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Retrofitting cavity walls – probabilistic study of energy savings and moisture risks

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ABSTRACT

Nowadays deterministic building simulation models are commonly used in building design. However, most of the parameters involved are stochastic variables and as a consequence, a probabilistic approach would give more information on the spread of the results. In the framework of IEA ECBCS Annex 55, it is the aim to develop a method to estimate the balance between energy savings and risks, such as mould growth, algae growth and low indoor air quality when retrofitting existing dwellings. Such a method, based on a probabilistic approach, would make it possible to choose the solution with the best balance between large energy savings and low risks. This paper illustrates a probabilistic approach for an old cavity wall which is retrofitted with post-injected insulation. It shows how a decision tool can be constructed and how it can be used in a retrofitting problem. With the developed methodology it can be decided which insulation material to choose to reduce the heat loss and to minimise the risk of mould growth. The aim of the paper is to illustrate the methodology and possibilities of a probabilistic approach.

1. Introduction

These days, it is common to retrofit old buildings to save energy. Unfortunately, it is difficult to predict the energy savings and there might also be a risk of hygrothermal failure when applying certain retrofit measures. So far, no real method is available to estimate the balance between energy savings and risks.

Deterministic building simulation models are commonly used in building design. However, most of the parameters involved are stochastic variables, e.g. material properties, workmanship, external climate and user behaviour. A probabilistic approach will yield knowledge of the possible spread on the results. This approach was introduced into building physics at the end of the eighties (Hokoi and Matsumoto 1988; Lomas and Eppel 1992). More recently the probabilistic modelling is developing very fast (MacDonald 2002, de Wit and Augenbroe 2002, Pietrzyk et al. 2004, Haarhof and Mathews 2006, Corrado and Mechri 2009, Domínguez-Munõz et al. 2010). They all focus on uncertainty or sensitivity analysis.

Within IEA ECBCS Annex 55 (Hagentoft 2010) it is the aim to develop a probabilistic framework for retrofitting existing dwellings. Such a method would make it possible to choose the solution with the best energy savings and the least side effects. These side effects can be mould growth, algae growth, low indoor air quality and so on.

This paper presents a probabilistic approach to evaluate energy savings together with hygrothermal risks. The case study focuses on mould growth, when retrofitting an existing cavity wall with post-injected insulation. The aim of this example is not to give correct solutions, but rather to illustrate the methodology and the possibilities of a probabilistic approach.

Section 2 describes the case study and the model used for the probabilistic analysis. The main sections handle the results of uncertainty analysis (section 3), a decision tool based on these results, which can be used to choose between retrofitting solutions (section 4), and a sensitivity analysis (section 5) to limit the input parameters which have to be taken into account. The final section deals with the different steps to come to a probabilistic approach with a decision tool as main result.

2. Case study: approach and variables

We consider an old brick wall with a cavity and a concrete floor slab which is anchored to the outer leaf as in Fig. 1. This is a common construction method for the first cavity walls in the 50’s and 60’s. There is no rain penetration into the concrete slab. The inside surfaces are finished with plaster and a floor decking. The rooms above and below the considered slab are assumed to be bedrooms. In this example, we consider three types of insulation material that can be used to fill up the empty cavity wall: PUR foam, EPS granules and mineral wool.

This case study illustrates the possibilities of a probabilistic methodology. To do so, we focus on the total heat loss in January and the yearly risk of mould growth in the upper corner of the lower bedroom, as these parameters indicate the energy use and one of the additional hygrothermal side effects.

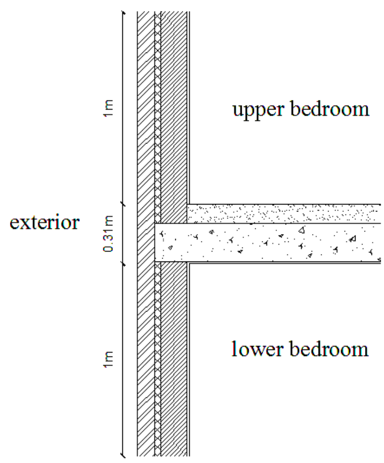


Fig. 1. Old brick wall with cavity

Table 1. Distributions of variable input parameters

Parameter	Distribution*
Lambda-value (W/mK)	PUR: N(0.04,0.004) EPS: N(0.10,0.018) MW: N(0.06,0.010)
Thickness of cavity (cm)	D(2,6)
Orientation of the wall (degrees from North)	U(0,360)
Inside temperature (°C)	N(18,1)
Hygric inertia (kg/m³%RH)	N(0.59,0.15)
Air change rate (1/h)	D(0.1,0.6)

* Explanation of the symbols used:
N(μ,σ): normal distribution with mean value μ and standard deviation σ
D(a,b): discrete uniform distribution between a and b
U(a,b): uniform distribution between a and b

2.1 Model

The heat and moisture response of the construction for one reference year were calculated with the use of the finite element code HAMFEM (Janssen 2007). Evaluation of the risk of mould growth is based on the isopleths of (Sedlbauer 2002). To take into account all stochastic variables a Monte Carlo simulation was implemented into the HAMFEM-code.

A Monte Carlo analysis aims to quantify the probability distributions of the preferred outputs by repeating the simulation several times while varying the values of the input parameters according to their probability density functions (pdf). Because a Monte Carlo simulation tends to be time consuming, an advanced sampling technique was applied (Janssen 2012). 105 samples were created with a space-filling, non-collapsing sampling scheme – maximin Latin Hypercube - (Husslage 2008). A Latin Hypercube design aims to optimally spread the samples for each of the input parameters. A 'maximin' design continues on that and aims to spread the samples as optimal as possible over the entire parameter space. The 105 samples were made in sets of 21 runs, a multiple of three because of the three insulation types. This was repeated five times.

For the brick and concrete slab the properties specified in the HAMSTAD benchmark case 4 (Hagentoft et al. 2004) are used. The climate used is the climate of a reference year in Essen, which is also used in Delphin (Delphin).

The risk on mould growth in the upper corner of the lower bedroom can only be evaluated correctly by taking the variable indoor vapour pressure into account. To do so also the hygric buffering of the room enclosure is considered (Janssen and Roels 2009). If we then assume ideal convective mixing and no surface condensation, supposing air exchange for both bedrooms with the exterior environment only, and neglecting the temperature dependency of the air density, the moisture balance for the room air can be written as (Vereecken et al. 2011):

$$\left(\frac{V}{R_v T_i}+\frac{100HIR^{*}V}{p_{v,sat}(T_i)}\right)\frac{\partial p_{vi}}{\partial t}=(p_{ve}-p_{vi})\frac{nV}{3600R_v T_i}+G_{vp} \quad (1)$$

with V (50 m³) the volume of the room, Rv (462 J/kgK) the gas constant for water vapour, Ti (K) the indoor air temperature, HIR* (kg/m³%RH) the production-interval adapted hygric inertia per cubic meter of room volume, pv,sat(Ti) (Pa) the partial vapour saturation pressure for indoor temperature Ti (K), pvi/e (Pa) the partial vapour pressure of indoor/outdoor air, n (1/h) the air change rate per hour, V/RvTi (m³kg/J) the moisture capacity of the zone air and Gvp (kg/s) the indoor vapour production set at 120 kg/s between 22h and 6h and 10 kg/s between 6h and 22h, corresponding to the moisture production in a two-persons bedroom.

2.2 Input parameters

The type of insulation and the thickness of the cavity wall are two of the stochastic parameters, which have to be considered in the model. In addition, the orientation of the wall is of influence as solar radiation and driving rain is taken into account. The user behaviour is also very variable. The inside temperature, the hygric inertia of the rooms and the air change rate are related to the users.

As seen in Table 1, the model has 6 variable input parameters. The other material properties and boundary conditions are deterministic and not described in this paper because the focus is on the probabilistic approach and not on the hygrothermal model.

2.2.1 Insulation

Three types of insulation are considered: PUR foam, EPS granules and mineral wool. Each of them has their own thermal conductivity, bulk density, thermal capacity and vapour diffusion. The thermal conductivity is not a deterministic value as this is influenced by workmanship. The mean value and spread on this mean are different for all insulation materials as some materials cause more execution difficulties as other materials. The distributions are shown in Fig. 2a. The mean values are based on measurements (Delghust 2010), but since only a limited amount of measurement points were available, a normal distribution is assumed.

2.2.2 Thickness of cavity

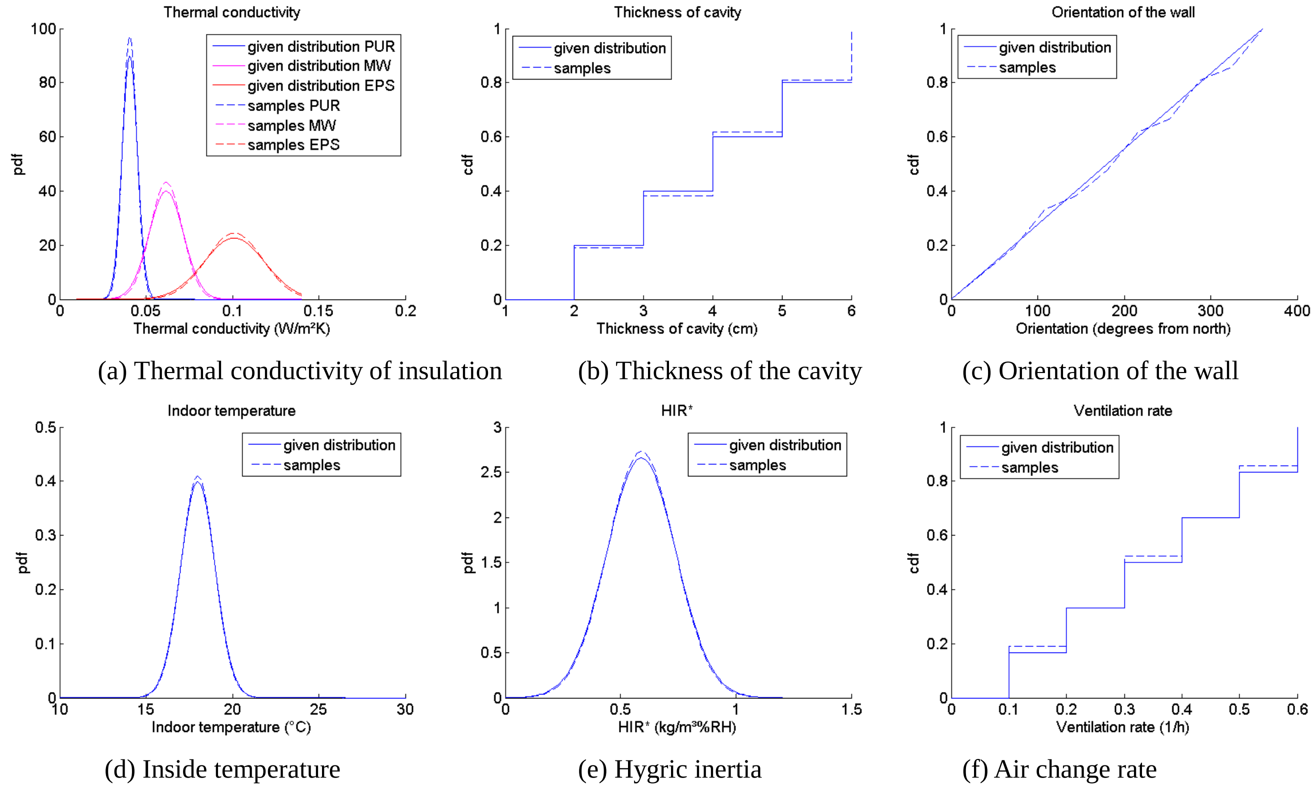
When a cavity wall is injected with insulation, besides the thermal conductivity of the insulation material, the thickness of the cavity determines the thermal resistance of the wall. The thickness is often not known. Therefore, in this case, it varies between 2 and 6 cm in steps of 1 cm.

2.2.3 Orientation of the wall

We do not impose restrictions on the orientation of the wall. Therefore, the value of the 'wall orientation' parameter can be anything with equal probability in the range 0 to 360 degrees as measured from the north.

2.2.4 Inside temperature

Because inside temperature is determined by user behaviour, it can not be assigned a deterministic value. Therefore, we assume that the inside temperature is constant and normally distributed around 18 °C with a standard deviation of 1 °C. The fact that people will often open windows when it is warm outside is included in the model by a simple algorithm: when the outside temperature is higher than the inside temperature, we fix the inside temperature to be the same value as the outside temperature.



(a) Thermal conductivity of insulation (b) Thickness of the cavity (c) Orientation of the wall

(d) Inside temperature (e) Hygric inertia (f) Air change rate

Fig. 2. Distributions of input parameters - given distribution compared to created distribution

2.2.5 *Hygric inertia*

The production-interval adapted hygric inertia HIR*, as seen in Eq. (1), is considered as a normal distribution with mean value 0.59 kg/m³%RH and standard deviation 0.15 kg/m³%RH. This takes the moisture buffering of the building enclosure into account (Janssen and Roels 2009).

2.2.6 *Air change rate*

Both bedrooms are ventilated by natural ventilation by opening the windows and due to air leaks in the building envelope. This ventilation rate is dependent on user behaviour. Per Monte Carlo run the ventilation rate is taken constant with a rate between 0.1 and 0.6 changes per hour with steps of 0.1 per hour. When the outside temperature is high, people tend to open windows. Therefore, when the outside temperature is higher than the inside temperature, the ventilation rate is set to 1 per hour. Note that the air change rate only intervenes to calculate the indoor vapour pressure (Eq. 1) and not the indoor temperature.

2.2.7 *Comparison of the given and created distributions*

Fig. 2 compares the distributions based on the 105 samples created with the 'maximin'-design with the given distributions of the input parameters. A good agreement is observed. Therefore, the output will be representative.

3. Uncertainty analysis

As mentioned in section 2, we choose to focus on the total heat loss in January and the risk of mould growth in the upper corner of the lower bedroom for a reference year. Both performances are predicted by the Monte Carlo simulation and indicate the energy use after retrofitting and the additional hygrothermal side effects.

Fig. 3 shows the distribution of the total heat loss per meter construction node in January. One meter construction node corresponds to 1.31 m² façade (Fig. 1). The distribution has a mean value of 37 kW/m construction node. Fig. 4 shows the distribution on the amount of hours with a risk of mould growth, with a mean value of 344 hours. This distribution is based on the isopleths of (Sedlbauer 2002), see e.g. Fig. 5, which shows the coupled temperatures and relative humidities per hour in the upper corner of the lower bedroom for the first run of the Monte Carlo simulation, in this case with 6cm PUR. The values of the remaining parameters are randomly drawn from the distributions mentioned in section 2.2 as well. It is assumed that when the coupled temperature and relative humidity exceed the limit, mould growth can occur. The distribution of the sum of all exceeding hours is plotted in Fig. 4.

The results show the importance of a probabilistic approach. A deterministic calculation would be dependent on the chosen input parameters and would lead to results that can not be generalized, corresponding namely only to one point of the obtained distribution.

4. Decision instrument

Based on the methodology presented in this paper, one can create a decision instrument like Fig. 6 and Fig. 7, which compare the different solutions for cavity filling. The different approximations of a normal distribution are shown.

This is a more objective way to choose which retrofit solution should be preferred. For the case analysed, when looking at a

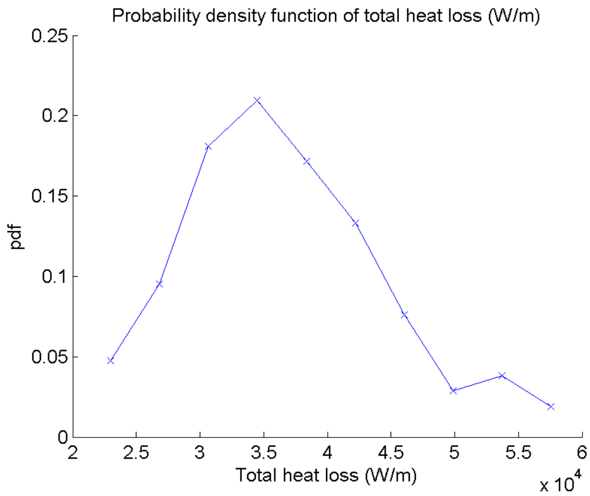


Fig. 3. Distribution total heat loss January

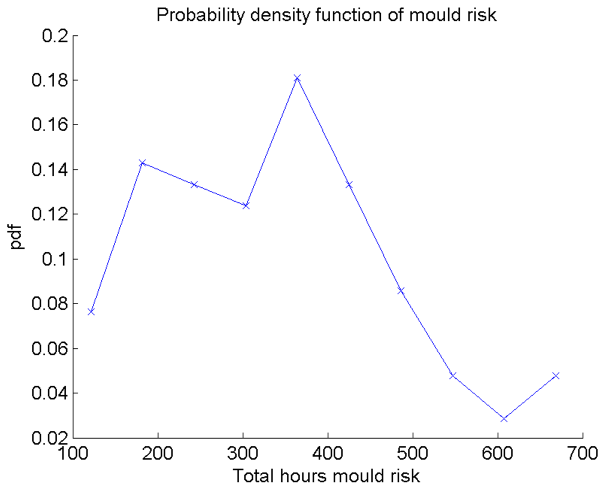


Fig. 4. Distribution total hours of mould risk

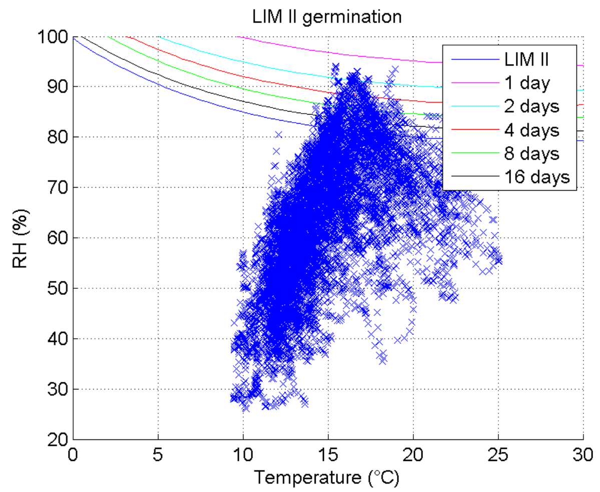


Fig. 5. Isopleth with coupled temperatures and relative humidities as calculated for one of the Monte Carlo runs (6cm PUR)

minimum heat loss with the risk of mould growth as low as possible, we would choose PUR as insulation material. In this case, PUR has the lowest mean value for both heat loss and risky hours, respectively 32 kW/m construction node and 333 hours of risk. PUR also has the smallest standard deviation for heat loss, which means that we are more certain of the obtained retrofitting result, corresponding more or less to the mean value.

The results show that for this academic case using PUR provides the best results in general. It might be interesting to also investigate the results for different cavity thicknesses. Fig. 8 shows the distribution of the risk of mould growth for the different thicknesses of PUR. We would expect that the risk of mould growth increases when the thickness decreases. Unfortunately, this is not entirely what we see. Because of the 'maximin' algorithm, one has to be careful with subsampling. The given distribution has to be approached by the subsamples to have reliable results, which is not the case for Fig. 8. To overcome this, enough samples are needed or the preferred parameter has to be excluded from the 'maximin' design.

Of course we need to take all side effects into account if we would like to have an overall decision instrument to assess the balance between energy use and all possible risks. If we are able to gather all risks and their hygrothermal behaviour in a probabilistic model, we could make a reliable decision. This kind of decision tool should be expanded with life cycle costs of the retrofitting options.

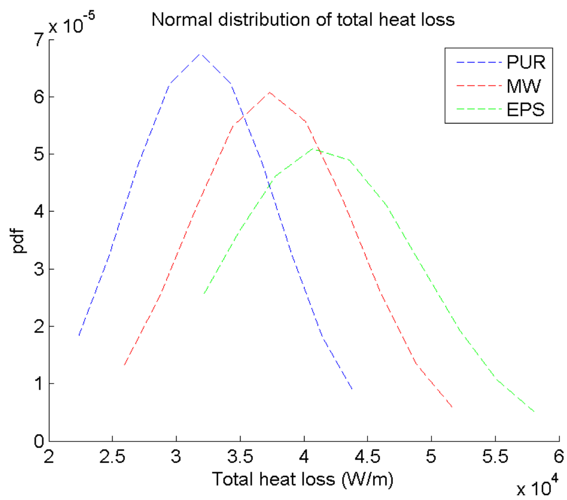


Fig. 6. Decision instrument: normal distributions of total heat loss for different insulation types

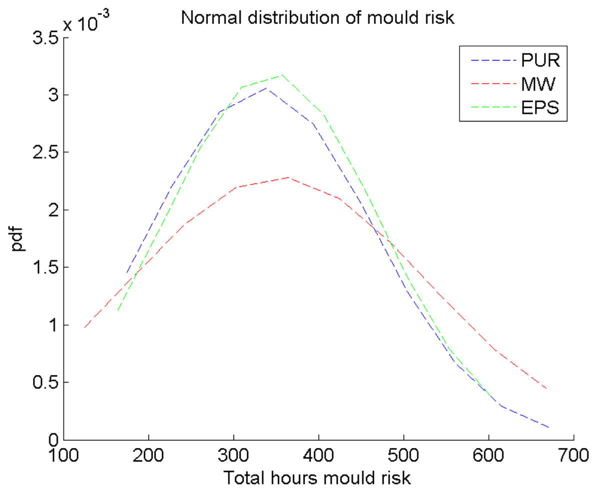


Fig. 7. Decision instrument: normal distributions of total hours of mould risk for different insulation types

5. Sensitivity analysis and discussion

Comparing Fig. 6 with Fig. 2 learns us that the distribution of the insulation type has a large impact on the heat loss. As the distributions are now based on a limited number of measurements, this means that more measurements would be

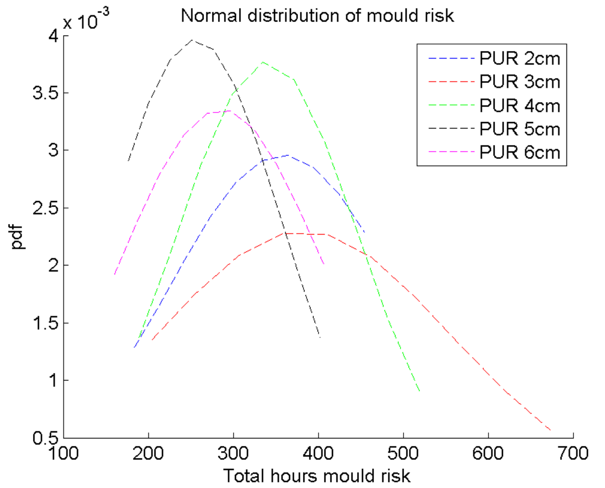


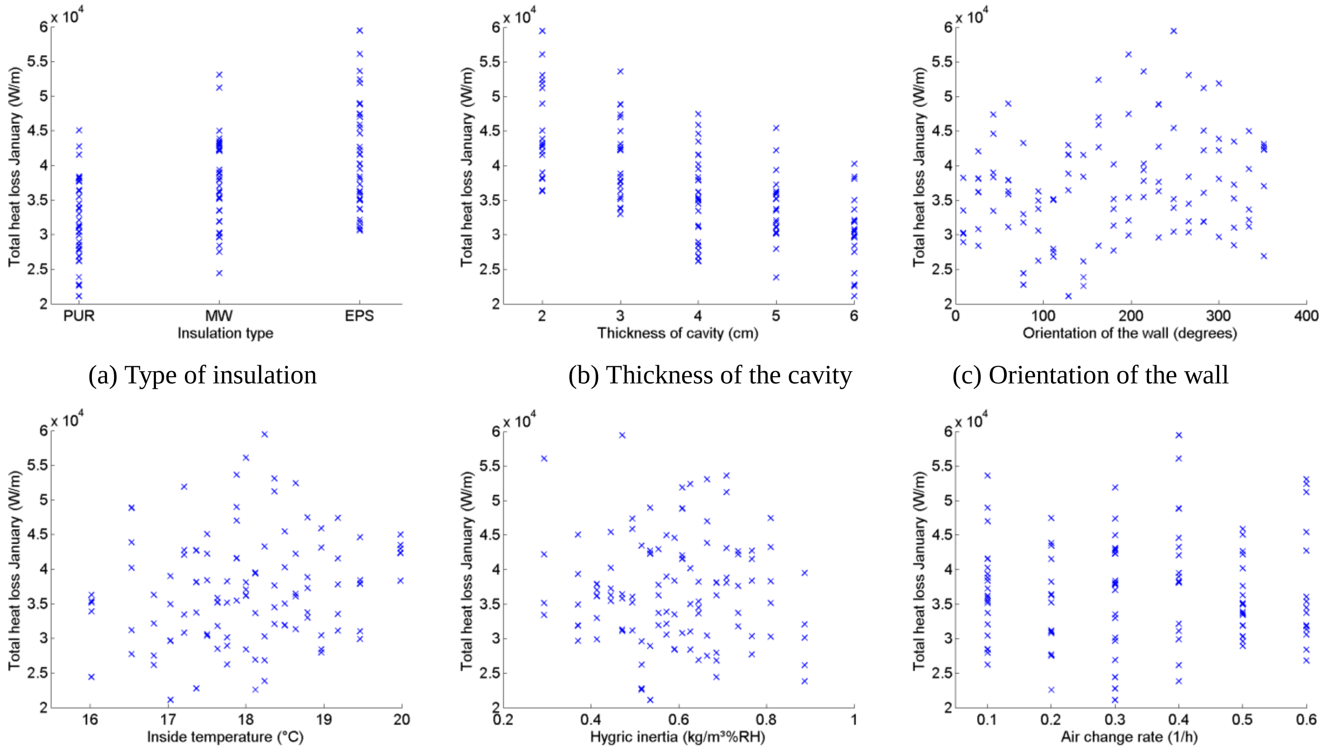
Fig. 8. Decision instrument: normal distributions of total hours of mould risk for different thicknesses of PUR

needed to increase the accuracy of the distributions and hence the reliability of the output.

To investigate the most important variables (those variables for which a reliable input distribution is crucial), a sensitivity analysis can be performed. One of the most visual methods is the use of scatter plots (Hamby 1994). This method plots one output parameter against one input parameter to analyse the correlation between them, as can be seen in Fig. 9 and 10.

As concluded before, the insulation type (Fig. 9a), the thermal conductivity and the thickness of the cavity (Fig. 9b) are influencing parameters for the total heat loss in January. As can be expected, the orientation is important as well (Fig. 9c). Fig. 10d shows that there is a high correlation between the inside temperature and the risk of mould growth. As seen before, the insulation type is also an influencing parameter (Fig. 10a).

This way, for real cases, a sensitivity analysis beforehand could help to reduce the amount of variable parameters to take into account. As the needed number of runs for a Monte Carlo analysis based on basic random sampling is defined by the internal standard deviations (Wikipedia 2011), the needed number of runs won't be reduced while reducing the amount of input parameters. However, reducing the amount of parameters will also reduce the needed number of runs for a 'maximin' design as the design for a certain number of samples is more uniform for fewer dimensions (Fang 1980). Moreover, in some cases it can be valuable to check for which parameters a distribution is needed, because collecting all distributions for all parameters is very time consuming.



(a) Type of insulation

(b) Thickness of the cavity

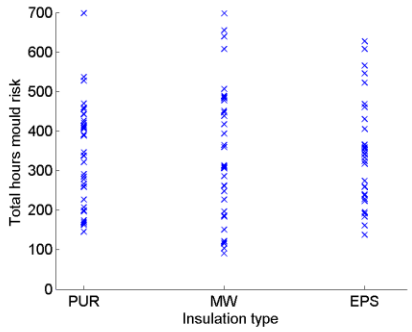
(c) Orientation of the wall

(d) Inside temperature

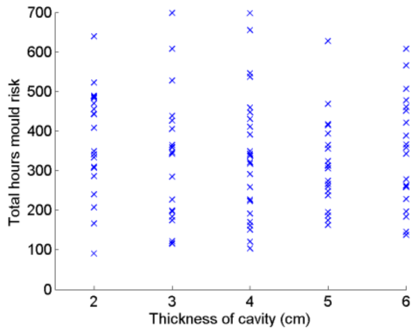
(e) Hygric inertia

(f) Air change rate

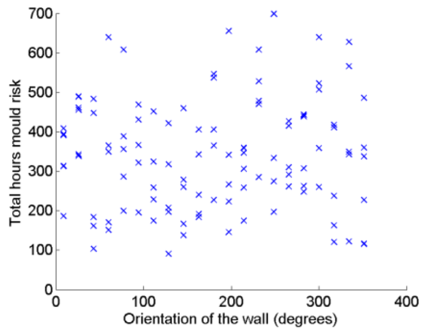
Fig. 9. Scatter plot for correlation between input parameters and total heat loss in January



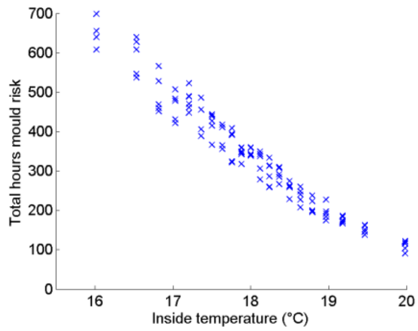
(a) Type of insulation



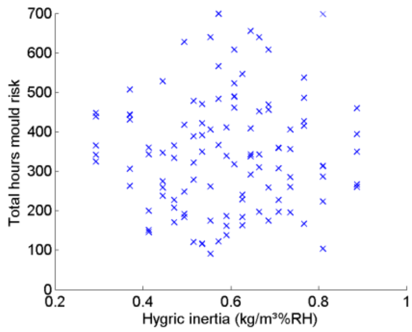
(b) Thickness of the cavity



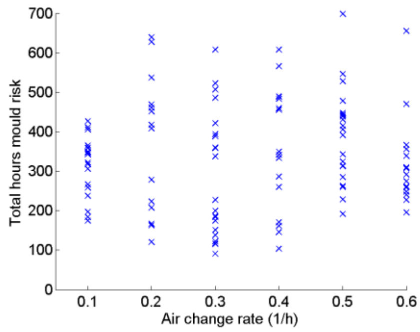
(c) Orientation of the wall



(d) Inside temperature



(e) Hygric inertia



(f) Air change rate

Fig. 10. Scatter plot for correlation between input parameters and total hours of mould risk

6. Probabilistic methodology

The previous case study illustrates the importance of a probabilistic approach. One of the main applications is a decision tool as described in section 4. This is the most objective way to select a retrofitting option with the highest energy savings and the smallest risks on hygrothermal side-effects. To come to a decision tool for one specific case, the following steps are needed:

1. Hygrothermal risks. One needs to decide which hygrothermal risks need to be taken into account. Here, one can rely on knowledge of experts. It is important to use the correct hygrothermal models to evaluate the risks.
2. Input parameters. One needs to decide which parameters need to be taken into account. If one is not sure whether a parameter is important or not, it's better to take this into account at first instance and drop after the sensitivity analysis (step 4).
3. Distributions. One needs distributions for all input parameters chosen in step 2. However, they don't need to be very accurate. It's enough that they match the whole range of possible values.
4. Sensitivity analysis. A Monte Carlo simulation, as explained in section 2.1, calculates distributions for the output parameters which are dependent of the selected case. One can plot the output parameters versus the input parameters, as described in section 5, based on this Monte Carlo simulation. Other sensitivity analysis methods are possible as well. Based on these result one can decide which distributions have to be investigated.
5. Distributions. To gather all necessary distributions, a lot of measurements are needed. However, some of them can be drawn up by the knowledge of an expert on the proposed case.
6. Uncertainty analysis. A Monte Carlo simulation is repeated to investigate the distributions of the output. One needs to check how many runs are necessary to have a reliable result. Stopping criteria are needed to do so. Based on the output different decision tools can be created. Of course other methods are possible as well. Calculation time is a very important criterion in this decision.
7. Decision tool. Based on the results of the uncertainty analysis, one can start developing a decision tool which takes all the uncertainties, all risks and all life cycle costs into account. Adding the life cycle costs should allow making an objective decision to choose between different retrofitting options.

Conclusions

Retrofitting old buildings is becoming more and more common. Unfortunately, at the moment, it is difficult to predict the actual energy savings and there might also be a risk of hygrothermal failure when applying certain retrofit measures. This paper illustrates the importance of a probabilistic approach and introduces a decision tool to estimate the balance between risks and energy savings. The aim of this paper was not to give correct solutions, but to show the possibilities of the developed methodology. This method makes it possible to choose the solution with the least side effects and the best energy savings.

As input distributions are mostly unknown, more research is needed here. The distribution of the input has a large influence on the outcome. Without these input distributions one can't get a reliable decision tool. A sensitivity analysis beforehand could help to reduce the amount of parameters to take into account.

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