Abstract

As the threat of climate change is exacerbated by increasing energy demand and the carbon emissions linked to it, driving down energy consumption is a goal that building professionals must seek to prioritize due to the key role that buildings play in global energy consumption. The use of insulation to drive down building energy consumption is an effective strategy in climates where a large temperature variation exists between indoor and outdoor conditions. While inorganic types of insulation may offer high resistivity (R Values) per square unit, their embodied energy might make their use pointless from a climate change perspective. Natural-based insulations, which are typically porous, offer an insulation solution with low to negligible embodied energy. The porosity of these materials however can decrease thermal performance due to moisture build-up. Simulating these effects generally requires Building Energy Modelling (BEM) software that utilizes advanced algorithms to factor this variability. Due to the need to employ these materials more commonly and to anticipate their behavior for more informed decision-making, we propose a computationally efficient model that discretizes porous insulation into three distinct layers: Solid, Air, and Moisture. The model associates moisture build-up in the pores using material-specific Sorption Isotherms. We run a simulation using our model on a building utilizing cellulose insulation. Results show that the model is validated by matching experimental data reported by other authors in terms of thermal conductivity and R-Value changes. Comparing the outcome to experimental values shows promise in mimicking thermal conductivity fluctuations in porous materials.

Key Innovations

- Developing a new computationally efficient model for factoring the effect of moisture on R-Value in porous insulation.
- Validating the model by demonstrating similar behavior of fluctuating thermal conductivity in relation to relative humidity using experimental data.

Practical Implications

Utilizing this model will allow the simulation of variable thermal conductivity in BEM engines that utilize a static thermal conductivity value without the need for advanced and computationally expensive hygrothermal models.

Introduction

Climate change challenges pose a growing threat to human lives. The role of building energy consumption in driving up CO2 emissions is becoming more evident with 76% of electricity and 40% of total energy consumption in the United States being consumed by buildings (US Department of Energy, 2015). As the world moves towards more sustainable sources for building materials that define energy efficiency, buildings need to meet the challenges of climate change and excessive energy consumption. In climates with high-temperature variations between indoor and outdoor conditions, insulation is a necessity to drive down consumption. Current widely used insulation materials range from thermoplastics and thermosets, which are plastic-based materials, to natural-based materials such as cellulose, Rockwool, and fiberglass. These types of materials present different advantages and disadvantages to the user which would help guide their selection process. However, as the challenges from resource depletion, environmental degradation, and climate change become ever more present, the material selection criteria will have to factor in embodied energy of production, material recyclability, and material disposal to meet these rising challenges, alongside the traditionally considered material performance, and cost. From a policy standpoint, perspective assessment should move from a focus on operational carbon to embodied carbon, as savings on the scale of operational carbon can take several decades to offset the embodied carbon utilized within the building (Shadram et al., 2019).

Operational vs Embodied Carbon

Insulation materials being are a main component in driving down energy consumption and contribute indirectly to decreasing carbon levels in appropriate climates (Simona et al., 2017). Natural-based materials such as cellulose, mineral wool, and fiberglass all offer thermal insulation properties, while having a much smaller embodied carbon footprint in comparison to industrial-based insulation materials. This was seen in research that surveyed 15 commonly used thermal insulation materials (Kunić, 2017). Using a Lifecycle Assessment (LCA) methodology (ISO 14040 and PAS) the researchers calculated the carbon footprint of the materials not only in terms of similar weight samples but more importantly in terms of similar performance using thermal transmittance (U Value) as a metric. In terms of
assessing the carbon footprint of samples that achieve a U Value of 0.20 W/(m²·K) Units, the results indicated that wood-based insulations have a minimal environmental impact (1.8 and 10 kg CO₂ – eq./ m² for low density and high-density wood fiber wool respectively) and recycled cellulose has a low environmental impact (4.6 kg CO₂ – eq./ m²) (Kunić, 2017). In comparison, industrial-based materials such as EPS, XPS, and PU Polyurethane have a higher environmental impact at 11.8, 33.6, and 22.9 kg CO₂ – eq./ m² respectively. With values per unit area being more carbon-intensive over the entire area of the building, these would compound to a large difference which should be taken into consideration in the material selection process.

To study the effectiveness of insulation R Values are a metric utilized to encompass insulation efficiency. R-Value is defined as the thermal resistance per unit area and describes the ability of an insulation material to resist heat flow (Aldawi & Alam, 2016). While boiling down thermal resistance to a single unit number would help communicate whether the material or assembly is a good insulator or not, and allow for both rating and quantifying it, this point-in-time approach presents an oversimplification of how thermal resistance works. Thermal resistance is contingent upon the various climatic conditions that are present, and a reported R-Value is dependent on the conditions of when it had been measured (Berardi & Naldi, 2017). While this can be convenient in a lab environment, in real-world applications the variable nature of R-Values can present an equally varying thermal performance for the building envelope. This can influence decisions made in insulation selection and the calculations on which they are based upon. Building Energy Modelling (BEM) engines that utilize a fixed R-Value in their calculation are thus inaccurate in how they approach quantifying time-based variable performance. The nature of the insulation material can define how variable the fluctuation can be. Porous insulation in particular is affected by fluctuating conditions, as air with higher relative humidity ratios can replace dryer air occupying the pores; decreasing the R-Value in the process (Rashidi et al., 2018). Variable thermal conductivity can also pose a problem in terms of condensation within envelopes, which can cause significant damage and mold growth (Berardi & Naldi, 2017). These factors create the imperative to factor in the fluctuating nature of thermal conductivity into BEM calculations to create a more streamlined decision-making process.

State of Current Software

BEM simulation tools handle variability in thermal conductivity differently. EnergyPlus, a current industry-standard software developed in 1996 by the US Department of Energy, runs simulations in timesteps that can simulate unsteady-state heat transfer through the envelope (EnergyPlus | EnergyPlus, 2021). Energy Plus can utilize different algorithms to compute heat transfer through the envelope, each requiring different material types and variables. The default algorithm is the Conduction Transfer Function (CTF), which can compute the surface heat fluxes without the need to calculate the temperatures within the material. It presents a static material property performance approach that can drive down computational time while presenting approximative results. In terms of thermal conductivity using CTF, the user assigns a fixed thermal conductivity value which is utilized across all the simulation timesteps (U.S. Department of Energy, 2018). EnergyPlus includes other algorithms that unlike the CTF can factor in changing material properties over time such as the Conduction Finite Difference Solution Algorithm, Combined Heat and Moisture Transfer (HAMT) Model, and the Effective Moisture Penetration Depth (EMPD) Model. According to the EnergyPlus Input/Output reference variable thermal conductivity is present in material types that work with the Conduction Finite Difference Solution Algorithm (ConFD). The ConFD algorithm requires the user to input the thermal conductivity value and the temperature which relates to it (U.S. Department of Energy, 2018). This method, however, does not take into account the effects of moisture on thermal conductivity where the HAMT Model does. The latter requires the user to input the following properties: Porosity, Initial Water Content, Sorption Isotherm, Suction, Redistribution, Diffusion, and Thermal Conductivity. The availability of information on these properties would pose a challenge for users to obtain it. And while the HAMT is available through EnergyPlus’s GUI OpenStudio as an algorithm, at the time of writing this paper the material type it requires does not, and thus would relegate its use to EnergyPlus simulations which are not user-friendly. WUFI is another tool that has been developed by the Fraunhofer Institute in Germany accounts for both thermal and moisture-based effects in its calculations. WUFI iterates on the Glaser Method that accounts for vapor diffusion in components by allowing the use of unsteady-state transport in their calculations (Karagiozis et al., 2001). Like EnergyPlus, WUFI requires information on material properties that may not be readily available which include the properties mentioned above.

DeterioRATE: A Discretized Porous Insulation Model

Traditionally users seeking to run a building energy simulation would either utilize a pre-set thermal conductivity value built into the simulation software material presets or acquire a thermal conductivity value from an external source that remains constant throughout the simulation. This affects the accuracy of the results as it does not factor in the dynamic nature of thermal conductivity in porous materials. While built-in or user-set values would ideally be based on experimental observations or validated simulation models they are only relevant to the conditions when the observations were being recorded or simulated and thus would not mimic variable real-life conditions across the timesteps. Rather than run a computationally expensive unsteady-state heat and moisture transfer algorithm that requires a multitude of variables to function properly, we propose a simplified discretized one-dimensional model. This model would approximate the moisture content in porous insulation in
relation to changing relative humidity conditions and the subsequent generation of modified thermal conductivity R Values accordingly. As the variability in thermal conductivity through a porous material is contingent on the moisture/air content ratio in the gaps due to the fact that air and moisture have different thermal conductivities themselves, this model utilizes this variable ratio to update the thermal conductivity value accordingly. To factor this into a BEM simulation, we propose treating porous materials as a hybrid assembly of three different layers in series: the solid insulation layer, the still air layer, and the moisture layer. This would effectively coalesce all the air gaps in the insulation as one layer and all the moisture particles that occupy them differentially as another (Figure 1). This extends to the user the advantage of factoring in these variations in a simplified 1D model that is compatible with most BEM platforms. The R-Value of the assembly accordingly will be computed in series per the equation:

\[
R_{\text{Insulation}} = R_{\text{Solid}} + R_{\text{Moisture}} + R_{\text{Air}} \quad (1)
\]

While the ratio of the thickness of the solid layer is fixed, the ratios of air and moisture are variable and subsequently, their layer thicknesses in the model are equally variable as seen in equations (2) and (3). The solid/gap ratio would be determined by the user’s set value of material “Porosity” multiplied by the total insulation layer thickness (4). As the total thickness is made up from the thickness of the solid insulation in addition to that of the gaps, the fixed solid insulation thickness is determined in equation (5) by subtraction of the gap thickness determined in equation (4) with that of the total insulation thickness. Within the gaps, the ratio of moisture and air would be determined using values identified from the insulation material’s sorption isotherms. Sorption curves relate the moisture content % in relation to the relative humidity of the air. Moisture content % values taken from the sorption curves would govern the ratio of moisture to air and subsequently the thicknesses of the air and moisture layers in the model as obtained in equations (6), (7). Equations (8) and (9) articulate the relationship between the % of air in the gaps and the thickness of the air layer.

\[
\begin{align*}
T_h_{\text{Total}} & = T_h_{\text{Solid}} + T_h_{\text{Gaps}} \\
T_h_{\text{Gaps}} & = T_h_{\text{Air}} + T_h_{\text{Moisture}} \\
T_h_{\text{Solid}} & = T_h_{\text{Total}} - T_h_{\text{Gaps}} \\
T_h_{\text{Moisture}} & = \frac{\% \text{ of Moisture}}{100} \times T_h_{\text{Gaps}} \\
T_h_{\text{Air}} & = T_h_{\text{Gaps}} - T_h_{\text{Moisture}} \\
\% \text{ of Air} & = \frac{(T_h_{\text{Gaps}} - T_h_{\text{Moisture}})}{T_h_{\text{Gaps}}} \times 100 \quad (8) \\
T_h_{\text{Air}} & = \frac{\% \text{ of Air}}{100} \times T_h_{\text{Gaps}} \quad (9)
\end{align*}
\]

\[ TH_{\text{Solid}}: \text{Thickness of Solid Insulation} \]
\[ TH_{\text{Gaps}}: \text{Thickness of Insulation Gaps} \]
\[ TH_{\text{Moisture}}: \text{Thickness of Moisture Layer} \]

**Figure 1** The traditional versus proposed model.

Applying this model in a building energy simulation the relative humidity values from the weather file would be used to extract the % of moisture content in the material using the user-provided sorption isotherm values at each time step. With the updated ratios of moisture and air plus that of the solid, the discretized model will create a new theoretical assembly of the three layers accordingly and its new R-Value would be calculated in series. This allows the R-Value of the insulation to be updated at each timestep reflecting changes in performance over time.

As this model is approximonal by nature it makes the following assumptions for purposes of computational simplification:

- The model assumes there is instantaneous local equilibrium between the vapor pressure in the air in the pores of the material and the moisture content of the material utilized as assumed with traditional Fickian models (Peuhkuri, 2003).
- The change of moisture content across the hour timestep would mimic that of changes indicated on the selected material Sorption Isotherm, as porous materials react quickly to changes in conditions.
- The model assumes the assembly can dry out without obstruction.
- Effects of hysteresis are ignored.
- The distribution of pores is uniform.
- The relative humidity of the air in the pores is assumed to be that of the outdoor air.
- Thermal conductivity of Air and Moisture layers are assumed at room temperature conditions.

This model presents advantages over the currently established models in being computationally inexpensive, where it can be embedded into different solutions that allow for coding simulation-based models. It also requires
fewer variables to factor in the fluctuating nature of R-Value in a BEM model over time. It is important to note that this model while focusing on moisture content, is primarily targeted towards variations in thermal conductivity, rather than calculations of the hygroscopic performance of envelopes. Thus, it simplifies the effect of moisture on thermal conductivity to increase practicality.

**Model Validation**

To validate our model we utilized experimental data recorded by (Hansen et al., 2001) as a reference for both sorption curve values and the effect of variable relative humidity on the thermal conductivity of a cellulose specimen. These were recorded using a modified guarded hot plate apparatus with conditioned air circulating in channels directly above and below the specimen. The researchers tested multiple insulation samples and recorded the results. Of relevance to our work was data recorded for a 63 kg/m³ density sample of cellulose (Cellulose-1) with a moisture content around 60% at 90% RH (Hansen et al., 2001). Using our model, we simulated this material using the referenced sorption curve (Figure 2). Comparing with the values for thermal conductivity increase recorded by Hansen et al. (Figure 3) The trend of increase in thermal conductivity was similar among both samples with both increasing in a comparable fashion (Figure 4). Additionally, we plotted the interpolation utilized by WUFI for Cellulose Insulation which yielded a varying result due to its implementation of a simplified linear model for the relationship between moisture content and thermal conductivity.

![Figure 2 Sorption Curves from Hansen et al. (Hansen et al., 2001)](image)

![Figure 3 Thermal Conductivity vs %RH from Hansen et al. (Hansen et al., 2001)](image)

Figure 4 Relative Humidity vs Thermal Conductivity of Cellulose for our model vs Hansen Et Al. vs WUFI

To study the effect of the increase of Relative Humidity on R-Values (Figure 5), we simulated a 15 cm sample of cellulose (40 kg/m³) based on another sample utilized in Hansen et. al’s work. Our model indicated that R-Value had decreased slowly until around 70% humidity then decreased exponentially for values >70%. This seems to be consistent with the findings of (Hansen et al., 2001) and earlier by (Tye & Spinney, 1979) which both indicate a similar pattern of slow increase in thermal conductivity for relative humidity values <70% and an exponential increase above 70%.

![Figure 5 R-Value decrease as a factor of Relative Humidity for the simulation model.](image)

It is important to note that this exponential decrease in R-Value above 70% is the result of condensation occurring within the pores of the insulation material. In relative humidity values, less than 70% the slow increase is the result of hygroscopic uptake from humidity in the ambient air (Hansen et al., 2001). Thus, further evolutions of this model should include the identification of condensation conditions as a step for refining the model’s predictions as well as experimental verification of results using data we gather for the purpose. This would aid in the identification of conditions that foster mold growth and
sagging which threaten the longevity and lifespan of the insulation material.

Simulation Case Study

To study the integration and effects of our model on a building energy simulation we integrated it within an EnergyPlus model utilizing the default CTF method that does not factor in varying thermal conductivity for materials. This BEM was run using Honeybee and Ladybug which are front-end open-source plugins for Grasshopper that facilitate the iterative interaction with EnergyPlus. The experimental workflow we utilized illustrated in Figure 6 was as such:

1) Use Typical Meteorological Year (TMYx) weather files to extract relative humidity values.
2) Use our model to break down the insulation layer into three discretized layers of Solid Material, Moisture, Air in series.
3) Calculate hourly R-Values for the year.
4) Run a constant R-Value simulation versus one that utilizes our model.
5) Analyze the results to evaluate the impact of relative humidity fluctuations on the assembly R-Value.

In terms of selecting an insulation material to study, we selected cellulose insulation. According to the US Department of Energy, blanket insulation which is composed of flexible fibers made from natural materials is the most common insulation utilized in the US (US Department of Energy, 2021). Thus cellulose, a natural-based thermal insulation material that is made from recycled paper or wood fiber mass is a good candidate that is widely utilized. As observed in work by (Kunič, 2017) cellulose has a low embodied energy value in comparison to inorganic insulation materials which makes it an ideal candidate to use in our simulation. It has a thermal conductivity between 40 and 50 mW/mK. These values however are contingent on the moisture content of the material where an increase in moisture content would increase thermal conductivity (Petter Jelle, 2016). To select the thermal conductivity of cellulose for our model the selection would be that of a high-density sample. We assume the value of 0.041 W/mK as detailed in work conducted by (Brzyski et al., 2019). One property shared among natural-based insulation is porosity since these materials are made through compacting and packing fibers of ground-up material. The porosity and density levels of cellulose allow air to be trapped within the material, effectivley creating a robust air barrier and increasing airtightness in an envelope (Knöll & Welteke, 1991). Cellulose is a hygroscopic material and the added mineral additives in the insulation can increase its water sorption capabilities (Popescu, 2017). We utilize the sorption curve of a 40 kg/m³ sample of cellulose as recorded by Hansen et al. (Figure 7). This Isotherm was measured at 20.0°C ± 0.5°C in a test chamber as described in prEN ISO 12571 (Hansen et al., 2001). This increased moisture content would alter the thermal properties as water particles have a variable thermal conductivity value in comparison to still air trapped within the pores. Sorption curves, however, are not uniform, and they are entirely dependent on the sample being examined and the conditions when the assessment was done. Thus, replication of the values will not be precise, but replication of the general behavior and trends should be concurrent. For the thermal conductivity of the coalesced air layer, we selected 0.026 W/mK, and for the moisture layer 0.60 W/mK. These values were assumed according to the thermal conductivity of air and water at 20°C.

In terms of the building energy model, multiple prototypical residential units were placed surrounding the unit under study to reduce the impact of direct climatic exposure from all directions. The area of the red highlighted room, depicted in Figure 8, is 20m² (5m(L) x 4m(W)). The volume of the room is 60m³ given a 3m height. The model has a southern-facing window at the narrow end with a window-to-wall ratio of 25%.
The thermal resistance (R-Value) of the exterior walls and roofs is a function of the cellulose insulation thickness used in the experiment. For the studies depicted in Figures 9-13 a cellulose insulation layer with a thickness of 15cm was used, which resulted in an initial R-Value of 4.55 m²-K/W at dry conditions. The effect of humidity displacing air in the porous material and subsequently reducing the overall R-Value of the assembly is then calculated. This is in turn mapped in studies 9-10 and compared to the initial starting R-Value in Figures 11-13. For the HVAC system to remain as general as possible, the Ideal Air Load option was used. The cooling and heating setpoints were set to 22 °C and 25°C respectively and loads for lighting and equipment were fixed throughout the simulation process. The default ladybug occupancy, lighting, and equipment schedules were used for the residential building program and were kept at a constant value for all iterations.

Regarding Typical Meteorological Year (TMYx) weather files utilized we selected the cities of Miami, Houston, Atlanta Albuquerque, Chicago, and Milwaukee as representatives for ASHRAE climate zones 1 to 6 respectively. The outputs being monitored here are the calculated and the combined Heating/Cooling thermal load of the simulated unit.

**Results**

The first investigation entailed a compilation of calculated R-Values for each hourly index of the year for Atlanta, Georgia. The output, depicted in Figure 9, illustrates the mapping of those hourly R-Values. When compared to that originally set R-Value of 4.55 m²-K/W, theoretical reductions ranging from 0% to 24.2% were observed for 8580 hours of the year. For outlier relative humidity values of 100%, R-Values dropped from 4.55 to 2.35 m²-K/W across 180 hours. This constitutes an R-Value reduction of 51.64% due to a relative humidity-induced increase in insulation moisture content.

In the second study, R-Values were calculated and mapped for January 21st and December 21st for Atlanta, Georgia to study changes across the day. The results depicted in Figure 10 are overlaid on the relative humidity profile to showcase how R-Value fluctuation occurs gradually along the day based on changing relative humidity levels. This indicates the relation that as relative humidity values rise, the performance of the wall drops consequently concurrent with data seen in Figure 3.

The third study involved a comparison of the relative humidity-induced impact on R-Values, between the proxy cities of Miami, Houston, Atlanta Albuquerque, Chicago, and Milwaukee. For each hourly index of the year, the R-Value was determined with our model using the corresponding relative humidity value, and the change from the starting R-Value was then calculated. These changes were then averaged and used as a measure of the impact of humidity on R-Value in the corresponding city. The results recorded in Figure 11 showcased that the highest affected city is Houston with an average reduction in R-Value of 19.07% and the least affected was Albuquerque with 10.05% respectively. This indicates the capability of the model to add a layer to envelope performance variation by climate that is ignored in fixed R-Value models.
The fifth examination, illustrated in Figure 13, is a seasonal observation of R-Value reduction. While some cities like Atlanta, Chicago, Milwaukee experienced stable trends across the year, other cities like Albuquerque, Houston, and Miami exhibited significant seasonal deviations. Minimum impacts were most evident between April and August, while maximum impacts were concentrated around November to January. The least impacted city was Albuquerque while the highest was Houston. This indicates how seasonal variations in relative humidity values in relation to the climate zone can have a significant effect on simulation results and should be factored in.

The final study depicted in Figure 14 examined the energy consumption for the building energy model using the Atlanta, Georgia weather file. Two simulation workflows were utilized to calculate annual energy use for the modeled unit. In the first simulation approach, a constant R-Value was applied for the assembly throughout the entire year. We utilized a 15 cm Cellulose Sample with an R-Value of 4.55 m2-K/W. In the second approach, R-Values were first established for each hourly index of the year using our model. Average R-Values corresponding to each day of the year were then calculated by averaging the distinct hours of that day and utilizing the subsequent output for every individual day distinctly across the 365 timesteps. The results recorded in Figure 14 show divergences between the two models in different magnitudes depending on the day and its conditions. To quantify these divergences from an energy consumption perspective the cumulative energy consumption was then examined in Figure 15 for both models. The results of our variable model showed a 2.1% increase in energy demands when compared to the constant R-Value model. Such variations are climate dependent and if significant enough can influence the designer’s choice of R-Value for the wall assembly and HVAC sizing for the building.

**Discussion**

The findings indicate that the model successfully indicated the ability to simulate variable R-Values for an insulation material with a method that previously did not have that capability. The model had shown that the relationship between R-Value and relative humidity is not linearly proportional corresponding with the data recorded by Hansen et al. Concurrent with behavior seen in Figure 5 higher humidity values exhibited a larger impact on R-Values due to the properties of the material-specific sorption curves. In terms of computational time, the calculation of the new R-Value is instantaneous for the entirety of the 8760 hours in question.

Our studies have shown that the influence of relative humidity on assemblies utilizing porous materials should not be ignored. Figure 12 had shown that during sunrise hours the R-Value of an assembly can vary by 25%. Such variations can have potentially harmful effects on the assembly. Moisture-induced deterioration of insulation materials in high-performance envelopes can result in problems such as mold growth and physical damage in the form of sagging in insulation layers. If drying mechanisms do not permit moisture to escape wall assemblies, the performance of the wall can be severely impacted in the long term. Thus, extending the capability of the model to identify periods of sustained high moisture content would allow the model to go beyond energy simulation to deterioration identification. Even in cases that variations are not significant enough this computationally negligible model should be implemented...
to obtain more accurate representations of wall performance with no effect on simulation time.

Conclusion and Future Directions
This paper presented a computationally inexpensive modeling approach that can mimic thermal conductivity fluctuation across porous materials. By discretizing the elements of porous materials, it allows the user to mimic their fluctuating transient thermal behavior and simulate their use more accurately in relation to real-life conditions. Building upon the results produced using the experimental data utilized by Hansen et al., for the next step we plan to use our own experimental data for validation on samples of different porous materials. The next step includes creating a workflow within EnergyPlus to update the material properties on an hourly basis within the simulation and then comparing annual energy loads calculated with a traditional fixed material property model which would replace the average daily R-Value approach we utilized in this paper. Finally, we will be conducting a comparative framework with other tools that can simulate variable thermal conductivity to identify accuracy thresholds and benchmark computational times.

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