APPLICATION OF PROBABILISTIC SIMULATION AND BAYESIAN DECISION THEORY IN THE SELECTION OF MOLD REMEDIATION ACTIONS

Hyeun Jun Moon[1], Godfried Augenbroe[2]

[1] Department of Architectural Engineering, College of Architecture, Dankook University, Seoul, 140-714, Korea
[2] Doctoral Program, College of Architecture, Georgia Institute of Technology Atlanta, GA, 30332-0155, USA

ABSTRACT

This paper utilizes a probabilistic mold risk assessment method, introducing a novel mold risk indicator (MRI). The MRI captures the risk of mold occurrence at identified "trouble spots" under uncertainty. It will show how the MRI can enhance decision-making in a mold remediation case. When used in decision making under uncertainty, the MRI enables the best selection of remediation actions in the light of given preferences of the decision maker. In particular, decision makers are empowered to make a more rational decision based on a mold risk assessment that exceeds the usual deterministic performance evaluations. We will apply the Bayesian decision theory to the decision-making problem that involves the selection of two possible remediation actions in an existing building case. This approach demonstrates how to use additional information from mold simulation and uncertainty analysis in practical decision making problems and increasing the confidence of the decision maker.

KEYWORDS

Uncertainty analysis, Mold risk assessment, Bayesian decision theory, Building simulation

INTRODUCTION

In many cases, mold occurs in buildings as a result of local, situational, and sometimes unexpected or even idiosyncratic conditions during the actual occupancy and operation of the building. These unexpected behaviors are virtually disregarded by current deterministic simulation methods. To respond to this situation, Moon (2005) has developed a probabilistic performance indicator for mold growth by treating mold as a risk linked to a limit state phenomenon. This approach led to a so-called mold risk indicator (MRI). Its determination requires the extension of the simulation capacity offered by current standard tools and a reliable aggregation method that quantifies mold growth risk as a probability density function. The extended simulation capacity combines the different mechanisms that govern mold growth. In this approach, mold germination is considered the limit state criterion for risk. In other words, every time when an ambient condition persists long enough for germination to occur at a trouble spot, adds a unit of risk for mold occurrence at that spot. The analysis is based on a combined heat and moisture simulation of the whole building, along with detailed simulation of local conditions around trouble spots. These local conditions are assessed against potential mold occurrence risk by applying mold germination graphs. The local environmental conditions are calculated from hygrothermal models (Moon 2004). The functionality of current standard heat and moisture simulations had to be extended to account for additional mechanisms that affect the mold phenomenon. Four major categories of mechanisms were identified where an extension of simulation capabilities would be needed in order to produce accurate assessments. Each category represents a special "root cause" of mold germination as was found from an analysis of field data from real mold cases, i.e., spore source availability, substrate condition, HVAC maintenance and operation, and building detailing. Each mechanism requires a specific local or global simulation approach that is not available in the current generation of whole building simulation tools. In our approach they are accounted for in the simulation by using a combination of existing stand-alone simulation tools; each specialized in a particular domain of heat, air, and moisture transport.

Another major ingredient of the MRI approach concerns the inclusion of uncertainty in the simulation. Those uncertainties are represented as probability distributions of values for the building parameters (rather than one deterministic guess). The uncertainties are introduced to represent our lack of knowledge in a range of areas, such as the natural variation of hygrothermal properties of building materials, the deviation between "as-designed" values and the actual "in-use" values of the parameters, and other sources of uncertainties in simulation as well. The uncertainties of each building parameter are expressed by upper/lower values with a probability distribution based on available data in the literature, in mathematical models, or from field measurements. Once the uncertainties of the parameters are quantified, they can be propagated through the set of mixed simulation runs using a

Monte Carlo method. In this case a special technique, called the Latin Hypercube Sampling method is used (Wyss 1998). This technique reduces the number of samples that would have to be computed using the original brute force Monte Carlo method. The method is particularly suited for our purpose as one typically has a large number of uncertain parameters in a mold risk assessment. The uncertainty analysis is based on the repeated simulation with sampled building parameter values, eventually providing the mold growth risk as an outcome in the form of a probability distribution at each selected trouble spot in a building.

In the MRI approach the identification of the dominant parameters, i.e., those parameters that have a major influence on mold risk, is performed using a parameter screening technique suggested by Morris(1991). Knowledge of these dominant parameters is vital, as they may point to the factors that require special attention to guarantee a low mold risk environment over the life cycle of the facility. This is especially true if it is found that large uncertainty in a particular parameter adds substantially to the uncertainty in the outcome of the mold risk. It can then be researched whether reduction of the uncertainty will reduce the mold risk. If that proves to be the case, one can pay special attention to this parameter and make sure during the delivery and use of the facility that this parameter is subjected to rigorous quality control. One example would be the amount of uncontrollable air infiltration through a curtain wall façade. From known cases of the application of this technology in similar projects, one is able to estimate that range in values of the leakage factor up front. If the analysis shows that this creates a substantially increased mold risk, one could check what range of the unknown leakage factor would be allowable. If this range cannot be guaranteed for the chosen curtain wall technology, one could decide to select another façade type or make other design changes. In some cases, the manufacturer and the installer might guarantee the limited range of the leakage through the facade, if very special care is dedicated to it. Such stipulations could be written into performance contracts, assigning the risk to increased leakage to the manufacturer/installer. In some case, one might find that a manufacturer cannot accept this risk in view of the inherent uncertainty in the installation and on site assembly of the system. In that case, one might have to abandon a curtain wall in the given project.

The MRI approach has proven to be capable of explaining unexpected (i.e., non-deterministically predictable) mold growth occurrences. In many cases, such an unexplained and unanticipated mold occurrence is associated with the increased risk that the MRI calculation reveals. Such increased risk occurs as the result of combinations of parameter values within their uncertain range. The additional information from the MRI, i.e., probability distribution of mold risks at specific locations in a building is obviously the key to making provisions to avoid mold in the first place or remediate it when it has occurred. Most importantly, one can now make rational decisions concerning remediation actions in existing buildings weighing different options against each other, both in terms of cost and the risk mitigation they deliver. In the following sections, it will be shown how the MRI approach empowers decision making in a specific mold remediation case. To show the value of the MRI, we utilize a decision theory that focuses on the decision maker (DM) in mold remediation, if confronted with the choice between discrete remediation options.

DECISION THEORY

When a DM is handed a probability distribution of a performance indicator (like the MRI in our case), it is not intuitively clear how this may influence the DM in reaching a (different) decision based on the additional information. We need a theory that enables us to introduce the decision makers' preferences and decision criteria based on probability. For our purposes, we utilize the Bayesian decision theory (Berger 1985).

In Bayesian decision theory, uncertainty information is incorporated in the DM's preferences. The underlying certain rules or axioms that support the DM's rationality are weighted and formulated explicitly in his decision process. This is a normative theory rather a descriptive theory (behavioral model of the decision process). A normative theory tries to construct a model that ensures how a rational decision maker keeps his preference over a certain attribute consistent in his decision-making tasks. We assume a completely rational way of reaching a decision, only influenced by the DM's a-priori preferences and the information of the consequence of different options given to him or her. Detailed discussions on the underlying decision theory can be found in Bedford and Cooke (2001), French (1986), Press (1989).

The theory of normative decision making is based on the concept of utility, which enables the ranking of available actions in order of the decision maker's preference (Savage 1972). The main idea of this theory is as follows. If a decision maker prefers action *a* (or object *a*) to action *b* (or object *b*), there is a utility function, i.e., u(.), that representing the preference structure.

$$a \succ b \Leftrightarrow u(a) \succ u(b) \qquad (1)$$

When a decision maker is prepared to measure his utility values in a set of actions in a certain way, the action with the maximum utility is preferred. If the outcomes of consequences are to some extent uncertain, the decision maker chooses the action with the maximum expected utility. The decision maker's preferences over available actions can be observed through simple physical mechanisms, e.g., a probability wheel (French 1986). The observation of his a-priori preferences regarding a specific action or object leads to the construction of a utility function. Depending on the attitude towards risk, different shapes of the utility curve result, e.g., different curves that represent a risk averse, risk prone, or risk neutral attitude.

In this paper, the decision-making theory is demonstrated in the selection of a mold remediation action in an existing building. We introduce two different types of decision maker, one with a risk neutral attitude (DM 1) and one with a risk averse attitude (DM 2). Before applying the decision-making theory, the decision maker should understand the current status of mold risk in the building under remediation. The next section describes the selected building for this study and the MRI result for the as-is case.

SIMULATION RESULTS

MRI Approach for the as-is case

The MRI approach is applied to an existing building case with mold problems. The selected building case is a dormitory building located in Atlanta, USA, where the summer climate is warm and humid and the winters are moderate. The building has experienced repeated mold infestation on the inside surfaces of exterior corner walls for many years. Although the building management team has repeatedly removed mold on the walls by using a spray application, mold has come back every time. Corner rooms have shown most extreme mold growth, while the middle rooms have not.

Figure 1 shows the room (3.4m×5m×3m) of the building under study. The location of concern for mold growth is highlighted. In this building, the exterior walls are composed of brick, air cavity, and concrete block without insulation. Each floor has 20 dorm rooms and a common space is located in the center part of every floor, where a shower facility and the bathrooms are located.

Before starting the simulations, 21 uncertain parameters were identified in this specific case. Base and the lower/upper values that quantify the uncertainty were derived from inspections, statistical analysis and on-site observation (See Moon 2005 for details). The mixed simulation runs were conducted for a six months period covering the heating season in the Atlanta climate. The uncertainty analysis was conducted with a sampling size of 60 and propagation of the parameter uncertainties in the mixed simulation approach discussed earlier. As described in (Moon 2005) a useful unit of measure of the MRI is the so-called "risky day".

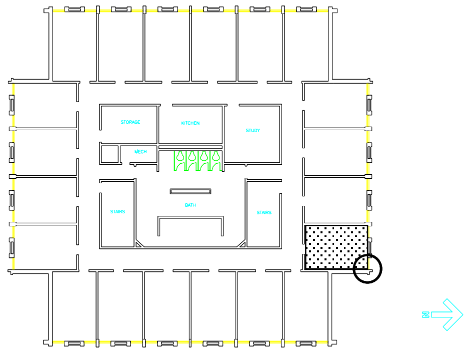

Figure 1 Plan of the building and the room under consideration

The results of the analysis can be seen in Figure 2. The expected mean value of risky days is 33.7 and the standard deviation is 88.7, with median value of 11.5. In this analysis the variation is significant as the coefficient of variation ($C_v = \sigma/\overline{X}$) is 2.63. The uncertainty propagation shows mold growth risks in all 60 samples, ranging from 1 to 110 (out of a potential maximum of 180 risky days), which predicts, theoretically, some level of mold growth in all possible combinations of uncertain parameters in this particular case. The mold risk is obviously linked to a couple of easily identifiable sources: the potentially high moisture content in the air from inadequate ventilation and extraction of the common shower and kitchen areas, and the inadequate U value of the un-insulated corner walls. It should be stipulated here that further research is needed to link the MRI measure to an "absolute" mold risk. Such a link could for instance result in the statement "if the probability that more than 60 risky days occur is over 30%, the absolute risk of mold growth is unacceptable." As long as this link has not been established, the MRI has limited use in the prediction of mold occurrence. However, this approach is very suitable to perform comparative analysis. This is exactly the purpose of using the MRI in the dormitory case.

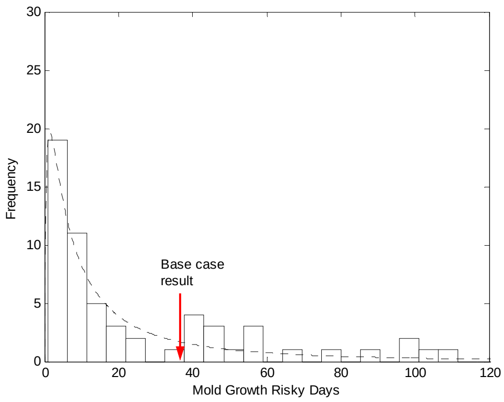

Figure 2 Histogram of the performance indicator using the MRI approach with Latin Hypercube sample size of 60.

Options for remediation actions

In the dormitory case, we found severe mold risk with small probability. With the MRI result, a decision maker (DM) may want to know what possible options he/she has to reduce the mold risk in the given building. We assume that the following two options are suggested to the DM, i.e., addition of insulation in the cavity walls and installation of a new rooftop HVAC for the common space.

In the analysis of dominant parameters in the MRI approach with the above as-is case, the temperature factor is found as one of the dominant parameters. Since the exterior wall have no insulation inside the cavity, it contributes to mold growth during the heating season, especially at thermal bridge locations, i.e., in corners. Putting insulation material in the cavity of the exterior wall will therefore reduce the mold growth risk (option 1).

The second option is to install a rooftop HAVC that retrieves moist air from the common space. Since in the current situation, the increased moisture level from shower facility in the common space may transfer to the rooms. It may lead to high room air relative humidity. The consultant suggests a small rooftop HVAC with perfectly balanced air supply and return (a ventilation rate of 2 h^{-1}). In this case, a typical CAV system is installed. The HVAC system is assumed to run 24 hours and appropriate outside air flow rate is introduced to make up for exhaust air.

The DM requests a performance study using the MRI approach. We assume that a thorough MRI approach is conducted for the two suggested remediation actions. In this paper, we assume that the decision maker is the owner of the building for the simplicity of the decision problem.

DECISION MAKING

This section discusses the relevance of the probabilistic information from the MRI approach in practical decision-making situations. It is a logical step to follow up a quantitative uncertainty analysis by quantitative decision analysis (Bedford 2001). Decision makers can make a more rational decision by using enhanced information, i.e. information that exceeds the usual “point sample” from deterministic performance evaluation. De Wit (2002) showed the relevance of uncertainty information in a simple decision problem in a thermal comfort analysis. We will apply a similar approach to the decision problem that involves the selection of two possible remediation actions in the dormitory case.

MRI results for option 1 and 2

The MRI assessment for options 1 and 2 will show the effect of each remediation action. In the assessment, additional uncertain parameters and uncertain ranges that are linked to the application of each option need to be considered.

In the assessment of option 1, six additional uncertain parameters related to the insulation material are introduced with lower/upper values. These parameters relate to the physical properties of insulation materials (density, porosity, heat capacity, heat conductivity, diffusion resistance, moisture storage function). The choice of the ranges in these parameters also reflects that potential defects in the installation of the cavity insulation. The temperature factor (a macro factor indicating the thermal bridge effect) for the exterior wall with insulation material in the cavity is also recalculated using KOBRA (PHYSIBEL 2002) and has a modified range of lower/upper values with a 95% CI.

In the second option, four additional uncertain parameters are required in relation to the rooftop HVAC, including outside air flow rate, zone set point temperature control deviation, supply air temperature, and supply air flow rate. The uncertainties are derived from an industry analysis of typical CAV systems and their operation in real life.

The MRI analyses are conducted for options 1 and 2 with a sample size of 60. Both options show significant reductions of the mold risk compared to the as-is case (Figure 3). Although both cases still have high upper bound of risky days, the probability that this occurs is much less than the as-is case.

A lognormal distribution was found as the best fit for the distribution of risky days (Figure 4). Both options show similar distribution but option 2 has a little bit higher probability for higher numbers of (normalized) the mold risky day value. The normalized mean values of option 1 and option 2 are 0.04 and 0.06, respectively. The obtained standard deviation is equal at 0.08 in both cases.

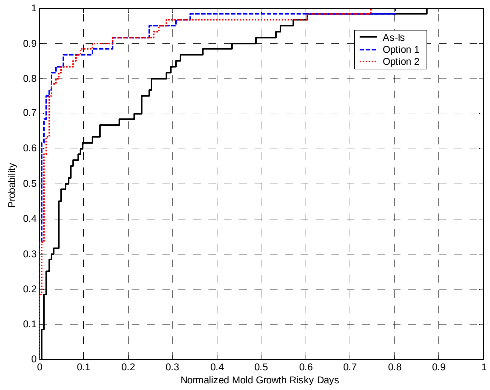

Figure 3 Empirical cumulative density function of the results of as-is, option 1 and option2

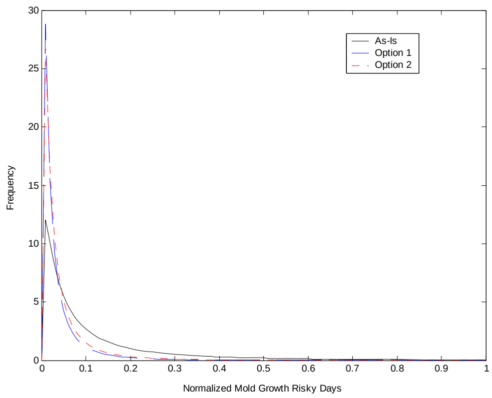

Figure 4 Distribution of normalized mold growth risky days for as-is, option 1, and option2 case

The probability information about the MRI will support a decision maker to choose between options, depending on performance and other criteria such as costs. First and foremost, a decision maker will look for the guarantees that a remediation option will achieve the desired result. For example, the DM may measure the (in)effectiveness of a remediation action by the total probability that the normalized MRI is above a target value Y. This can be expressed as a conditional probability, i.e. $P(x \geq Y)$; the smaller this probability, the more effective the remediation action is expected to be. We can simply calculate this value for every remediation options and compare different options against each other. This could also be done for different choices of the value of Y, related to the risk acceptance of the DM. In this case, option 1 results in $P_1(x \geq 0.1) = 0.08$ at the performance target value of 0.1 whereas $P_2(x \geq 0.1) = 0.11$ in the option 2. The decision maker may select option 1 if that satisfies his performance criterion. However, as mentioned before, no proven criterion between a guaranteed mold-free buildings and mold-problem buildings has been established yet in terms of MRI distribution. Further research is required to set practical performance criteria, before the mold risk indicator can be used as an absolute guarantee or as the basis for a “mold avoidance” building regulation. Although this means that we cannot set an absolute performance criterion for the MRI at this time, the conditional probabilities introduced above can be used to compare options in the practical decision case. It informs decisions in a way that is vastly superior to point sample comparisons obtained from deterministic analyses. The next section discusses how this helps the decision maker in the selection of remediation actions.

Decision making under uncertainty

In the previous section, we introduced two alternative options that either decision maker can choose from to reduce mold growth risk in the dormitory building. There are two concerns that motivate the decision maker: (1) the adverse occupants’ health effects due to environmental conditions (2) the costs to procure the remediation action. This leads to two objectives that the DM tries to satisfy (1) minimize investment cost (X) and (2) minimize mold risk (Y). As shown, the mold risk in each case was expressed as the MRI distribution. The required cost for each action is quoted as $\$100 \times 10^3$ (option 1) and $\$60 \times 10^3$ (option 2), respectively. It is assumed that there is no uncertainty in the projected monetary investments in this demonstration.

In this example, we assume that DM1 holds a linear marginal utility for X (investment cost, unit: $\$10^3$) and Y (normalized mold risk, 0 to 1). DM1 prefers less investment cost and less mold risky days. The process of elicitation of the utility function for each attribute is not discussed here but we assume that each utility function exists and can be generated from observations about the decision makers. Details about the elicitation of the marginal utility function is provided in (French 1986). In the establishment of a multi attribute utility function, the decision maker’s preferences are assumed to be mutually utility independent. When X and Y are mutually independent, we can calculate utility function u(x, y) as follows:

if (x_0, y_0) is such that $u(x_0, y_0) = 0$,

$$u(x,y) = u(x,y_0) + u(x_o,y) + k \times u(x,y_0) \times u(x_o,y) \quad (2)$$

DM1 holds the following utility function,

$u(x_0, y_0) = u(100, 0.2) = 0$ (3)

$u(x_1, y_1) = u(0, 0) = 1$ (4)

From the above utility functions, we can set x_0 = 100, y_0 =0.2, x_1 = 0.0, y_1 =0.0. Since the marginal utility function for X is linear, the DM1's utility function forms, $u(x, y_0) = (x, 0.2) = (100-x)/100$, when u(0, 0.2) = 1 and u(100, 0.2) = 0.

In the same way, the marginal utility function for Y can be calculated as $u(x_0, y) = (100, y) = (0.2-y)/0.2$, with an assumption of u(100, 0.0) = 1 and u(100, 0.2) = 0. DM1's marginal utility function for Y is shown in Figure 5 (DM 1).

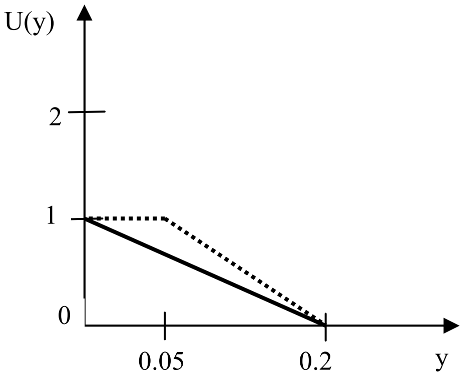

Figure 5 Marginal utility functions for decision maker 1 (solid line) and decision maker 2 (dotted line)

By substituting $u(x, y_0)$ and $u(x_o, y)$ into the equation (2), we get the decision maker's utility function over X and Y.

$$u(x,y)=\frac{100-x}{100}+\frac{0.2-y}{0.2}-\left(\frac{100-x}{100}\right)\left(\frac{0.2-y}{0.2}\right), \quad (5)$$

His expected utility function is then

$$E\{u(x,y)\}=\frac{100-x}{100}+\frac{0.2-E\{y\}}{0.2}-\left(\frac{100-x}{100}\right)\left(\frac{0.2-E\{y\}}{0.2}\right),$$
(6)

As a result of this expected utility function, we can calculate an expected utility of action 1 and action 2.

Action 1: $E\{u(x,y)\} = E\{u(100, 0.04)\} = 0.8$

Action 2: $E\{u(x,y)\} = E\{u(60, 0.06)\} = 0.82$

These results suggest that action 2 is the most preferred action for DM 1.

Imagine now that a decision maker (DM 2) has a previous experience of mold infestation in his buildings and became more conscious about mold problems. He may not want to accept even the slightest risk of mold in the dormitory. In this case, the decision maker holds a different preference over mold risky days from the previous decision maker. Let us assume this risk averse DM2 holds a utility function over Y as shown in Figure 5 (dotted line).

He satisfies his building conditions if the normalized mold risky day is 0.05 or less in this building and does not take much risk that he would end up with a building with 0.2. He has an identical perception of the decision problem and shares his preferences with the DM1, except for his marginal utility for y. In this case, the marginal utility function over Y became, for DM2:

$$u(x_0, y) = (100, y) = \frac{0.2-y}{0.15} \text{ (for } y>0.05),$$

$$(100, y) = 1 \text{ (for } 0 < y \leq 0.05), \quad (7)$$

The resulting expected utility of action 1 and 2 would be 1.067 and 0.957, respectively. In this case, action 1 is the most preferred action of this decision maker, which is more expensive but provides the smaller mold risky.

The foregoing shows how additional information acquired from uncertainty analysis can be used for real decision-making problems in the context of mold growth. The implication of feeding uncertainty information into a decision-making problem is a significant step to use probabilistic simulation to support decisions. It is most important when different preferences and risk attitudes govern the decision problem, especially in limit state cases such as mold, when deterministic point samples do not provide any insight into the real risks and how they can be controlled by choosing different design options or remediation methods.

CONCLUSION

The main premise of this study is that uncertainty should be taken into account in mold risk evaluations, and that this will lead to better informed rational decision-making by improving the decision maker's confidence in the evaluation. This study also showed that decision makers with different preferences might make a different decision in the selection of remediation actions in specific cases. The new approach provides a strong case to mold consultants when making recommendations about design or remediation options, or empowering them to make unbiased rational choices.

Uncertainty analysis is rarely used in current building performance evaluation practice. If building physics consultants would start employing the quantification and propagation of uncertainty in their practice, it could be a significant step forward in finding the optimal response to known building deficiencies. Uncertainty analysis is not simple and can be quite time consuming, however. Tools with uncertainty analysis modules do not yet exist in mainstream practice. The tools that exist are research oriented and require extensive preparation and computation times. Libraries of quantified uncertainty in building materials, building and occupancy schedules, weather data, and other input parameters would greatly facilitate uncertainty analyses, but they do not exist yet.

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