on the calculated failure probability under a real fire condition. Using the updating procedure and Monte Carlo simulations, the failure probability under a real fire condition was calculated for the range of test failure times from 110 to 150 min and it ranges from $8.35 - 2.03 \cdot 10^{-3}$. It was also observed that the variability of the concrete slab capacity in the case of a natural fire is mainly determined by the uncertainty of the fire exposure and that a reduction of the uncertainty of material properties obtained with this method has a small but distinctive effect. It must be noted that this study's results are limited to the behaviour of the reinforced concrete slab, where the failure is mostly a consequence of strength reduction of the reinforcement due to the elevated temperature. In the cases of other materials and structural members, the effectiveness of this approach might differ. Nevertheless, this presents an improvement in the use of the furnace test results as this approach tackles one of its biggest flaws, correlation to the real fire behaviour, and shows that they can be used to quantitatively assess the safety level of a structure in case of a real fire.

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