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A MIXED SIMULATION APPROACH TO ANALYZE MOLD GROWTH UNDER UNCERTAINTY

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ABSTRACT

The paper presents a new approach for analyzing mold growth risk in buildings, based on a mixed simulation approach with consideration of uncertainties in relevant building parameters. The approach is capable to predict and explain unexpected mold growth occurrences that would typically not show up in standard deterministic simulation.

This study simulates the local environmental conditions at material surfaces in buildings by using a mix of standard simulation tools. By introducing uncertainties in relevant input parameters, this approach generates a statistical distribution of time aggregated mold growth conditions at a number of "trouble spots" in a specific building case. This distribution is then translated into an overall mold risk indicator. In addition, our method identifies those parameters whose uncertainty range has a dominant effect on an increase in mold risk. By thus identifying the critical influence of building components, building operation and maintenance factors on the increase in risk, appropriate actions during the building design and procurement process can be set up to address these risks.

INTRODUCTION

Many modern buildings continue to suffer from harmful levels of mold growth. This poses a major health and liability issues in the building industry. As a result, there is an increasing need to develop reliable methods to predict mold growth under uncertainty. Currently available evaluation methods use hygrothermal models based on the first order physical principles of heat and mass transfer. A good example is WUFI (Kuenzel, Karagiozis 2000) which solves the non linear coupled heat and mass transfer equations in local 1D and 2D geometries. Although these simulation models are accurate, their limitation is that they typically operate on as-designed information. They produce deterministic results for a "design-interpreted idealization" of a building. This idealization does in reality not reflect the local, situational, and sometimes idiosyncratic aspects of a building during its operation. Our study starts from the hypothesis that it is exactly this type of unexpected behavior that leads to the failure or below standard performance of building systems which can eventually lead to mold growth problems. It is concluded that the deterministic use of the current simulation models are less adequate for assessing all possible types of mold risks in real-life buildings.

Mold will germinate when 1) the physical environmental conditions provided by building systems, 2) the nutrient factors of building materials, and 3) the spore availability. The methods for nutrient effects and spore transportation have been studied in earlier research efforts (Moon and Augenbroe 2004). The emphasis of the following sections will be on the prediction of the environmental conditions that influence mold growth on material surfaces.

Local indoor environmental conditions are driven by multiple mechanisms that need to be considered on different building granularities. Our method uses a separate dedicated simulation approaches for each mechanism. We use a whole building simulation for zone level considerations, combined with a detailed simulation of local envelope details. This is accomplished by a mixed simulation approach which we will discuss in detail in the next section.

The second part of the paper will deal with the deployment of the mixed simulation approach to study the effect of uncertainties in input parameters. To this end, the uncertainties are propagated through the mixed simulation. We will concentrate on the mechanisms and parameters that govern mold growth risks. Performing the mixed simulations with uncertain parameters will reveal the influence of each parameter on local mold growth conditions.

The merits of the method will be shown in a case study. We will discuss how this work will ultimately lead to the development of a comprehensive building performance indicator, i.e. a normative indicator that expresses the relative risk of a given design or of an existing building that it will grow mold over its service life.

MIXED SIMULATION APPROACH

Local environmental conditions (i.e., surface temperature and relative humidity) directly affect mold growth at material surfaces. Local conditions are governed by heat and moisture transport in the material and at the air-material interface, boundary airflows, material composition and properties, HVAC system operation, outside air infiltration, building maintenance activities, and so on. These mechanisms are of varying nature and need to be studied at different building granularities. Our method uses a mix of existing simulation tools sequentially, each specialized in a particular domain of heat, air, and moisture transport. In the mixed simulation approach, the simulation inputs are initially prepared by hand. The transfer of output from one simulation to the boundary condition of the next model are hardwired into the simulation inputs. This approach gives relative performance evaluation results that are sufficient for the purpose of the study, i.e., relative mold growth risk.

Figure 1 shows the modeling procedures and simulation tools that are used. Their choice is driven by the need to cover every mechanism that affects the local conditions at material surfaces. Each box represents a step in the simulation, i.e., deployment of particular simulation tool. The outcomes of the steps are combined to provide the full assessment, as shown in figure 1. The objective is to simulate the mold growth conditions on a set of specific locations ("trouble spots") on interior surfaces. The mixed simulation is typically performed for a whole building or large enough building zone in a given geographic location with known (micro-) climatic conditions. Within the simulated building zone, a set of trouble spots is identified, typically in corners, at edges, or at spots where deficient building detailing has been established or may be suspected. The latter distinction may need some explanation. In a given building case, a thermal bridge may actually exist in the design specification. In that case, this is treated as a deterministic input for the design reference case (the reference case uses best estimates of all variables as they would be chosen in a standard deterministic simulation). The thermal bridge may also be the result of an uncertainty analysis, e.g., resulting from an analysis of the likelihood that bad workmanship would lead to certain deficient building details. One needs to model the probability that a deficient building detail of a certain type and severity will be present in the building. The probability would be derived from what is known about the occurrences of deficient details in similar buildings with similar technologies.

The following sections describe the steps in the flow chart of figure 1.

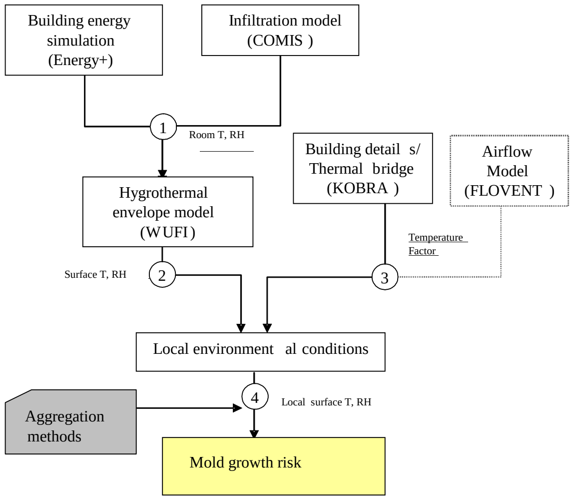

Figure 1 Flowchart of mixed simulation approach

Hygrothermal Models (1, 2)

The analysis starts with a standard building energy simulation model that is capable to give zone level information with respect to temperature and relative humidity over time. Any whole building energy and moisture simulation model is a good candidate in this step. In (Moon and Augenbroe 2004) EnergyPlus, Esp-r, BSIM 2002, are compared for this purpose. EnergyPlus and COMIS were chosen in this study for the heat transfer and airflow model respectively, since both software tools can easily be combined.

To predict detailed moisture behavior on specific locations on interior surfaces of the building envelope, hygrothermal envelope models such as 1-D HAM, WUFI and MOIST are good candidates. We chose WUFI for our purpose as it is ideally suited to simulate moisture transport in multi-layered envelopes and surrounding environment. It provides a detailed moisture transfer analysis with additional functionality, such as the specification of initial moisture content in building materials and rainwater penetration. The mixed EnergyPlus/COMIS calculation results in zone air temperature and relative humidity (1) which are subsequently used as an interior boundary condition in WUFI's hygrothermal envelope model (2).

Building Details and Thermal Bridges (3)

Mold does not typically occur on the undisturbed wall. Rather it prefers to grow at line or node joints, i.e., where certain building details negatively influence the surface conditions. These situations occur where insulation materials are improperly designed or installed with bad workmanship, causing condensation problems due to bad building detailing, leading for instance to unwanted thermal bridge effects. They typically give rise to lower internal surface temperatures in cold and higher temperatures in hot climates, which may increase or decrease mold growth risk. Deficient building detailing usually occurs at wall/window connections, wall/floor intersections, wall/foundation intersection, but many other types of thermal bridges may occur depending on construction technologies used for the installation of the envelope components.

Thermal bridge assessment can be based on simple steady state assumptions, which allow straightforward classification in thermal bridge categories. Alternatively, one could opt for a detailed 3D simulation in a whole building model. Clearly, for the purpose of our study, such an integrated dynamic study would overkill the problem as we only need to assess the effect of the uncertain location and uncertain severity of a set of (not precisely known) building details. It was decided to use the stand-alone tool KOBRA (PHYSIBEL 2002) that offers flexible configuration of thermal bridge types. It qualifies the severity of a thermal bridge by a "temperature factor" which is defined as the inside surface temperature that results from an indoor-outdoor temperature difference of 1°C. The temperature factor is taken as the key building detail parameter that will be an uncertain input parameter in the simulation roadmap of figure 1.

Local indoor environmental conditions at envelope surfaces are also affected by indoor airflow patterns. It is often reported that mold occurs behind furniture pieces and in internal room zones with poor air circulation such as behind cupboards or inside wall closets. It is well established that adequate air circulation can effectively remove moisture from surfaces (Jing, Aizawa 2003). Indeed, good air circulation creates relative high boundary air velocities at material surfaces at trouble spots. A CFD simulation is most adequate to study the effects of poor local ventilation. In the CFD simulation, different ventilation strategies can also be studied to give an indication of how bad pressure calibration or blockages of air ducts could lead to stagnant airflows around trouble spots. A fundamental analysis would require the full coupling of the CFD simulation with the heat, air, and moisture transfer models. For our purposes this is, however, not necessary as we are only interested in the probability that certain deficiencies in the ventilation flows will cause surface conditions to be more or less favorable to mold growth. The following approach is proposed: a set of CFD simulations is performed on the design reference case with varying assumptions about the quantity and placement of airflow obstructions, and with the assumption of potential deficiencies in the airflows that are produced by the HVAC system, due for instance to bad installation, stuck vents, bad pressure calibration, etc. The choice of obstructions and deficient airflow regimes are based on observations in typical usage settings. The choice should represent the statistical distribution of obstructions and HVAC flow deficiencies as observed in similar settings. For each case, a CFD simulation is performed and the outcomes are interpreted for each trouble spot, leading to the derivation of a reduced surface convection and surface moisture diffusion coefficients. It is expected that both these outcomes can then be aggregated with the temperature factor as indicated in Figure 1. In the current stage of the research this approach is still under development and not yet used in this paper.

Local environmental conditions (4)

The calculation of the hygrothermal envelope model gives overall surface temperature and relative humidity at the interior surface of a wall. This result is derived for an undisturbed plane wall, assuming uniform distribution of temperature and relative humidity. By mixing the temperature factor that accounts for the disturbed temperature field at certain building details in this calculation, the local conditions at a trouble spot can be approximately represented. For this, it has to be assumed that the moisture distribution in a wall is uniformly distributed at the surface of the wall (i.e., at the surface not disturbed by the building detail). With this assumption, the adjusted local surface temperature and relative humidity at the presumed trouble spot can be calculated using only the temperature factor. This approximation has still to be validated and will be part of follow-up research.

The following section describes the type and magnitude of uncertain parameters in the mold growth simulation.

UNCERTAINTY IN MOLD GROWTH ANALYSIS

Uncertainties in hygrothermal simulation within an envelop system has been recently conducted as models have become robust (Holm and Kuenzel 2002; Salonvaara, Karagiozis 2001). It was concluded that variations of material properties could result in higher variations in moisture contents in the wall. These studies are restricted to hygrothermal material properties. In mold growth analysis, all building properties and usage factors, such as indoor moisture generation, infiltration and ventilation, cleaning, air flow patterns, thermal bridge effcets and even bad workmanship, enter into the analysis.

As discussed above, the main motivation for this study is that the phenomenon of mold growth in buildings typically occurs unexpectedly and in many cases unexplained by current standard simulations. The objective is therefore to express the relative risk that harmful levels of mold growth will occur. In order to quantify this risk, we perform an uncertainty analysis on the basis of the mixed simulation approach sketched above. This analysis quantifies the uncertainties in mold growth and expresses the likelihood that mold will occur during the service life of the building.

The assessment of building performance uses descriptive building information as its input. This information consists of a building model (geometry, material data, HVAC configuration, etc) and a "scenario". Building model data describe an abstraction of the building design (specification). The scenario contains the information that one knows about the environment and use of the building. It specifies the external conditions to which the building model is exposed over time and contains climate data, number of occupants and building usage schedule, HVAC system operation and set points, building cleaning and maintenance policy, and so on. In this study, we assume scenario information to be fixed, i.e., not having any uncertainty associated with it. The uncertainty analysis is confined to the uncertainties in parameters of the building simulation models. The separation between building and scenario information allows a building to be analyzed for a variety of plausible scenarios and to study potential mold growth risks in each scenario separately.

Uncertainty in the building model parameters are captured as probability distributions of model parameters. The distributions express the estimates of the deviations between "as-designed" values and the actual "in-use" values of the parameters. Deviations arise from normal spreads in building component properties, common defects in construction, unknown effectiveness of cleaning and maintenance operations, errors in operation set points, drifts in thermostats, etc. Other deviations between the idealized simulation and reality are systemic to the simulation itself, i.e., attributable to the simplifying modeling assumptions that underlie the simulation. The normal approach is to represent the modeling uncertainty in a set of surrogate parameters contained in the simplified model. The uncertainty analysis studies the combined effects of all above deviations on the physical states of a building. It does so by performing simulations for all combinations of realizations of the uncertain parameters. The uncertainty in the parameters is thus propagated through the simulation. The expected (uncertain) behavior of the building can consequently be aggregated as a probability distribution. An important first step in the uncertainty analysis is the identification of uncertain parameters and the quantification of their uncertainty.

Uncertain parameters

Previous researches on mold problems in buildings have suggested several important causes and mechanisms related to the phenomenon (Burge 2002; Shakun 1992). These studies are an important source for the identification of uncertain factors in mold growth causes. Causes that are frequently mentioned in these studies are outdoor air infiltration through cracks, indoor moisture sources, deficient building detailing, and improper HVAC operation.

Each cause may require the introduction of uncertainty in one or several physical parameters. Infiltration, for example, is linked to the combination of pressure difference and crack flow through façade components. The governing parameters in this case are the wind pressure coefficient at critical areas of the facade and the mass flow coefficient through the type of cracks that are known to occur in the given façade. Based on theoretical models and/or data analysis, the uncertainty of each parameter is described as upper/lower values with a probability distribution (Table 1). A base value represents the deterministic value that a designer or engineer would use for standard idealized simulation based on sound engineering judgment (in most cases the commonly accepted mean values of parameters). With these base values as input, the simulation for the reference case produces a deterministic outcome of the mold growth conditions.

Quantification of uncertainty in building parameters

Uncertainties associated with model parameters can be quantified based on available data from literature (material properties), scattered results of different calculation algorithms (e.g. pressure coefficient, mass flow coefficient), or field measurements (thermal bridges). This section briefly illustrates two examples: the air mass flow coefficient and the temperature factor, both of which have been introduced above. A detailed description of these and other uncertain parameters will be published elsewhere (Moon 2005).

Air infiltration introduces uncontrolled amounts of outside air into a building through cracks in façade components and through uncontrolled openings. The characteristics of crack flow were studied using the power law equation that contains the air mass flow coefficient. Uncertainty of this coefficient was derived from air leakage test data for different building types. For the test case, this resulted in the lower and upper values listed in table 1, parameter 7. The base value was assumed to be the default value given by COMIS.

To arrive at the uncertainty in the temperature factor for our test case, one particular type of thermal bridge was assumed to be present. Their presence was established from the analysis of trouble spots in buildings with a similar type of facades (cavity walls) as the test case. In these walls, vertical line joints at exterior wall corners constitute inherent thermal bridges due to the difference of surface areas of interior and exterior walls. The research team conducted field measurements and linked the results with KOBRA simulations to derive the uncertainty in the severity of the selected thermal bridge type. This resulted in the values given for parameter 33 in Table 1. The given values represent the combined uncertainty of the deterministic thermal bridge effect of the line joint and potential bad workmanship that exacerbates the effect.

CASE STUDY

A case study was conducted to test the developed approach. The objective of this case study is to find the distribution of mold growth conditions, and identify the dominant parameters that contribute the most to the mold growth risk at a specific locations in the building (in this case: the interior surface at the corner of an exterior wall).

Building model and scenario

The selected reference building is a one-story office building located in the city center of Miami. The reference area has a typical urban setting with surrounding buildings. This building is composed of four office rooms (6m×6m×3m) and one corridor (12m×2m×3m). Each room has one operable window (4m×1m) in the exterior facade. Figure 2 shows the plan of the reference building, and location of concern for mold growth.

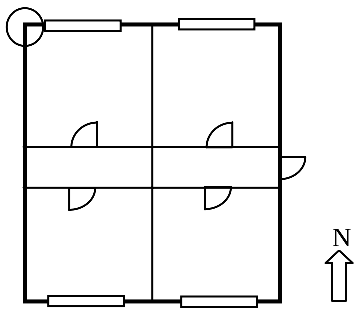

Figure 2 Plan of the reference building and location of concern for mold growth

The exterior walls are composed of brick, air gap, insulation, and gypsum board. Four persons are assumed to be working in each room during normal office hours (8:00 – 18:00). In the scenario that is reported below, the HVAC system is operated during the occupied time, and only during weekdays. In the simulation, the HVAC system with VAV is controlled to meet the set temperature of 20°C (±2°C) and minimum 45% RH (±10%). Indoor moisture sources include four office workers with light activity, regular wet cleaning of the floor, one frost-free fridge, and two small plants per rooms.

In the mixed simulation, the building zone was set up for a yearly simulation with the Miami climate. The simulation was conducted in Monte-Carlo style to analyze the mold growth conditions at the trouble spot under uncertainty. In order to translate the conditions into an aggregated mold risk factor, two alternative methods were used. Both methods are based on a count of the yearly average number of "risky days for mold growth" (a value between 0 and 365). The first method is based on the germination graph method discussed in (Moon and Augenbroe 2004). The second is based on the 80% RH criterion recommended by IEA (1991)as a threshold for preventing mold germination (IEA 1991). This method counts a day as risky if the daily average surface relative humidity exceeds 80% of RH. Both approaches can be viewed as leading to the quantification of a "mold performance indicator."

Uncertain parameters

After constructing the input model for the reference case, all relevant uncertain building parameters were identified and their level of uncertainty quantified with similar techniques as mentioned above. Table 1 shows the selected 33 parameters with base values and the lower and upper values that quantify the uncertainty.

Table 1 Uncertain parameters and their upper and lower values

	Parameters	Base	Lower	Upper
1	Outside air flow rate (m^3/s)	0.16	0	0.16
2	Zone set point temperature control deviation (°C)	0	0	2
3	Minimum RH deviation (%)	0	0	10
4	Supply air temperature(°C)	14.5	13	16
5	External convective heat transfer co. (W/m^2K)	18	9	27
6	Internal convective heat transfer co. (W/m^2K)	2.4	1.59	3.21
7	Air mass flow coefficient (-)	0.001	0.0004	0.0051
8	Discharge coefficient (-)	0.675	0.6	0.75
9	Wind pressure coefficient (South) at wind direction 0°	-0.37	-0.6	-0.1
10	Wind pressure coefficient (North)	0.6	0.02	0.9
11	Wind pressure coefficient(West)	-0.56	-0.9	-0.23
12	Wind pressure coefficient(East)	-0.56	-0.9	-0.23
13	Wind velocity profile exponent (α)	0.33	0.33	0.4
14	Moisture source (g/h) at un occupied hours	37.7	24	51.4
15	Brick: density (kg/m^3)	1650	1100	2150
16	Brick: porosity (m^3/m^3)	0.41	0.11	0.41
17	Brick: Heat capacity (J/kg K)	850	830	920
18	Brick: Heat conductivity (W/m K)	0.6	0.397	1.08
19	Brick: Diffusion resistance (-)	9.5	8	17

20	Brick: Moisture storage function (kg/m^3) at RH=1	370	192	370
21	Insulation: density (kg/m^3)	60	8	190
22	Insulation: porosity (m^3/m^3)	0.95	0.25	0.95
23	Insulation: Heat capacity (J/kgK)	850	837	850
24	Insulation: Heat conductivity (W/mK)	0.04	0.0303	0.045
25	Insulation: Diffusion resistance (-)	1.3	1.3	3.4
26	Insulation: Moisture storage function (kg/m^3) at RH=1	0	0	297
27	Gypsum Board: density (kg/m^3)	850	618	850
28	Gypsum Board: porosity (m^3/m^3)	0.65	0.305	0.65
29	Gypsum Board: Heat capacity (J/kgK)	850	837	870
30	Gypsum Board: Heat conductivity (W/m K)	0.2	0.152	0.23
31	Gypsum Board: Diffusion resistance(-)	8.3	7.3	13
32	Gypsum Board: Moisture storage function (kg/m^3) at RH=1	400	264.4	707.5
33	Temperature Factor (-)	0.86	0.68	0.78

Propagation of uncertainties to find the distribution of the performance indicator

The propagation of the parameter uncertainties leads to a statistical distribution of mold growth conditions in the specific building case. The parameter ranges in table 1 are interpreted as central 95% confidence intervals. Due to the lack of explicit information on the parameter distribution, normal distributions were assumed for all parameters.

The Latin Hypercube Sampling (LHS) method was used for the uncertainty propagation. LHS is one of the Monte Carlo simulation techniques (Wyss and Jorgensen 1998) that is particularly suited for our needs. This method has been proved suitable for complex, non-linear models and demonstrated in building simulation (De Wit and Augenbroe 2002). LHS is a form of stratified sampling. The domain of each parameter is subdivided into N disjoint intervals with equal probability mass. In each interval, a single sample is randomly drawn from the associated probability distribution. Application of this technique provides a good coverage of the parameter space with relatively few samples compared to simple random sampling. Parameter samples were generated using an LHS algorithm in SIMLAB (European Commission - IPSC 2004). A total of 60 samples were generated and propagated through the mixed simulation toolset. The number of samples generated are well above the minimum required value ($4k/3$ = 44). The results of the propagation of 60 samples are shown in figure 3 and 4 for the germination graph method and 80% RH criterion method, respectively. The distribution (dotted line) was found for each case by using fitting techniques.

In the case of the germination graph method (figure 3), the mean value of risky days is 12.9 and the standard deviation is 7.35 with a variance of 54.0. In this analysis, variation is significant as the coefficient of variation ($C_v = \sigma/\overline{X}$) is around 0.57. A lognormal distribution was found as the best fit for the distribution of risky days.

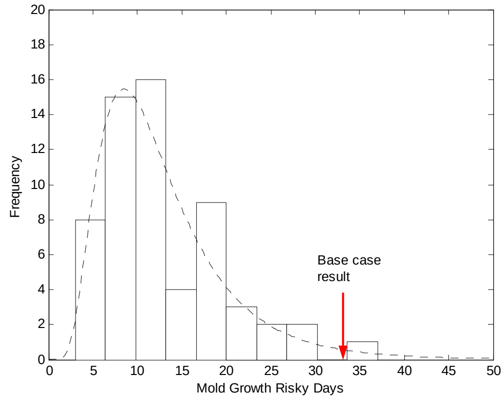

Figure 3 Histogram of the performance indicator using mold germination graph method from the Latin Hypercube sample size of 60.

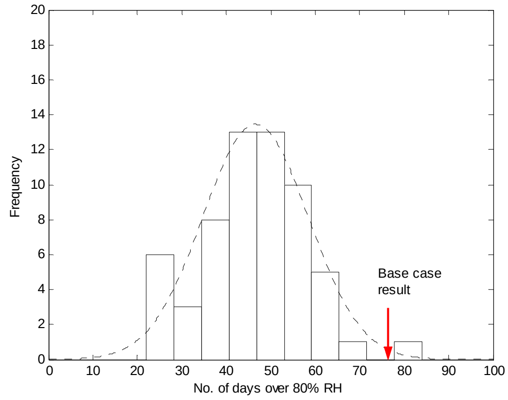

Figure 4 Histogram of the performance indicator using 80% criterion from the Latin Hypercube sample size of 60.

The uncertainty propagation results showed mold growth risks in all combinations of parameters, which predict, theoretically, some level of mold growth in all possible combinations of uncertain parameters in this particular case. It is plausible that only if the number of yearly risky days is above a certain threshold, harmful, visible mold growth will actually occur. In order to find this threshold value, we need to calibrate the outcomes of figure 3 for a large set of building cases with established mold problems in those buildings. This is an area of important follow-up research. It should be noted that in this particular case, the distribution in figure 3 shows median value of 11 and a long tail that indicates possible severe mold occurrence with relatively low probability. The analysis with the base parameter values resulted in 34 risky days, which is at the upper end of the distribution, i.e., in this case a deterministic simulation would predict a relative high mold risk, which has relatively low probability of occurring in the actual building. It is atypical that the deterministic simulation produces a risk value that is considerable higher than the median of the distribution that results form an uncertainty analysis. In this particular case, the base value for the air mass flow coefficient was selected from the default value in COMIS. As it happens, this parameter proves to have a dominant influence on the mold growth (as shown below). As table 1 shows, the base value is close to the lower bound of the uncertainty range of the parameter.

Figure 4 shows the results of uncertainty analysis using the 80% RH criterion with a mean value of 46.5 and standard deviation of 11.8. The normal distribution was found as the best fit in this case. It should be noted that the 80% RH criterion only accounts for the surface relative humidity without considering the effect of temperature and nutrition of building material to mold growth. The deterministic simulation with base values now results in 76 risky days. Again, and in line with what we found above, the resulting value is to the high end of the risk, with relatively low probability due to same reason above.

The numbers of risky days using the two criteria differ substantially. Little significance can be attributed to this as the “scale” of both distributions has only relative value. Future research will have to establish the correlation between the risky days in either distribution and actual occurring mold. Both criteria could be used for this purpose, but it is expected that the germination graph will show a stronger correlation due to the better representation of the fundamental mold growth mechanism.

Identification of dominant parameters

The identification of dominant parameters is performed using a parameter screening technique suggested by Morris (1991). This method ranks parameters in the order of their importance, i.e., their individual contribution to the uncertainty in the model output based on elementary effects. An elementary effect of a parameter is the change in the model output as a result of a change (Δ) in that parameter, while other parameters are kept at a fixed value. The results of the analysis can be examined by plotting sample mean and standard deviation of the elementary effects for each parameter. A large mean value or a large standard deviation of the sample indicates overall importance of the corresponding parameter on the output.

In our test case, the 33 parameters were discretized on a 6-level grid (p=6) and the predefined elementary step Δ was chosen to be 3/5. Samples were generated by using the Morris method algorithm in SIMLAB. A total of 5 independent samples of the elementary effects were assessed in 170 simulation runs. The parameters that explain about 80% of total variance are considered the dominant parameters.

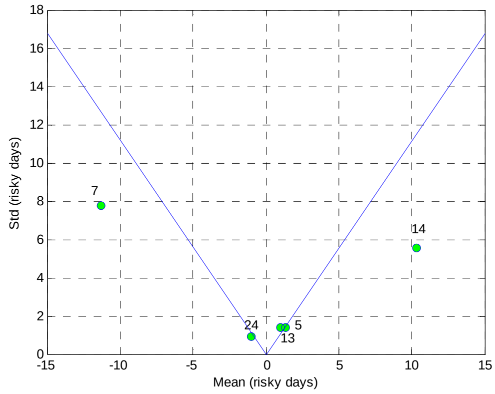

Figure 5 Ranking results for top 5 dominant parameters for mold germination graph method

Table2 Top 5 dominant parameters using mold germination graph method

RANK	PARAMETERS	INDEX
1	Air mass flow coefficient	7
2	Moisture source	14
3	External convective heat transfer coefficient	5
4	Wind exponent	13
4	Insulation conductivity	24

Figure 5 and table 2 show the result of the sensitivity analysis using the mold germination graph method. Only the identified dominant parameters are shown in the figure. In the distribution of elementary effects, the lines corresponds to $m_d = \pm 2S_d / \sqrt{r}$ (r = no. of independent samples). An elementary effect above the line indicates parameter interaction or non-linear effect. In the study of the elementary effects for each parameter, five dominant parameters were identified. The top two parameters (air mass flow coefficient and indoor moisture source) accounted for about 72% of the total variance. Almost identical results were found if the 80% RH was used.

It is interesting to note that the air mass flow coefficient shows negative correlation with mold growth risk, i.e., minus mean value. This reveals that decreased infiltration rate increases mold growth risks. This is because in the studied scenario, the HVAC system only works on weekdays, i.e., not in weekends or on holidays. As it happens, most mold growth risks occur during the system off period. In general, HVAC system turn-off with continuous moisture sources in rooms during weekends contributes to higher indoor humidity ratios than outdoors and thus constitutes a substantial risk for mold growth. However, higher infiltration of outside air mitigates this risk! This explains the unexpected high risk that was found in deterministic base case simulation where the mitigating effect was underestimated. This post analysis shows the power and versatility of the uncertainty analysis, as it helps to indicate those factors that need to be controlled and procured in a way to keep mold risks under acceptable levels. It should also be noted that for this particular building in this particular location, the risk analyses for different scenarios reveals that the chosen HVAC operation leads to unacceptable risks, and a HVAC shut down is not acceptable.

CONCLUSION

A new approach is introduced that is capable to explain unexpected and non-deterministic mold growth occurrences in buildings. Moreover, it identifies the parameters with dominant effects on the increase of mold risk. The latter provides crucial information for designers and engineers to guarantee better building performance. The approach is currently being applied to other case studies that will lead to more general conclusions with respect to the calibration and applicability of the mold risk indicator. We can draw a number of preliminary conclusions from the case study reported above:

1) The approach looks promising as a more realistic prediction of the mold risks going beyond the deterministic assessment

2) The similarity of the results using two different mold risk criteria is encouraging. Further calibration of both distributions on a larger set of real cases will have to show which of the two criteria leads to superior validation of the approach.

3) The identification of the parameters that have a major influence on mold risk can provide a long awaited breakthrough for early mold risk control, i.e. during design, commissioning and A/E procurement.

An important next step in the research is to calibrate the developed theoretical risk prediction with hard evidence from mold occurrences. The developed mold risk approach does not cover the effect of building defects, system breakdowns and other catastrophic events, such as a water leak from a broken pipe. Such events are part of the scenario selection which dive each particular uncertainty analysis. These and many other practical issues (e.g., rain penetration, moisture migration from a foundation) will be dealt in the futur research.

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