TOPIC
Challenges of the future
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An analytical method for calculating the thermal conductivity of a twin pipe in district heating system

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SUMMARY:
In this paper a simple analytical method is introduced for calculating the overall thermal conductivity of a twin pipe in district heating network. The method is developed based on calculating the conductive and convective heat transfer around the casing pipe in different perimetal sections. Temperature inside the supply and return pipes and also over the heating pipe is measured on different points. These data are imported to a computer program which was written to calculate the heat loss and the total conductivity of the heating pipe. The method has shown good agreement with measurements and it is simple and quick enough in calculating the thermal conductivity of asymmetric geometries and their temperature distribution. The method is capable to make calculations for more complicated geometries, such as heating pipes with heterogeneous insulating materials.

1. Introduction

District heating systems are widely used in Sweden, mainly for residential and commercial space/water heating. The common medium for the distribution is water. Heat is distributed through underground networks of insulated pipes which consist of supply and return pipes. The higher the temperature difference between supply and return, the higher the efficiency of the delivered energy.

By improvements in insulating buildings in Sweden there is less heating demand which results in lower temperature difference between the supply and the return pipes. As a consequence heat losses from the pre-insulated pipes to the surrounding environment apportion larger percentage of heat losses of the district heating network. Having the vision of energy plus buildings, smart grids and smart energy networks between buildings, motivates to make pipes better insulated and more efficient, i.e. more complex and more efficient designs such as twin pipes insulated with new materials such as vacuum insulated panels. Effectiveness of new designs and the efficiency of heating pipes are usually assessed by the combination of measurements and numerical simulations, which can be expensive and time consuming. More complex designs, geometries and materials, increase the complexity of the measurements and calculations. Therefore having easier methods for measuring/calculating the thermal performance of heating pipes is desired.

A simple analytical method for calculating the overall thermal conductivity of a twin pipe is presented in this paper. The experimental setup which was used to measure the temperature profile of the twin pipe and surrounding air is described briefly. The measured temperatures were used to calculate the thermal conductivity analytically.
# 2. The experiment

## 2.1 The experimental setup

Experiments were performed using a “guarded hot pipe” (more information available in (Berge 2013) and (ISO 8497:1994)) based on the standard for twin pipe assembly of steel service and return pipes, polyurethane thermal insulation and outer casing of polyethylene (15698-1:2009). A schematic figure of the twin pipe, casing and two steel pipes inside the casing, and the installed thermocouples is shown in FIG 1. One of the twin pipes is to supply heat (the pipe ion the bottom - red colour) and the other one contains the return flow (the pipe on top - blue colour). One heat rod was placed inside both of the supply and return pipes to simulate the warm fluid inside pipes. The electrical current in the heat rods were set to get a constant heat power depending on the desired temperature. Thermocouples were placed over the casing, 16 positions, and inside the steel pipes, 4 positions in each pipe – not visible in the figure – to measure temperature at different points. Temperature of the heat rods and the ambient air were also measured. The measured data were collected by two software programs. All the programs and thermocouples were calibrated before running the experiment to make sure about the accuracy of the collected data.

![FIG 1. Position of thermocouples on the casing pipe for the vertical position of the twin pipe. The red pipe (bottom) represents the supply pipe and the blue pipe (top) represents the return pipe.](image)

## 2.2 Measurements

Measurements were done in four different steps:
1. Horizontal: Supply flow of 78°C – Return flow of 78°C (supply and return pipes lay side by side)
2. Vertical: Supply flow of 78°C – Return flow of 78°C
4. Vertical: Supply flow of 80°C – Return flow of 40°C

Measurements were performed for two positions of the twin heat pipe; horizontal and vertical (as FIG 1). The aim was investigating the effects of rotating the twin pipe on the temperature distribution over the casing, since it affects the convective heat flow pattern around the casing. All the heat from the twin pipe transfers to the ambient air through natural convection, which the pattern of the air flow and its thermal properties can be influenced by the temperature profile on the casing and its variations. Comparing horizontal and vertical positioning (steps 1 and 2) helps to investigate the importance of positioning and the consequent difference in flow patterns on the temperature profile over the casing pipe. Main differences of the temperature profile are shown in FIG 2; the maximum difference caused by rotating the casing is for point A which its temperature increases for 2.6% when the casing turns to...
the vertical position. Since the actual position of the twin pipe is vertical most of the measurements were performed for this position. Although for the real case the surrounding environment is soil and very different from air, but this sensitivity test enables to estimate the maximum divergence in results caused by positioning and the consequent difference in natural convection around the casing.

FIG 2. Differences in the temperature distribution on the casing caused by rotating the casing of the twin heat pipe.

3. The analytical method for calculating the thermal conductivity

An analytical method was developed to calculate the overall thermal conductivity of the twin pipe. The method is based on calculating the conductive and convective heat transfer around the heating pipe in different perimetral sections when steady state condition is achieved.

Imagine a circle tangent to one of the steel pipes as shown in FIG 3. The amount of heat which passes through the imaginary dashed circle is equal to the heat which transfers to the surrounding air through the casing (the thermal capacity of the insulation and the casing is neglected, moreover measurements were done for steady-state condition). Assuming an infinite narrow section, the amount of conductive heat transfer from the imaginary circle, point B in FIG 3, is equal to the amount of convective heat transfer from the blue point on the casing to the air.

\[
\frac{\lambda_{\text{insulation}}}{R_{\text{inner}}} \cdot \frac{T_{\text{inner}} - T_{\text{casing}}}{R_{\text{casing}} - R_{\text{inner}}} = h_{\text{air}} \left( T_{\text{casing}} - T_{\text{air}} \right)
\]  

(1)
Where \( \lambda_{\text{insulation}} \) thermal conductivity of the insulation [W/m/K],
\( h_{\text{air}} \) convective heat transfer coefficient of air [W/m\(^2\)/K],
\( R_{\text{casing}} \) radius of the casing [m],
\( R_{\text{inner}} \) radius of the imaginary inner circle [m],
\( T_{\text{air}} \) temperature of the surrounding air [K],
\( T_{\text{casing}} \) temperature on the casing at the considered point [K],
\( T_{\text{inner}} \) temperature on the imaginary circle at the considered point [K].

\( T_{\text{casing}} \) is known for the 8 measured points on the casing and \( T_{\text{inner}} \) is known for the point on the steel pipe, point B on FIG 3. Since the geometry is not perfect the imaginary circle is not tangent to the other steel pipe and consequently temperature is assumed unknown for the imaginary circle located on the other steel pipe. The aim is finding the temperature profile of the imaginary circle based on equation (1). Three parameters are unknown in the equation; \( \lambda_{\text{insulation}} \), \( T_{\text{inner}} \) and \( h_{\text{air}} \).

The thermal conductivity of the insulation can be defined as a function of its temperature (Berge 2013):

\[
\lambda_{\text{insulation}} = 26 + 0.1(T - 50)
\]  
(2)

Where the unit for conductivity in the equation is [mW/m/K].

Coefficient of the convective heat transfer for air, \( h_{\text{air}} \), can be calculated in two ways:

1. By knowing \( T_{\text{inner}} \) for point B and using equation (2), \( h_{\text{air}} \) is calculated for that section of the casing. Afterwards the same \( h_{\text{air}} \) is used for all the other points around the casing.

2. The amount of heat which is generated inside the twin pipe is known. All the heat transfers to the surrounding air according to the following equation:

\[
Q = h_{\text{air}} A_{\text{casing}} (T_{\text{casing}} - T_{\text{air}})
\]  
(3)

Where \( T_{\text{casing}} \) is the average temperature of the measured points over the casing and \( A_{\text{casing}} \) is the surface area of the casing for a unit length. Using equation (3) it is possible to find an average \( h_{\text{air}} \) which can be used in the calculations.

Using the above mentioned equations and assumptions, \( T_{\text{inner}} \) is calculated for 8 points on the imaginary circle corresponding to the 8 measured points on the casing. The resulted temperature profile for the insulation inside the casing, located on the imaginary circle, helps to calculate the heat conductivity according to equation (2). Temperature values which are used in equation (2) are the average temperature of the casing and the imaginary circle:

\[
T_{\text{insulation},i} = \frac{(T_{\text{inner},i} + T_{\text{casing},i})}{2}
\]  
(4)

\( \text{for } i=1, 2, \ldots, 8 \)

A Matlab program was written which reads the measured values out of experiments and calculates heat losses and the thermal conductivities based on the developed method.

4. Results and the calculated thermal conductivity

Measured and calculated temperature profiles for the four steps of the measurements are presented here. Thermal conductivity is calculated according to the previous section for 8 sections around the twin pipe. An average thermal conductivity is calculated as the mean value of the thermal conductivities at 8 points. The average thermal conductivity can be interpreted as the overall conductivity of the whole setup since it is based on the calculation of the amount of heat flow from the
twin heating pipe to the surrounding air. The following figures show the distribution of temperature and the thermal conductivity around the twin heating pipe. Tables compare the calculated thermal conductivities, calculated based on the two methods for calculating $h_{\text{air}}$.

4.1 Horizontal – Supply flow of 78°C – Return flow of 78°C

\[ T_{\text{casing}} = 25.42 \quad T_{\text{inner}} = 78.73 \quad T_{\text{mean}} = 52.075 \]

$\lambda_{\text{setup}}$ was calculated as a mean

4.2 Vertical – Supply flow of 78°C – Return flow of 78°C

\[ T_{\text{casing}} = 23.11 \quad T_{\text{inner}} = 49.02 \quad T_{\text{mean}} = 36.065 \]

$\lambda_{\text{setup}}$ was calculated for point B

\[ h_{\text{air}} = 24.6 \]

\[ h_{\text{air}} = 24.4 \]

\[ h_{\text{air}} = 24.3 \]

\[ h_{\text{air}} = 25.9 \]

\[ h_{\text{air}} = 25.5 \]

\[ h_{\text{air}} = 24.8 \]

\[ h_{\text{air}} = 23.9 \]

\[ h_{\text{air}} = 24.8 \]

\[ h_{\text{air}} = 24.7 \]

FIG 4. Temperature distribution over the casing and the imaginary circle (dashed green line). The calculated heat conductivity is shown at each section in mW/m/K.

TABLE 1. The calculated thermal conductivities for the twin district heating pipe at 8 points and the average value. Values are compared for the two methods of calculating the convective heat transfer coefficient of air.

<table>
<thead>
<tr>
<th>Temperature</th>
<th>$\lambda_{\text{setup}}$ (or $\lambda_{\text{setup}}$) [mW/m/K]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$h_{\text{air}}$ was calculated for point B</td>
</tr>
<tr>
<td>1</td>
<td>25.42</td>
</tr>
<tr>
<td>2</td>
<td>23.11</td>
</tr>
<tr>
<td>3</td>
<td>22.24</td>
</tr>
<tr>
<td>4</td>
<td>22.95</td>
</tr>
<tr>
<td>5</td>
<td>24.9</td>
</tr>
<tr>
<td>6</td>
<td>23.81</td>
</tr>
<tr>
<td>7</td>
<td>22.31</td>
</tr>
<tr>
<td>8</td>
<td>23.67</td>
</tr>
<tr>
<td>Mean</td>
<td>39.07</td>
</tr>
</tbody>
</table>
FIG 5. Temperature distribution over the casing and the imaginary circle (dashed green line). The calculated heat conductivity is shown at each section in mW/m/K.

TABLE 2. The calculated thermal conductivities for the twin district heating pipe at 8 points and the average value. Values are compared for the two methods of calculating the convective heat transfer coefficient of air.

<table>
<thead>
<tr>
<th>Temperature</th>
<th>$\lambda_{\text{insulation}}$ (or $\lambda_{\text{setup}}$) [mW/m/K]</th>
<th>$h_{\text{air}}$ was calculated for point B</th>
<th>$h_{\text{air}}$ was calculated as a mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_{\text{casing}}$</td>
<td>$T_{\text{inner}}$</td>
<td>$T_{\text{mean}}$</td>
</tr>
<tr>
<td>1</td>
<td>25.82</td>
<td>78.78</td>
<td>52.3</td>
</tr>
<tr>
<td>2</td>
<td>22.8</td>
<td>41.74</td>
<td>32.27</td>
</tr>
<tr>
<td>3</td>
<td>22.24</td>
<td>34.17</td>
<td>28.205</td>
</tr>
<tr>
<td>4</td>
<td>23.49</td>
<td>50.61</td>
<td>37.05</td>
</tr>
<tr>
<td>5</td>
<td>25.22</td>
<td>71.8</td>
<td>48.51</td>
</tr>
<tr>
<td>6</td>
<td>23.27</td>
<td>47.87</td>
<td>35.57</td>
</tr>
<tr>
<td>7</td>
<td>22.11</td>
<td>32.51</td>
<td>27.31</td>
</tr>
<tr>
<td>8</td>
<td>23.14</td>
<td>46.13</td>
<td>34.635</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
<td>36.98</td>
</tr>
</tbody>
</table>

4.3 Vertical – Supply flow of 70°C – Return flow of 50°C

FIG 6. Temperature distribution over the casing and the imaginary circle (dashed green line). The calculated heat conductivity is shown at each section in mW/m/K.
In this case the calculated temperature for the imaginary inner circle is overestimated since it is higher than the temperature of the supply pipe (steel pipe on the bottom). Calculations were performed again by assuming temperature of the supply pipe as known, instead of the return pipe. There was almost no difference in the calculated conductivity; hence the overestimation of the calculation method could be neglected.

**TABLE 3.** The calculated thermal conductivities for the twin district heating pipe at 8 points and the average value. Values are compared for the two methods of calculating the convective heat transfer coefficient of air.

<table>
<thead>
<tr>
<th>Temperature</th>
<th>$\lambda$ isolation (or $\lambda_{setup}$) [mW/m/K]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_{casing}$ $T_{inner}$ $T_{mean}$ $h_{air}$ was calculated for point B $h_{air}$ was calculated as a mean</td>
</tr>
<tr>
<td>1</td>
<td>22.88 49.27 36.075 24.6 24.4</td>
</tr>
<tr>
<td>2</td>
<td>21.43 22.52 21.975 23.2 23.2</td>
</tr>
<tr>
<td>3</td>
<td>22.55 24.83 23.69 23.3 23.3</td>
</tr>
<tr>
<td>4</td>
<td>23 51.54 37.27 24.7 24.5</td>
</tr>
<tr>
<td>5</td>
<td>24.56 77.29 50.925 26.1 25.7</td>
</tr>
<tr>
<td>6</td>
<td>22.91 49.85 36.38 24.6 24.4</td>
</tr>
<tr>
<td>7</td>
<td>21.73 27.93 24.83 23.5 23.4</td>
</tr>
<tr>
<td>8</td>
<td>21.88 31.16 26.52 23.7 23.6</td>
</tr>
<tr>
<td>Mean</td>
<td>32.21 24.2 24.1</td>
</tr>
</tbody>
</table>

### 4.4 Vertical – Supply flow of 80°C – Return flow of 40°C

![Temperature distribution over the casing and the imaginary circle (dashed green line). The calculated heat conductivity is shown at each section in mW/m/K.](image)

**TABLE 4.** The calculated thermal conductivities for the twin district heating pipe at 8 points and the average value. Values are compared for the two methods of calculating the convective heat transfer coefficient of air.
5. Discussion and conclusion

According to the results, the two methods for calculating of the convective heat transfer coefficient of air do not affect the calculated thermal conductivity of the setup considerably. The maximum difference between the overall thermal conductivities is around 1.2% for the fourth case. For this case the maximum difference for $\lambda_{\text{insulation}}$ at a point happens at point 5 (see TABLE 4) on the bottom of the heating pipe; 3.5% difference. Therefore it is possible to conclude that both methods for estimating $h_{\text{air}}$ are valid. However using more accurate techniques to calculate $h_{\text{air}}$ may give better results, although it will increase the complexity of the calculations and measurements.

The maximum difference between the calculated overall thermal conductivities is around 3.3% between the first case, 24.9 [mW/m/K] in TABLE 1 for the mean temperature of 39.07°C, and the third case, 24.1 [mW/m/K] in TABLE 3 for the mean temperature of 32.21°C. This maximum difference is induced by different positioning of the casing and also different temperatures. These two cases show the maximum differences in both positioning and temperature among the four cases, which induces the maximum difference in the air flow around the casing and its thermal properties. This results in the maximum difference between the calculated $\lambda_{\text{insulation}}$.

Although there are differences between the calculated thermal conductivities, there are small enough to have a good estimate for the overall thermal conductivity of the twin heating pipe. The proposed method for calculating the thermal conductivity of the twin district heating pipe is simple and quick. Moreover it is not very dependent on the geometry inside the casing, for example it might be possible to use the same technique for estimating the conductivity of a twin pipe insulated partly by vacuum insulation panels. However more experiments and calculations will be performed in future.

References


Comparative assessment of in-situ thermal characterisation techniques.

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KEYWORDS: In-situ thermal characterisation; Thermal performance; Building component testing; Full-scale testing; Dynamic data analysis

SUMMARY:
A more precise knowledge of the as-built thermal performance of our buildings’ fabric is of prime importance for the ongoing tendency to more stringent building performance demands. The methods that are commonly used for on-site thermal characterisation, such as the average method and linear regression technique, are based on stationary boundary conditions. As the latter are never encountered on site in practice, the methods’ validity depends on outdoor weather conditions. This paper examines the practical applicability of different in-situ thermal characterisation methods based on simulated data for an insulated cavity wall. Common semi-stationary methods are compared with a more advanced dynamical data analysis method, giving special attention to the reliability of the methods’ estimation results when confronted with data sets of limited measurement time spans and different measurement periods throughout the year. From this research, it can be stated that the use of semi-stationary methods for the characterisation of an insulated south-faced cavity wall can lead to accurate results in realistic measurement time spans when applied during winter months. The methods become less reliable when the temperature difference across the wall decreases. The dynamic method showed to be less sensible to the measurement period, provides more accurate results and needs shorter measurement time spans. The analysis itself however, showed to be more time consuming.

1. Introduction
A precise knowledge of the actual thermal performance of our buildings’ fabric is of prime importance in the debate on energy efficient dwellings. Currently, the building envelope is assessed by a performance label in the design phase based on calculated thermal resistances of the consisting building components. Some studies, however, show that these theoretical values do not necessarily correspond with the as-built thermal performance of the building elements (Hens et al. 2007), (Lowe et al. 2007). The differences can among others be attributed to the applied materials that differ from the designated ones, poor detailing and/or workmanship issues and physical phenomena such as thermal bridging, wind washing, air looping, etc. The on-site thermal characterisation of building components is therefore an important step to bridge this gap between theory and reality.

The methods that are commonly used for in-situ characterisation, such as the average method and linear regression technique, are based on the linear steady state relationship between the thermal resistance of, the heat flux through and the temperature difference over the studied element. Yet, steady state boundary conditions are never encountered on site in practice and the methods require averaged data as an approximation for measurements under stationary conditions. For the methods to be valid, the averages should be taken over a sufficiently long period of time, which limits the practical applicability of the methods, as one wants as shortest measurement time spans as possible. Besides, the methods are dependent of the measurement period throughout the year: they are not valid when the heat flow through the element is negligible when compared to the heat storage in the wall. This means that small temperature differences between outside and inside boundary conditions,
typically occurring during the summer period, result in small fluctuating heat flows around zero and jeopardize the R-estimates of the semi-stationary analysis methods. In contrast with the quasi-stationary methods, more advanced dynamical data analysis techniques exist. The latter take advantage of the dynamic boundary conditions, as dynamics are an express condition for the functioning of the method. The use of dynamic parameter estimation in the field of thermal characterisation is rather new and the question can be raised whether they perform better than the quasi-steady state methods.

2. Methodology

This paper examines the practical applicability of different in-situ thermal characterisation methods. Common semi-stationary methods are compared with a more advanced dynamical data analysis method, giving special attention to the reliability of the methods’ estimation results when confronted with data sets of limited measurement spans and different measurement periods. Ideally, however rarely the case, a good thermal estimation is independent of the measurement period throughout the year, i.e. in winter or summer, and results from short measurement terms. Most methods are accompanied by limiting conditions regarding the applicability and validity of the test method, however, these are not literally translated into a minimum test duration or delimited test period throughout the year. This paper aims to give an idea about those values in the case of a south-faced insulated cavity wall by applying the studied methods on various measurement data sets of this wall. The measurement data is generated by simulations in HAFMFEM, a finite element model based on the standard partial differential equations of heat, air and moisture transfer in porous building materials, developed at the KU Leuven. First the applied characterisation methods studied are presented, then the particularities about the wall’s properties and simulation assumptions are described.

2.1 In-situ thermal characterisation methods

2.1.1 Average method

The International Standard ISO 9869 (1994) proposes an average method for the estimation of the thermal resistance of building elements from in-situ measurements. The method departs from the principle that the R-value can directly be obtained by measuring the heat flow rate through an element, together with the surface temperatures on both sides of the element in steady state conditions. However, since steady state conditions are never encountered on a site in practice, the method assumes that the mean values of the heat flow rate and temperatures over a sufficiently long period of time give a good estimate of these values in stationary conditions, leading to equation (1)

\[ R = \frac{\sum_{j=1}^{n} \Delta T_{st/se,j}}{\sum_{j=1}^{n} q_{j}} \]

Where

- \( R \) total thermal resistance of the element ((m².K)/W)
- \( \Delta T_{st/se,j} \) difference between the internal and external surface temperature of reading j (K)
- \( q_{j} \) heat flow rate of reading j (W/m²)

The assumption of averaging data equalling steady state data results in a valid method only if (1) the thermal properties of the materials and the heat transfer coefficients are constant over the range of temperature fluctuations occurring during the test and if (2) the change of amount of heat storage in the element is negligible when compared to the amount of heat going through the element. Besides these general conditions, the norm formulates additional criteria which determines, during the course of the measurements, when sufficient data has been recorded. These criteria include minimum test durations and minimum deviations between the subsequently obtained R-estimates computed after each measurement. According to the International Standard, the recording measuring interval is
typically 0.5h to 1h. In this paper, the average method is applied on (simulated) hourly measured data sets.

2.1.2 Average method with correction for thermal storage

The International Standard ISO 9869 provides criteria, indicating when sufficient data recordings for the average method have been obtained. If these criteria are not fulfilled, a correction procedure needs to be applied. The latter involves a rectification of the heat flow rates according to the thermal storage capacities of the element and is relevant for structures of high R-value and high thermal mass. The adjustment results from the assumption that all the heat flux measured at the interior surface passes through the test element. Strictly speaking, this will only be the case if the temperature profile throughout the element remains the same during the test. Equation (2) represents the adjustments to the measured heat flux at each data point, involving internal and external thermal mass factors for the structure concerned.

\[ \sum q_j - \frac{F_i \delta T_i + F_e \delta T_e}{\Delta t} \]  

Where

- \( \Delta t \) the interval between readings (s)
- \( F_{i/e} \) internal/external thermal mass factor, relying on reasonable estimates of the thermal mass and resistance of the various layers of the structure
- \( \delta T_i \) the difference between internal temperature averaged over the 24h prior to reading j and internal temperature averaged over the first 24h of the analysis period (K)
- \( \delta T_e \) the difference between external temperature averaged over the 24h prior to reading j and external temperature averaged over the first 24h of the analysis period (K)

In this paper, hourly data is used as an input for the analysis procedure. According to the standard, the correction often permits a shorter measurement time.

2.1.3 Simple linear regression method

In essence, the simple linear regression technique fits a straight line through a set of points in such a way that the sum of the squared vertical distances between the points of the data set and the fitted line are as small as possible. To retrieve the R-value out of heat flux and surface temperature measurements, the stationary linear correlation between \( q \) and \( \Delta T \) is assumed, as is the case for the average method. Equation (3) represents the equation of the resulting regression line approaching the relationship between the dependent variable \( q \) and the explanatory variable \( \Delta T \).

\[ q = \frac{1}{R} \cdot \Delta T_{st/se} + c \]  

In contrary to the other methods, daily averages will be used for the application of the linear regression technique, for this permits to cancel out short-term effects of thermal mass (Bauwens et al. 2012). Theoretically, the regression line should go through the origin, which in practice will rarely be the case. Therefore, in this paper, this is forced by fixing the constant \( c \) at zero.

2.1.4 Dynamic parameter analysis

In contrast to the quasi-stationary analysis methods that are commonly used for in-situ thermal characterisation, this paper includes the application of a more advanced dynamic analysis technique. Essentially, dynamic parameter estimation is a way of inverse modelling: the method estimates the parameters of a physical model by tuning the behaviour of this model to the observed behaviour of the physical object, both subject to the same boundary conditions. The assumed physical models, or so called grey-box models consist of a set of continuous stochastic differential equations formulated in a state space form. The use of grey-box models is an approved method for identifying systems in a lot of...
domains and is explored for modeling the heat dynamics of buildings and reported already in (Madsen & Holst 1995) and (Andersen et al. 2000).

The state space model structure used in this paper for modeling the insulated cavity wall is derived from the resistance capacitance model represented in FIG 1. The model’s input variables are the in- and external surface temperatures $T_{si/e}$ of the wall, while the internal heat flux $q$ serves as observation variable or output. This means that similar measurements as for the quasi-stationary methods are required. A third-order model is considered, meaning that the thermal mass of the wall is lumped to three capacitances. The state variables $T_{wi}$ of the model represent the internal temperatures of those thermal capacitances. The estimation parameters of the model are the three capacities $C_{wi}$ and the four linking thermal resistances $R_{wi}$. The total resistance $R$ of the wall equals the sum of the individual model resistances. Note that the latter are not necessarily equally distributed over the wall: the identification procedure determines the values of the model resistances and controls the location of the capacities in the modeled wall. The model’s parameters are estimated using the Continuous Time Stochastic Modelling (CTSM) toolbox implemented in the statistical software R (Rune et al. 2013). CTSM uses maximum likelihood estimation to identify the unknown parameters for the given model structure.

![FIG 1. Representation of the studied insulated cavity wall and its thermal properties (top) and representation of the 3rd order resistance capacitance model used in the dynamic parameter analysis (bottom)](image)

2.2 Case study

In this paper, an insulated south-facing brick cavity wall is observed, as depicted in FIG 1. The measurement data for the in- and external surface temperatures and for the internal heat flux through the wall are simulated in HAMFEM, a finite element model based on the standard partial differential equations of heat, air and moisture transfer in porous building materials, developed at the KU Leuven (Janssen et al. 2007). A refined mesh of 201 nodes is used. The thermal properties used for the one-dimensional simulations are represented in FIG 1. The goal value for the total thermal resistance of the cavity wall is calculated from the simulation’s input properties and adds up to 3.82 (m².K)/W. A simulation with the length of one year and a calculation time step of one minute is performed for the typical moderate climate of Uccle (Belgium). Irradiance and outdoor air temperature data with a time resolution of 1 minute is obtained by Meteonorm v6.1 based on the period of 1981-2000. Other climate data is obtained with a time resolution of 1 hour and is interpolated to minutely data. For the inside boundary conditions, a constant indoor air temperature of 20°C is maintained during the whole year. This implies heating during the winter months and cooling during summer. The measurement output, e.g. surface temperatures and heat flux, are calculated at each minute of a whole year. This data is averaged to an hourly data set for the application of the average method, the average method with correction for thermal storage and for the dynamic parameter estimation method. For the simple linear regression method, daily averaged data is used.
3. Results

For comparison of the different analysis techniques, various data sets are considered: (1) data sets with different lengths ranging from 1 to 30 days and (2) data sets starting on the 1\textsuperscript{st}, 2\textsuperscript{nd}, \ldots, till the 30\textsuperscript{th} of January, April and July. The resulting estimates for the thermal resistance of the cavity wall are represented in FIG 2. The charts with heading \textit{January} contain the results of the data sets with a starting day in January. The charts with heading \textit{April} and \textit{July} respectively contain the results of the data sets with a starting day in April and July. From here the data sets with a starting date in January will be denoted as the data sets in January, while they partly encompass data points in February. Analogous denotations will be used for April and July. The results are plotted in function of the length of the dataset. So, in January, there are 30 data points corresponding to a data set length of, for example, 20 days, notably the data set ranging from the 1\textsuperscript{st} of January till the 20\textsuperscript{th} of January, till the data set ranging from the 30\textsuperscript{th} of January till the 18\textsuperscript{th} of February. In fact, the different data sets are a moving window advancing with a step of one day, repeated for different window lengths. The results for the different analysis methods are ordered vertically, with a repetition of the results of the average method as a reference. Remark that the boundaries of the y-axis are adjusted for the results of the reference method in January and April and that some data points corresponding to the other methods or to July fall outside the boundaries of the graph.

Looking at the results of the \textbf{average method}, it can be seen from FIG 2 (first line) that in January all estimates of $R$ lie within a 5\%-accuracy band around the goal value for data sets with a length of 20 days or longer. All $R$-estimates resulting from data sets of minimum 7 days already satisfy the required accuracy of 10\%. In April, the requisite length of the data sets for obtaining the defined accuracies of 5\% or 10\% increases to approximately 25 and 10 days respectively. In July, no meaningful estimates of $R$ are acquired. This phenomenon of poorer estimates for warmer periods can be explained by the validity of the averaging method only in stationary conditions: the method assumes that the mean values of the heat flow rate and temperatures over a sufficiently long period of time give a good estimate of these values under steady state conditions. This assumption is no longer justified when the heat storage in the element is large compared to the amount of heat going through the element. Typically, the heat flow rate in summer is limited due to the small temperature differences between the inside and outside environment. For the studied case, cooling is allowed and larger negative temperature differences can be maintained during hot periods when compared to a situation without cooling. The latter situation would involve fluctuating small positive and negative heat flows through the element during the summer period. This situation is even less favourable than the studied one and implies worse results than those represented.

If the \textbf{correction for the storage effects}, as formulated in ISO 9869, is applied on the data (second line on FIG 2) an improvement of the estimation results in January and April are found compared to the average method. In January all results lie in the accuracy band of 10\% and 5\% for data sets of two and three days or longer respectively. In April, the required data set length reduces to 5 and 13 days for characterising a 10\% and 5\% accurately estimated $R$-value. The applied adjustments correct the measured data for the fact that not all the heat flux measured at the interior surface passes through the test element. For this cavity wall, an element with high $R$-value and high thermal mass, FIG 2 endorses the technique’s potentials to shorten the required measurement time span for accurately characterising. Yet, it needs to be noticed that the thermal mass factors rely on estimates of the thermal mass and resistance of the various layers of the structure, which are exactly known for the studied wall. In reality, accurate thermal properties will often not be known and the improvement of the correction can be less effective. Besides that, by looking at the results for July, it is seen that the correction is not able to solve the problems when the measurements include small heat flow rates fluctuating around zero.
FIG 2. Comparison of the different analysis techniques regarding the data set length and period. The dotted lines and grey areas correspond to the 5% and 10% accuracy band.

method * average method * dynamic parameter estimation * linear regression * storage effects
The results for the linear regression method (third line on FIG 2) applied on daily averaged data points are similar to the results of the average method. As the same assumptions are made for both techniques, this may not surprise.

Finally, the results for the dynamic parameter estimation method are studied. At first sight, it is seen from FIG 2 (fourth line) that the estimation method achieves a fast and accurate convergence to the goal value in January and April. Nevertheless, some data points are missing because the estimation procedure did not converge to a parameter set that fits the adopted differential equations and observations. Next to that, a lot of solitary outliers are located outside the boundaries of FIG 2’s graph. Yet, there is no stratification from the goal-value to these outliers, as it is for the other methods. This encourages the presumption that the outliers are due to unsatisfactory model assumptions. Contrary to the other methods, the application of the dynamic parameter estimation technique is not straightforward: initial values for the model parameters and model states have, among others, to be assumed and can affect the estimation results. The reliability of the assumed initial values and retrieved estimates can be examined by a set of post processed evaluation criteria. With this information reapplication of the estimation procedure with adapted initial values can still lead to correct R-estimates. However, this assessment procedure is not automatized and has not been applied for the series of dynamic estimations in this paper. Looking at the results for July, it is remarked that the presence of small heat flow rates does affect the dynamic estimation procedure too. Nevertheless, a denser cloud around the goal value is remarked. Further investigation should tell whether the application limitations due to limited heat flow rates are less tight than for the other methods.

4. Conclusions and discussion

To evaluate the reliability of the different methods in more detail, the standard deviation of the R-estimates is investigated for the different analysis methods as a function of the length of the measurement time span.

FIG 3. Standard deviation of R-estimates for a certain data set length and for each analysis method. The dotted lines and grey areas correspond to a deviation of 5% and 10% of the goal value.

The results are summarised in FIG 3. The graph represents the mean deviation from the goal value for the considered data points. Comparison of the semi-stationary results in January and April learns that the average method and the linear regression method with daily averages attain a similar accuracy for their results. The accuracy improves when the correction for the storage effects is applied, yet in contrast to real situations, in this study precise information about the thermal properties was present for the calculation of the in- and external thermal mass factors. The standard deviations for the dynamic estimation method show an irregular development for the shorter data set lengths. This is due
to the presence of large individual outliers. The presence of outliers disappears from a certain data set length, +/-15 days in January and +/-7 days in April. The question raises whether an individual assessment of the model assumptions could avoid outliers for shorter data set lengths. A look on the results of July learns that the average method, with or without a correction for thermal storage, is not valid in the presence of small heat flows. The linear regression methods appears to perform well, however, FIG 2 shows a convergence to a wrong value. The dynamic estimation method shows the smallest mean deviation from the goal value, however, the confidence intervals of the obtained results are larger in summer than in winter and do barely reach the defined accuracy band.

In general, it can be stated that the use of semi-stationary methods for the characterization of an insulated cavity wall can lead to accurate results in realistic measurement time spans, i.e. +/-5 till 7 days, when applied during the winter months. The dynamic estimation method is less sensible for low heat flow rates, provides more accurate results and, when individually assessed, in shorter measurement periods. One can question whether the additional time consumed on evaluation and reapplication of the method is worth the reduction in measurement time and the improved accuracy. However, the possibilities of a dynamic analysis procedure reach far beyond those of the stationary techniques. Where the latter are limited to the estimation of stationary parameters, the dynamic method is not. One can imagine the identification of a thermal resistance that includes it’s temperature dependency or the identification of an R-value including dynamic effects as wind washing or air looping around the insulation layer, etc. As these dynamic phenomena do occur in practice, the potentials of the dynamic estimation method should be further investigated, for the possibility to characterise and quantify dynamic effects on the thermal performance of building components would be a significant improvement for in-situ characterisation.

5. Acknowledgements

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References


The energy performance of urban rooftop greenhouses

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KEYWORDS: Urban agriculture, greenhouse, rooftop food production, energy

SUMMARY:
In many cities worldwide there is an interest in exploring food production within appropriate urban spaces. Rooftops have been identified as such an opportunity and increasingly rooftop growing spaces have been established in several major projects. To increase productivity and extend the growing season some projects have used greenhouses on top of buildings. These greenhouses are often operated year round and demand significant energy to maintain optimal growing conditions. This can significantly add to the carbon impact of the food that is produced within them. In general there has been little exploration of how the energy and water systems of such a food producing greenhouse can integrate with the systems of the building below to exploit synergies and reduce resource needs.

The paper reports on a study that explores the impact of adding a rooftop greenhouse to a typical six storey, detached office building design in Toronto. The research uses energy simulation software to explore the synergistic impacts on the total energy consumption of both office building and greenhouse, and how the specification of key parameters such as glazing, thermal mass, and location of roof insulation impact performance. The results provide a better understanding of how to design rooftop greenhouses to benefit from their unique location on top of a building.

1. Introduction

Urban agriculture is increasingly seen as an important step towards food security in cities. While there is considerable discussion about the proportion of food that can be supplied by urban food production (MacRae et al., 2010), urban agriculture is increasingly being considered as a potential sustainable food source in many cities. Furthermore, rooftop space is abundant in many cities, and is often an untapped resource that can accommodate various forms of urban agriculture. Specific examples of recently implemented projects include the rooftop farms such as Brooklyn Grange in New York City and Carrot Commons in Toronto, and commercial rooftop greenhouses such as Lufa Farms in Montreal and Gotham Greens in New York City (Gorgolewski, 2011). Such projects serve to intensify the use of urban land and diversify urban employment opportunities. Rooftop food production in the city provides opportunities for food education, reduces the distance that food has to travel, can improve nutrition, and, depending on agricultural intensity, can provide appealing leisure space for users of the host building. Their proximity to consumers also necessitates a level of accountability on the part of the growers and delivers unparalleled freshness.

Rooftop farming has significant technical implications on the buildings beneath, including: structurally, functionally and for maintaining appropriate internal environments. In particular, rooftop greenhouses can offer benefits from thermal integration both of envelope and HVAC systems. This paper presents an investigation using energy modelling of the potential impact of adding a rooftop greenhouse to a six storey, detached office building in Toronto on the total heating and cooling energy consumption of both structures operated year-round.
2. Background

According to Rodriguez (2009), a “very conservative” estimate of the productive potential of rooftops in London, UK, using greenhouse hydroponic production is 300 tons/ha/yr. This correlates well with the yields achieved by Lufa Farms in Montreal (Figure 1), a 2,880m² (0.288 ha) commercial operation that produces up to 100 tons of produce annually, which is the equivalent of nearly 350 tons/ha/yr, and feeds 2,500 people in Montreal (Rathmell, 2013).

Little research has been conducted on the energy performance of urban rooftop greenhouses, however, the idea has similarities to the concept of attached sunspaces and the impacts that these may have on the host building. Considerable research has been carried out on the passive benefits of attached sunspaces. Findings suggest that the parameters of the glazed space can be modified to decrease heating and/or cooling requirements in the host building although some studies suggest that without active heat transfer (by a ventilation system, or otherwise) this effect is not large (Hastings, 1981; Swann, 1996). Key parameters seem to include the form, glazing type, level of separation and insulation between host and sunspace, and the amount of thermal mass within the spaces.

Delor (2011) investigated building integrated agriculture focusing specifically on hydroponic rooftop greenhouses and found that a well-insulated office building, with the addition of a well-insulated rooftop greenhouse, could benefit from a 13% decrease in annual heating energy as compared with the identical separated building and greenhouse. In a poorly insulated building, the addition of a rooftop greenhouse saved 41% energy annually. This assumes an active transfer of waste heat from the greenhouse to the office building, and vice versa. Delor also indicates that while green roofs perform better than rooftop greenhouses to prevent heat loss, rooftop greenhouses can be used for both solar heat gains and evaporative cooling.

Also of relevance are studies of the effect of green roofs on the energy performance of buildings. Considerable research in recent years has found that green roofs provide reductions in cooling load and to some degree heating load of buildings through evapotranspiration of plants, and shading from foliage (Jaffal et al., 2012; Niachou et al., 2001).

![FIG 1. Lufa Farms greenhouse in Montreal](image)

3. Methodology

A typical six-storey, steel-framed office building in an urban location in Toronto, Canada was used as an example of a host building for this study which used IES-VE energy modelling software to investigate the impact of an agricultural greenhouse, operated year round on the rooftop. The thermal characteristics of the host office building remained the same through all iterations, except for the level of roof insulation between the building and greenhouse. The greenhouse was designed based on the office building roof conditions and geometry, and information from the Lufa Farms greenhouse.
Modelling was carried out using IES Virtual Environment (IES-VE 6.4.0.12) with Toronto climate data. The focus was to evaluate trends in the delivered energy required annually for heating and cooling in both the greenhouse and office building and to gather data on indoor environment. This paper will focus on the following variables:

1. Insulation levels between the top floor of the office building and the greenhouse.
2. Location of insulation below or above the roof slab which affects whether thermal mass of the roof slab is exposed to the greenhouse or to the top floor of the offices.

The heating, ventilation and air conditioning (HVAC) systems were separate for each structure to allow for independent simulation of the greenhouse and the office building, and to distinguish to what extent each structure is impacted by their connection.

3.1 Office

A six-storey office building with 1,411 m² per floor for a total floor area of 8,467 m² was used as the host building. It was assumed to have sufficient structural capacity to support a rooftop greenhouse, have access to unobstructed sunlight, and the addition of a rooftop greenhouse is assumed to comply with zoning limitations. The specifications of the office building were to ASHRAE’s Advanced Energy Design Guide (AEDG) for Small to Medium Office Buildings (ASHRAE, 2011).

The office building was divided into 7 thermal zones per floor, according to the recommendations for zoning set out in the EE4 Modelling Guide (Natural Resources Canada, 2008). Each zone was given internal loads corresponding to their use as laid out in the ASHRAE 90.1 standard, for equipment, lighting, and occupancy (ASHRAE, 2010). The heating system for the office is assumed to be a VAV-reheat with a condensing boiler (90% rated efficiency), and a EWC chiller.

3.2 Greenhouse

The 988 m² greenhouse was designed to cover the largest possible area of the roof, approximately 70% of the office building roof, to deliver the maximum floor-to-wall-area ratio, in an east-west orientation for maximum solar radiation exposure. It is set back from the edge of the roof to allow for maintenance, some HVAC exits where necessary, and for compliance with fire code (i.e. glazing, in an urban fabric, requires a minimum separation from adjacent buildings).

The greenhouse is a typical Venlo design – multi-span construction with gable roofs – based on the operating rooftop greenhouse of Lufa Farms in Montreal; 4.2 m to the gutter, and an additional 1.5 m to the gable (Figure 3). The geometry was simplified in order to input the design into IES-VE simulation software; a pointed gable roof instead of curved vaults. It is assumed to be heated by a condensing gas boiler (90% efficient) with radiators.
FIG 3. Office roof plan, greenhouse footprint, and axonometric

Shading in a greenhouse by the roof structure is typically between 5-6%, while the structure of the greenhouse accounts for additional 3% shading, therefore the overall vision area of the glass is 91%. Typically glazing for a greenhouse is 4mm tempered single pane glass, which has both high visible transmittance for good crop growth and high impact resistance for durability. This was the base case used in the simulations.

The minimum recommended temperature in a greenhouse is 10°C, however lettuce, tomato and cucumber night temperatures should be in the range of 13-18°C (55-65°F) (Aldrich & Bartok, 1994). Plant development is hinged on the daily average temperature, which is recommended to be around 21°C. Thus, the greenhouse heating set-point temperatures were 22°C during the day in the heating season, 18°C at night (based on those at the Lufa Farms greenhouse). In the cooling season ventilation only was used to try to keep temperatures within the limits acceptable for plants. Due to the poor thermal characteristics of the glass and the lack of active cooling, a certain lack of controllability in the greenhouse was accepted, and it was found that the temperature ranged from 10°C to 38°C. In the summer, temperatures approaching the maximum high are approached on almost a daily basis, while the minimum temperatures (when they fall far below the set-point temperature) are typically only reached a dozen or fewer times in the heating season and indicate that the heating system has trouble adjusting quickly to changing loads.

The basic internal loading was based on ASHRAE 90.1 space-by-space method for ‘Active storage’, with a moderate equipment and lighting load (ASHRAE, 2010). This moderate loading was recommended to best represent limited equipment use, and periodic task lighting (separate from supplementary crop lighting) (Truyens, 2013).

3.3 Variables

The following variables were investigated:

- Roof insulation- For this variable, the baseline for the thickness of insulation between the office and rooftop greenhouse was taken as RSI 5.28 m²K/W as recommended by ASHRAE AEDG for Small to Medium Office Buildings. This parameter was varied from RSI 0, 0.88, 1.76, 3.52, 5.28, 7.04, 8.81 and 10.6 m²K/W.

- Thermal mass - Baseline simulations used roof insulation located on top of the concrete roof slab, thus insulating the thermal mass from the greenhouse space but making it accessible to the office space below. In subsequent simulations this was modified so that thermal mass was incorporated into the greenhouse by modifying the roof assembly of the office building so that the concrete layer was exposed to the rooftop greenhouse with insulation below. This inverted assembly was tested with the same levels of insulation as in the previous roof insulation simulations, except placed below the concrete slab.

- Glazing – The purpose of a greenhouse envelope is to create an interior environment conducive to plant growth, which includes, in a northern climate, both thermal resistance, and high visible transmittance in the range of photo-synthetically active radiation of light (PAR), between 400-700nm. This corresponds closely to the visible spectrum, and therefore translates well to the visible transmittance property of glazing. The visible transmittance of the cover material can vary depending on the light needs of the crop grown in the greenhouse, though many agricultural crops typically grown in greenhouses (lettuce, cucumber, tomatoes) require mid to high light levels to thrive (Aldrich & Bartok, 1994). Ideally, an agricultural greenhouse will have a visible transmittance of 89-90%. In general, single pane horticultural glass is used due to its high light transmission qualities compared to double pane glass despite a large energy penalty. Double pane glass suffers from reduced light transmission both through the glass and resulting from a heavier support structure, resulting in overall reductions of plant...
growth and yield. The baseline glazing in the greenhouse in this study was 4mm single-glazing. This was modified to test the effect of increasing the thermal resistance (but reducing light penetration) by using double-glazing, and glazing with low emissivity reflective coatings.

4. Results

The IES predictions of annual space heating and space cooling energy use (on site delivered energy) for the office building and greenhouse were compared, and internal temperatures in the greenhouse were also considered. Conversion to primary energy or resulting carbon emissions were not considered in this study. The predicted baseline simulation for the office heating and cooling energy use was 769 MWh and a total energy use (including appliances, pumps, fans, lighting, etc.) was 1667 MWh/yr or the equivalent of 200kWh/m²/yr, which compares reasonably with a low energy office in the Toronto location. Commercial greenhouses typically use between 315.4-788.7 kWh/m² to maintain temperatures in the heating season, and 3.59-10.76kWh/m² over the cooling season (Aldrich & Bartok, 1994). The baseline simulated greenhouse uses 787.9 kWh/m² for heating, and 4.9 kWh/m² for ventilation.

4.1 Roof insulation

The results show the simulation with the lowest total annual heating and cooling energy for the office and greenhouse combined is achieved when there is no insulation in the office roof below the greenhouse (Table 1). Additionally, in this simulation, the maximum temperature in the greenhouse is shown to be lowest while the minimum temperature is highest of all the simulations. This suggests that there are benefits from thermal integration of the spaces. However, the variation is small and within the accuracy of the modelling. Nevertheless, this suggests that integration of the systems should be further investigated.

The trend in energy consumption in the greenhouse may also be explained by the effect of thermal mass: the simulation with no insulation separating the greenhouse from the office building leaves the 100mm concrete roof deck exposed to the interior of the greenhouse. When insulation is added above the deck, the thermal resistance isolates this mass from the space and so solar gains into the greenhouse become less useful. This highlights the importance of thermal mass in a highly glazed space. This also explains the trend of increasing heating consumption in the greenhouse (as the thermal mass is covered up), which levels out with resistances higher than RSI 1.76 m²K/W in the separation. This phenomenon is discussed and tested further below.

The simulations for RSI 1.76 and 3.52 m²K/W experienced instability and the only solution was to run the simulations using a much shorter time-step between calculations; 2 minutes and 6 minutes for RSI 1.76 and 3.52 m²K/W respectively, instead of the typical 10 minutes. The annual results when run at a shorter time step tend to be higher therefore the results from these two simulations are less comparable to the other six points. It remains, however, that there is a trend towards higher heating and cooling energy consumption as insulation is added on top of the office roof.
### TABLE 1. Effect of roof insulation (insulation above the slab), baseline simulation highlighted

<table>
<thead>
<tr>
<th>Insulation level (m²K/W)</th>
<th>Office Annual space heating (kWh/y)</th>
<th>Greenhouse Annual space cooling (kWh/y)</th>
<th>Total (kWh/y)</th>
<th>Office Annual space heating (kWh/y)</th>
<th>Greenhouse Annual space cooling (kWh/y)</th>
<th>Total (kWh/y)</th>
<th>Total system (kWh/y)</th>
<th>Max. temp. (°C)</th>
<th>Min. temp. (°C)</th>
<th>Hours above 30°C</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSI 0</td>
<td>683,427</td>
<td>67,212</td>
<td>750,639</td>
<td>830,798</td>
<td>3,288</td>
<td>834,086</td>
<td>1,584,725</td>
<td>35.34</td>
<td>16.91</td>
<td>306</td>
</tr>
<tr>
<td>RSI 0.88</td>
<td>685,645</td>
<td>50,441</td>
<td>736,086</td>
<td>874,670</td>
<td>4,780</td>
<td>879,450</td>
<td>1,615,536</td>
<td>37.82</td>
<td>13.96</td>
<td>581</td>
</tr>
<tr>
<td>RSI 1.76</td>
<td>697,230</td>
<td>49,878</td>
<td>747,108</td>
<td>896,869</td>
<td>4,582</td>
<td>901,451</td>
<td>1,648,559</td>
<td>38.15</td>
<td>13.53</td>
<td>451</td>
</tr>
<tr>
<td>RSI 3.52</td>
<td>687,706</td>
<td>46,851</td>
<td>734,557</td>
<td>892,538</td>
<td>4,857</td>
<td>897,395</td>
<td>1,631,952</td>
<td>38.39</td>
<td>13.19</td>
<td>571</td>
</tr>
<tr>
<td>RSI 5.28</td>
<td>684,635</td>
<td>45,816</td>
<td>730,451</td>
<td>885,886</td>
<td>5,064</td>
<td>890,950</td>
<td>1,621,401</td>
<td>38.44</td>
<td>13.05</td>
<td>635</td>
</tr>
<tr>
<td>RSI 7.04</td>
<td>684,251</td>
<td>45,563</td>
<td>729,814</td>
<td>884,826</td>
<td>5,114</td>
<td>889,940</td>
<td>1,619,754</td>
<td>38.51</td>
<td>12.99</td>
<td>628</td>
</tr>
<tr>
<td>RSI 8.81</td>
<td>684,151</td>
<td>45,337</td>
<td>729,488</td>
<td>883,998</td>
<td>5,125</td>
<td>889,123</td>
<td>1,618,611</td>
<td>38.53</td>
<td>12.96</td>
<td>642</td>
</tr>
<tr>
<td>RSI 10.6</td>
<td>684,306</td>
<td>44,955</td>
<td>729,261</td>
<td>884,070</td>
<td>5,138</td>
<td>889,208</td>
<td>1,618,469</td>
<td>38.55</td>
<td>12.94</td>
<td>646</td>
</tr>
</tbody>
</table>

**FIG 4: Effect of insulation in the roof between office space and greenhouse on the annual heating energy of office and greenhouse**

Despite wide variations in roof insulation level, the office building does not differ in annual heating energy by more than 1%, (when the simulations with 1.76 and 3.52 m²K/W insulation results are discounted because of instability in the simulation model). Even when those simulations are included, the variation is not more than 2% (Figure 4). This indicates that even when no insulation is present in the separation (and since the greenhouse envelope itself has little resistance), some property of the greenhouse must be providing a measure of thermal performance similar to additional insulation. This is likely due to the buffer effect as described by Swann (1996). As insulation in the roof increases the annual cooling energy in the office building decreases, while the greenhouse ventilation energy increases and the number of hours of extreme temperature also increase. This suggests that as the two structures decrease in thermal connection, the office building needs less cooling in order to compensate for the additional heat provided by the greenhouse, while the greenhouse begins to struggle to maintain acceptable temperatures particularly in the cooling season.

### 4.2 Thermal mass

As discussed previously, it appears that thermal mass in the greenhouse is a significant factor in the total annual heating/cooling load. The roof insulation simulations show lower total energy
consumption when the roof assembly incorporated no insulation on top of the roof slab allowing the thermal mass to be exposed to the greenhouse and the office space.

Further simulations (Table 2, Figure 5) included insulation in increasing thicknesses below the slab, thus providing increased isolation from the office but more effective use of mass for the greenhouse. These simulations show further benefit to the overall building energy use by added insulation below the slab. In contrast with the simulations reported above where insulation was above the roof slab, insulation placed below the slab marginally reduced the office annual energy use with increased RSI, and reduced greenhouse annual energy use. Thus overall energy use was reduced. However, the increased separation between the spaces led to an increase in the number of hours of extreme temperature in the greenhouse.

### TABLE 2. Effect of thermal mass (insulation below the roof slab)

<table>
<thead>
<tr>
<th>Insulation level (m²K/W)</th>
<th>Office</th>
<th>Greenhouse</th>
<th>Greenhouse</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual space heating (kWh/y)</td>
<td>Annual space cooling (kWh/y)</td>
<td>Total (kWh/y)</td>
</tr>
<tr>
<td>RSI 0</td>
<td>683,427</td>
<td>67,212</td>
<td>750,639</td>
</tr>
<tr>
<td>RSI 0.88</td>
<td>687,399</td>
<td>50,813</td>
<td>738,212</td>
</tr>
<tr>
<td>RSI 1.76</td>
<td>703,741</td>
<td>51,412</td>
<td>755,153</td>
</tr>
<tr>
<td>RSI 3.52</td>
<td>687,212</td>
<td>46,473</td>
<td>733,685</td>
</tr>
<tr>
<td>RSI 5.28</td>
<td>686,809</td>
<td>45,904</td>
<td>732,713</td>
</tr>
<tr>
<td>RSI 7.04</td>
<td>687,270</td>
<td>45,711</td>
<td>732,981</td>
</tr>
<tr>
<td>RSI 8.81</td>
<td>687,540</td>
<td>45,450</td>
<td>732,990</td>
</tr>
<tr>
<td>RSI 10.6</td>
<td>687,565</td>
<td>45,164</td>
<td>732,729</td>
</tr>
</tbody>
</table>

N.B.: Again, there were problems with the simulation with RSI 1.76 m²K/W insulation because of instability in the software

### FIG 5: Annual energy required to heat and ventilate the greenhouse with insulation under the slab and over

#### 4.3 Glazing

The results in Table 3 show, as expected, that as the U-value of the glazing decreases in the greenhouse, the annual heating energy also decreases significantly, while ventilation in summer increases marginally. This is consistent with the effect shown by Scott (2011) wherein an improved greenhouse envelope resulted in a lower heating requirement than single glazing. This confirms that glazing with better thermal resistance retains more of the heat, reducing the energy required for
heating. However, summer conditions lead to more overheating. The maximum greenhouse temperatures are highest with the best envelope (double glazed, low-e), consistent with the simulation of attached sunspaces done by Mihalakakou & Ferrante (2000). It is beyond the scope of this work to assess the reduced lighting impacts on the plants.

**TABLE 3. Effect of greenhouse glazing envelope variations (office floor insulation RSI 5.28 m²/WK above the slab)**

<table>
<thead>
<tr>
<th>Greenhouse envelope glazing</th>
<th>Office</th>
<th>Greenhouse</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Annual space heating (kWh/y)</td>
<td>Annual space cooling (kWh/y)</td>
</tr>
<tr>
<td>single</td>
<td>685,623</td>
<td>46,045</td>
</tr>
<tr>
<td>single low-e</td>
<td>679,629</td>
<td>45,912</td>
</tr>
<tr>
<td>double</td>
<td>681,732</td>
<td>45,920</td>
</tr>
<tr>
<td>double low-e</td>
<td>681,577</td>
<td>45,849</td>
</tr>
</tbody>
</table>

Insulation in this scenario is above the roof deck; in retrospect, taking into account the implications of the thermal mass investigation, this insulation may be better placed below the roof deck, exposing the concrete layer’s thermal mass to the greenhouse which may mitigate the additional cooling loads.

The issue of condensation is not addressed here and should be explored in future research as the simulation software gave preliminary indications of condensation on the greenhouse envelope, which can significantly reduce light transmission to plants in the greenhouse. Exploring other possible envelope systems including the numerous plastics available would be a logical next step, investigating combinations of high thermal resistance, and high transmittance. Plastic envelopes may have additional benefits because of their light-weight, although they are often less durable than glass.

### 5. Conclusions

This investigation of the performance of a rooftop greenhouse on an office building highlighted several key factors that affect energy and thermal performance. The first issue is the importance of thermal mass in the greenhouse. This is consistent with other studies on greenhouse or sunspace performance and suggests that integration of thermal mass can reduce heating and cooling loads and hours of extreme temperatures. Thus, insulation below the roof slab is preferable as this allows the slab to be thermally active within the greenhouse. Secondly, the glazing specification has the most significant effect on energy use. The energy use of a typical single glazed greenhouse can be reduced by 50% through the use of higher performance glazing. Although this will reduce visible light penetration, it may be possible that other benefits such as reduced condensation on the glass will to some degree compensate. These issues need to be investigated further.

Thus, it appears from the simulation results that the best performing rooftop greenhouses (i.e. with the lowest annual energy requirement for heating and cooling in the office building and greenhouse) will have a high thermal resistance greenhouse envelope and incorporate thermal mass in the greenhouse. With thermal mass present, the performance continues to improve as the level of insulation below the concrete roof slab is increased. Though it requires additional investigation, further improvement might be achieved by developing a separation with thermal mass facing both the office and the greenhouse, with insulation as an interior layer.

This study did not consider the potential of integrating HVAC systems of the greenhouse and office building, which may offer further benefits, particularly if the greenhouse can be used as a solar collector to warm air used for ventilation of the offices in the shoulder season, or if the expelled air...
from the office HVAC can be used in the greenhouse. This may have additional benefit for plant growth as higher CO$_2$ concentrations can increase plant growth rates.

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EU Maps of Climate Related Building Performances using State-Space Modeling

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**KEYWORDS:** Climate, Map, State-Space, Building, Performance, Future

**SUMMARY:**
Performances of building energy innovations are most of the time dependent on the external climate conditions. This means a high performance of a specific innovation in a certain part of Europe, does not imply the same performances in other regions. The mapping of simulated building performances at the EU scale could prevent the waste of potential good ideas by identifying the best region for a specific innovation. This paper presents a methodology for obtaining maps of performances of building innovations that are virtually spread over whole Europe. It is concluded that these maps are useful for finding regions at the EU where innovations have the highest expected performances.

1. **Introduction**

Due to energy efficiency, there exist a lot of studies on innovative buildings systems. The performances of these innovations are mostly very dependent on the external climate conditions. This also means that a high performance of a specific innovation in a certain part of Europe does not imply the same performances in other regions. Similar, innovations that did not perform very well due to local climate conditions, and therefore not commercialised, could still perform quite well in other climates. The latter can be seen as ‘wasted’ innovations. The mapping of simulated building systems performances at the EU scale could prevent this wasting of potential good ideas by identifying the best region for a specific innovation. This paper presents a methodology for obtaining maps of performances of building systems innovations that are virtually spread over whole Europe. This approach is based on previous research and literature: The model development, including State-Space models is presented in Kramer et al. (2012 & 2013). The use of Meteonorm (2013) climates files for generating maps is shown in van Schijndel & Schellen (2013). The computational tool HAMLab (2013) originating from van Schijndel (2007) was used to implement all models and climates. Finally the future climate files originates from the Regional Climate Model REMO by Jacob et al. (1997) and will become public available from July 2014 at the Max Planck Institute for Meteorology (2013).

The methodology consisted of (1) State-Space model development; (2) Validation with step-change experiments; (3) Simulation of one external climate; (4) Performance indicators; (5) Parameter study; (6) Mapping of using current external climates over the EU.

The above mentioned methodology covers a wide range of topics. Due to the length limitation of this paper, it is very difficult to provide all details for each topic. We try to focus on the most significant aspects taking the complete methodology into account. More details can be found in the references.

The next Section 2 demonstrates the method using a commercial case study. Section 3 presents a generalization of this approach by the development of a computational tool for simulation of performances using SS models and future climates. Section 4 provides the discussion and conclusions.
2. The simulated performance of a thermal active wall

A commercial case study is presented in this Section. Due to the patent protection of the industrial partner, some specific information is omitted without loss of generality. The innovation consists of a novel heat exchanger built inside a construction acting as a solar collector.

2.1 Modeling, validation and climate based performance

Figure 1 shows the principle construction of the solar collector (in reality this is much more complicated) and the involved mathematical model in the form of ordinary differential equations and State Space. The solar collector will be used for the heating of water that directly can be used or stored for later use.

\[ C_1 \frac{dT_1}{dt} = hA(T_{\text{amb}}(t) - T_1) - \frac{(T_1 - T_2)}{R_1} + a_1A I(t) \]
\[ C_2 \frac{dT_2}{dt} = \dot{m}c(T_{\text{sup}}(t) - T_2) + \frac{(T_1 - T_2)}{R_1} - \frac{(T_2 - T_3)}{R_2} \]
\[ C_3 \frac{dT_3}{dt} = \frac{(T_2 - T_3)}{R_2} \]

Figure 1. Construction of the solar collector (Left), the model representation in ODEs (Right)

Where Inputs \( T_{\text{amb}}(t) = \) ambient (external) air temperature [°C]; \( T_{\text{sup}}(t) = \) water supply temperature [°C]; \( I(t) = \) external solar irradiance [W/m²]; States \( T_1 = \) external surface temperature [°C]; \( T_2 = \) water return temperature [°C]; \( T_3 = \) internal wall temperature [°C]; Parameters: \( \dot{m} \) = water mass flow [kg/s]; \( c = \) heat capacity of water [J/kgK] ; \( a_1 = \) solar absorption factor [-]; \( h = \) heat transfer surface coefficient [W/m²°C]; \( A = \) surface [m²]; \( d_1 = \) distance pipe to surface [m]; \( d_2 = \) distance pipe to insulation [m]; \( k = \) heat conductivity of concrete [W/mK]; \( R_1 = \) heat resistance [K/W] = \( d_1/(kA) \); \( R_2 = \) heat resistance [K/W] = \( d_2/(kA) \); \( C_i = \) heat capacity [J/K];

The model was implemented using standard state-space modeling facilities of MatLab. State-space models (see for example Kramer et al. (2012 & 2013)) contain variables and matrices. Regarding the variables: We have 3 variables: the state vector \( x \), the input vector \( u \) and the output vector \( y \). For the ODEs of Figure 1 this means that, \( x=[T_1;T_2;T_3] \), \( u=[T_{\text{sup}}(t); T_{\text{amb}}(t); I(t)] \) and we chose \( y=x \). Regarding the matrices: \( A,B,C,D \) can be calculated as shown in Figure 2 by using \( \frac{dx}{dt} = Ax + Bu \) and \( y = Cx + Du \). To simulate state-space models in MatLab, two commands are important: (I) creating a state-space system from the matrices: \( G=ss(A,B,C,D) \); (II) simulate the system (G) using input data \( u \), time steps \( t \) and start values for \( x \): \( \text{lsim}(G,\text{InputData},t,\text{Startvalues}) \).
The next part shows the simulation and validations results. Laboratory experiments were used to validate the models. All experiments were simulated using the proper parameters and boundary conditions. The results were compared in order to evaluate the predictability of the model. In Figure 3 (Left) the results for a typical experiment, labeled A, is shown.

From Figure 3 left we observed that the predictability of model was satisfactory. All other tested configurations provided similar good results. Therefore we conclude that the model is quite usable for further use. The model configuration A was simulated using a reference standard Dutch climate of deBilt. The water supply temperature was constant held at 10 °C. The other two input signals: Ambient air temperature and solar irradiation were taken from the climate file. The main output signal is the return temperature (out). With this signal the output power can be calculated. This is shown in the next Section. Figure 4 shows details of the model A configuration performance results.

### Figure 2. The state space representation and simulation in MatLab

The state space representation and simulation in MatLab are given below:

\[
\begin{align*}
A &= \begin{bmatrix}
-(hA+1/R1)/C1 & 1/(R1*C1) & 0 \\
1/(R1*C2) & -(mdot*c+1/R1+1/R2)/C2 & 1/(R2*C2) \\
0 & 1/(R2*C3) & -1/(R2*C3)
\end{bmatrix}; \\
B &= \begin{bmatrix}
0 & hA/C1 & a1A/C1 \\
mdot*c/C2 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}; \\
C &= \text{eye}(3); \\
D &= \begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & 0 \\
0 & 0 & 0
\end{bmatrix}; \\
G &= \text{ss}(A,B,C,D); \\
lsim(G,InputData,t,Startvalues);
\end{align*}
\]

### Figure 3. Temperatures vs time Left: Validation experiment A: The measured supply water(sup), the measured ambient air (amb), the simulated return water (Ret sim 1 & 2) and the measured return water (Ret). Right: Simulation of configuration A using a reference standard Dutch climate of deBilt. including the external wall surface (opp), the water return (out), the mid wall (con),
The output flux $P_{out}$ is calculated by: $P_{out}(t) = \frac{m \cdot c \cdot (T_{ret}(t) - T_{sup}(t))}{A}$ [W/m$^2$]; The overall performance is evaluated as follows: Firstly, $P_{50}(t)$ is defined as $P_{out}(t)$ with a threshold of 50 W/m$^2$. Below 50W/m$^2$, the water return temperature drops below 10.7 °C and the wall system is too inefficient. For these values $P_{50}(t) = 0$. Secondly, two performance (PF) indicators are defined as follows: PF$_t$ = Percentage of time of $P_{out}(t)$ above threshold of 50 W, i.e. percentage of time of possible operation [%]. PF$_p$ = $100 \times \frac{\sum P_{50}(t)}{\sum I(t)}$, i.e. the yearly mean efficiency [%]. From Figure 4 it follows for configuration A, PF$_t$=31.5% and PF$_p$=41.5%.

2.2 Parameter study

The following parameters were varied for the parameter study:

* The distance from the pipe to the surface (default 35 mm) was varied: 20, 35 and 50 mm.
* The mass flow (default 1 kg/min) was varied: 0.5, 1 and 2 kg/min.
The results are shown in Table I and II.

Table I. Efficiency Performance

<table>
<thead>
<tr>
<th>Simulated yearly mean efficiency PFp [%]</th>
<th>d=20 mm</th>
<th>d=35 mm</th>
<th>d=50 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF=0.5 kg/min</td>
<td>30.6</td>
<td>24.7</td>
<td>20.2</td>
</tr>
<tr>
<td>MF= 1 kg/min</td>
<td>39.0</td>
<td>30.9</td>
<td>25.2</td>
</tr>
<tr>
<td>MF= 2 kg/min</td>
<td>44.3</td>
<td>34.8</td>
<td>28.0</td>
</tr>
</tbody>
</table>

Table II. Operation Time Performance

<table>
<thead>
<tr>
<th>Simulated Operation time PFt [%]</th>
<th>d=20 mm</th>
<th>d=35 mm</th>
<th>d=50 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF=0.5 kg/min</td>
<td>29.8</td>
<td>26.5</td>
<td>23.7</td>
</tr>
<tr>
<td>MF= 1 kg/min</td>
<td>33.1</td>
<td>29.5</td>
<td>26.5</td>
</tr>
<tr>
<td>MF= 2 kg/min</td>
<td>34.5</td>
<td>30.9</td>
<td>27.7</td>
</tr>
</tbody>
</table>

The optimal efficiency performance for a Dutch climate is 44.3% with the accompanying mass flow of 2 kg/min and pipe depth of 20 mm.

2.3 EU Mapping of the standard configuration

By replacing the Dutch climate with the climates of weather stations presented in Figure 3, it is quite easy to simulate the response of the system to each external climate. From the responses the performance indicators can be calculated (See previous Section). The results of the standard wall performances are shown in Figure 5. These results are still based on the standard wall configuration A.

Figure 5. Left: Efficiency (PFp) of the standard wall configuration. Right: Percentage of time operation (PFt) of the standard wall configuration.
2.4 Simulation of optimized wall configurations

All nine configurations of the parameter study (see Table II and III) were also simulated on the EU scale. For each weather station the best configuration out of nine was selected. These optimized wall configuration performances are presented in Figure 6.

![Figure 6](image)

*Figure 6. Left: Optimized wall configuration Efficiency (PFp). Right: Optimized wall configuration Percentage of time operation (PFt).*

From Figure 6 left, it can be seen that large parts of Europe have efficiencies of at least 45%. From Figure 6 right, it can be seen that the areas near the Mediterranean have percentages of time of operation above 60%. The latter means that the wall collector is also operational during parts of the night.

3. Towards a tool for State-Space model simulations with Future Climate

One of the benefits of simulating State-Space (SS) models is its outstanding computational efficiency. To illustrate this: It takes longer to plot the maps of figures 5&6 than simulating them. Due to this excellent computational performance a practical tool for general purpose of simulating SS models using hourly based future climates is developed and will be public available together with the availability of the future climate files by the REMO model (2013).

3.1 How to use future hourly-based climate files for building simulation

The EU-FP7 project Climate for Culture (2013) is one of the first projects where high resolution EU future climate files where used for building simulation. Due to the stochastic behaviour and the time scale of about 250 years of the REMO climate model, it is recommend use three 30-year-periods for comparison purposes: „Recent Past“ (1960 – 1990), „Near Future“ (2020 – 2050) und „Far Future“ (2070 – 2100). An example from Winkler (2013) is shown in Figure 7. The left part shows the mean indoor temperature from the recent Past of a reference building. To compare this with the Near Future, the Near Future was simulated and the recent Past was subtracted. This generates the middle figure Past to Recent Future. Similar the figure on the right Past to Far Future was obtained. The reader should notice that from the experiences of the above mentioned project, it was concluded that the one-year-periods includes too much noise to be useful for analyzing and comparing purposes.
3.2 Current mapping visualisation tool

A MatLab mfile was developed for visualisation of EU maps. The input of this tool is in a single text file with performances related to longitudes and latitudes of the locations of the climate files. An example is shown in Figure 8. Here, over 130 external hourly based climate files were produced using commercially available software (Meteonorm 2013) using the so-called wac format. Figure 8 presents the distribution of the locations over Europe.

3.3 State-space modeling and simulation tool

MatLab has been a very successful modeling tool for simulating state space systems over the last 20 years. For a recent built environment application, we refer to Kramer (2013).
4. Discussion and Conclusions

4.1 EU performance of the solar collector

Large parts of Europe have solar collector efficiencies of at least 45%, the exact details are provided in Figure 6. Furthermore, areas near the Mediterranean have percentages of time of operation above 60% (exact details are shown in Figure 6). The latter means that the solar collector is even operational during parts of the night. It is concluded that this study shows that the solar collector could be applicable in large parts of Europe. However, the reader should notice that the solar collector simulation results in this study are based on two assumptions: The supply water temperature is constant at 10 °C and all heat produced by the wall collector is usable at any time. Under most circumstances this is not very realistic. Therefore it is recommended to include buildings, systems and controllers details into the modeling for more realistic performance simulations and design of promising integrated configurations.

4.2 State-Space modeling tool using Future Climates

The main three work packages: (1) State-space modeling and simulation; (2) Getting reliable future hourly based climate data over the EU and appropriate use of them; (3) Visualisation of maps, are all implemented in MatLab. The complete tool, including climate files, will become public available after the official ending of the Climate for Culture project (2013). This is expected at July 2014.

References


Monitoring-based dynamically updated occupancy models for predictive building systems control

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KEYWORDS: Probabilistic occupancy models, predictive building systems control, evaluation statistics

SUMMARY: Knowledge of occupants’ presence and behavior in buildings is of central importance to the implementation efforts concerning predictive building systems control. Specifically, prediction of occupants’ presence in office buildings represents a necessary condition for predicting their interactions with building systems. Implementation of occupancy prediction models in existing buildings can benefit from available occupancy monitoring data. In the present contribution, we focused on the evaluation of monitoring-based probabilistic occupancy models of a single-occupancy office, which are intended to be used for predictive room control. Thereby, we examined various scenarios to process the monitoring occupancy data obtained from this office toward developing stochastic occupancy models. These scenarios differ in terms of the duration and horizon (moving versus static) of the training intervals, as well as the grouping of the week days. To evaluate the stochastic occupancy models, we performed a Monte-Carlo study. Toward this end, a number of evaluation statistics were defined and the monitored and predicted daily profiles of occupancy were compared for individual days as units of observation to obtain the statistics. The results facilitate a discussion of the potential and limitations of occupancy models intended for incorporation in the control logic of buildings.

1. Introduction

Occupants influence thermal behavior of buildings due to their presence (e.g., via releasing sensible and latent heat), and via operation of control devices such as windows, shades, luminaries, radiators and fans (Mahdavi 2011). Specifically, knowledge of occupants’ presence represents a necessary condition for the development of predictive control action models. Performance simulation tool users typically deploy libraries of diversity factors and schedules to represent occupants’ presence in buildings. These diversity profiles are derived from long term monitored data in different classes of buildings and are usually included in the simulation packages to facilitate the creation of building performance models. Obviously, in cases where the available information about the building in question differs from the default profiles, the modeler can modify these diversity factors and schedules. More recently, efforts are being made in the scientific and professional communities to develop probabilistic models that would capture the randomness of occupants’ presence. As one of the first attempts, Newsham et al. (1995) considered the probabilistic nature of occupancy while developing a stochastic model to predict lighting profiles for a typical office. Their model deployed the probability of first arrival and last departure as well as the probability of intermediate leaving and returning. Reinhart (2001) further developed this model by using the inverse transform method (Zio 2013) to generate samples from the distribution functions of arrival and departure times. Moreover, days were divided into three phases (morning, lunch and afternoon) for which the probabilities of start.
time and length of breaks were computed. Page et al. (2008) proposed a generalized stochastic model for the simulation of occupants’ presence using the presence probability over a typical week and a parameter of mobility (defined as the ratio of state change probability to state persistence probability). They also included long absence periods (corresponding to business trips, leaves due to sickness, holidays, etc.) as another random component in their model.

In all these studies, monitored data has been used to derive a probabilistic model that generates random non-repeating daily profiles of occupancy for a long-term (e.g. annual) building performance simulation. Hence, models are suggested to perform well, if the entire set of generated random realizations of the daily occupancy profiles agrees in tendency with the monitored data over the whole simulation period. However, the synchronicity of these realizations with the monitored data (one-to-one agreement of the generated and monitored daily profiles) is not taken into consideration. Even in the case of considering long absences (Page et al. 2008), the unoccupied days are scattered randomly through the year and they do not necessarily match the dates of absences in the measured data. Thus, these practices cannot be said to "validate" the proposed models, if the actual day-to-day prediction of occupancy and control action probabilities are to be considered. Specifically, in a run-time use of a simulation model in building operation phase, where short-term predictions of occupancy and weather data are incorporated in the model to predict the future performance of the building, the agreement between the predicted and real future occupancy profiles in each day is of utmost importance.

Moreover, most of the work on validating the probabilistic occupancy models has focused on comparing the model outputs with the very set of data which has been used to derive the model. In contrast, Liao et al. (2010) used a fraction of data for calibration and the rest of the data for the validation of an agent-based occupancy model. In our view, a scientifically sound model evaluation approach must clearly separate the data segments used for model development and model validation. This is especially important while evaluating the predictive potential of an occupancy model, which is intended to be used for model-predictive control in buildings.

In the present study, we focus on evaluation of a stochastic model of occupants’ presence to explore the potential of using past monitored data in predicting future presence of occupants. Toward this end, we selected a university campus office area, which is equipped with a monitoring infrastructure and includes a number of open and closed offices. For the purpose of this case study, we deploy long-term monitored occupancy data obtained from one office. Thereby, separate sets of monitored data are used to derive and validate the model. We examine various options to use monitored occupancy data toward developing occupancy models and we use a number of evaluation statistics to evaluate the model predictions. Thus, the results facilitate a discussion of the potential and limitations of occupants’ presence models intended for incorporation in the control logic of existing buildings.

2. Approach

2.1 Overview

In this contribution, we derive and evaluate a probabilistic model of occupant’s presence which is to provide predictions of daily occupancy profiles for predictive control of the building. We utilize monitored occupancy data obtained from a single-person office in Vienna University of Technology based on different scenarios to derive a stochastic occupancy model. To evaluate the model we use a number of statistics and a separate set of monitored occupancy data. Conducting a Monte Carlo simulation we evaluate the predicted daily occupancy profiles generated by the stochastic model and obtain the distribution of the statistics to discuss the reliability of predictions.

2.2 Data collection

To obtain occupancy data, wireless ceiling-mounted sensors (motion detectors) were used. The internal microprocessors of the sensors are activated within a time interval of 1.6 minutes to detect
movements. The resulting data log entails a sequence of time-stamped occupied to vacant (values of 0) or vacant to occupied (values of 1) events.

To facilitate data analysis, the event-based data streams were processed to generate 15-minute interval data, using stored procedures of the MySQL database (Zach et al. 2012). This procedure derives the duration of occupancy states (occupied / vacant) from the stored events and returns the dominant occupancy state of each interval. Occupancy periods before 8:00 and after 19:45 were not included in the study to exclude, amongst other things, the presence of janitorial staff at the offices. Occupancy data for a nine-month period (10th of November 2011 to 25th of July 2012) was used to derive and validate the occupancy model.

2.3 Data utilization scenarios for model extraction

We develop and validate a stochastic occupancy model, which is intended to be implemented in a continuous running mode in the building control system. In such an application, a number of questions arise with regard to occupancy data utilization: What length of past occupancy information shall be considered for model development? Would it be advantageous to differently treat days of the week? Shall the model training occur in static or shifting intervals?

To address these questions, we examined various scenarios in using empirical occupancy data to train the model. Concerning the number of days of monitored occupancy data as input to the model, we examined three alternatives, namely 5, 10 and 20 days. Days of the week were treated similarly in “All week's working days” mode and separately in “Specific week days” mode. Besides, fixed and moving training intervals were considered. In the fixed interval mode, the model is fed once with past data from a specific period (5, 10 or 20 days) and it predicts occupancy for future days (in this study, 90 working days). However, in the moving mode, the training interval advances as the model predicts the occupancy day by day. Table 1 summarizes different data utilization scenarios toward developing the occupancy model.

**TABLE 1. Different data utilization scenarios for model extraction**

<table>
<thead>
<tr>
<th>Interval</th>
<th>Fixed</th>
<th>Moving</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selected days</td>
<td>All week's working days</td>
<td>Specific week days in consecutive weeks</td>
</tr>
<tr>
<td>Number of days</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Scenario code</td>
<td>FW05</td>
<td>FW10</td>
</tr>
</tbody>
</table>

2.4 Stochastic model of occupants’ presence

To derive a probabilistic occupancy model, which captures the random nature of occupants’ presence, first, a specific period of the 15-min interval occupancy data (based on different data utilization scenarios) was deployed as the model input to extract following distributions:

1. The cumulative distribution function of first arrival times (CDFa);
2. The cumulative distribution function of last departure times (CDFd);
3. The probability distribution function of intermediate departure times (PDFid);
4. The distribution of the length of intermediate absences for different hours throughout the day.

Figure 1 shows an example of the above-mentioned distributions. A daily occupancy profile is then generated by identifying the first arrival time, last departure time, intermediate departure times and the associated length of intermediate absences as follows:
- Using a random number from the standard uniform distribution in the interval [0, 1] \( (u_1) \), the first arrival time \( (t_a) \) is derived from CDF\(_a\) such that CDF\(_a\) \( (t_a) = u_1 \).
- Using a random number from the standard uniform distribution in the interval [0, 1] \( (u_2) \), the last departure time \( (t_d) \) is derived from CDF\(_d\) such that CDF\(_d\) \( (t_d) = u_2 \).
- To decide if an intermediate departure event occurs at a certain time \( (t_m) \), a random number between 0 and 1 \( (u_m) \) is compared with the probability of intermediate departure at that time. Once an intermediate departure is identified \( (PDF_{id} (t_m) \geq u_m) \), the length of the absence is obtained randomly from the associated set of the length of intermediate absences.

Compared with the previously developed stochastic models of occupancy, this model is most similar to the adapted stochastic occupancy model developed by Reinhart (2001). The main difference is that in our model, we used the hourly distributions of the length of intermediate absences, while in the other model, only three probability distributions, namely morning, lunch and afternoon, were used to randomly select the break lengths.

![Diagram](image.png)

**FIG 1.** An example of distributions derived from monitored occupancy data. From left to right: The cumulative probability distributions of times of first arrival and last departure, the probability distribution of times of intermediate departures, the distribution of the length of intermediate absences.

### 2.5 Model evaluation

To evaluate the model, we compared predicted and monitored occupancy profiles of 90 working days between the 1st of April and the 25th of July 2012. This set of monitored data had not been used for deriving or calibrating the model. To evaluate the model predictions, we used five statistics:

1. **Duration error [hour]:** This metric represents the difference between the predicted and monitored daily presence duration. We calculated the presence duration by counting the number of occupied intervals.
2. **First arrival time error [hour]:** The predicted minus the monitored first arrival time.
3. **Last departure time error [hour]:** The predicted minus the monitored last departure time.
4. **Asynchronicity index [-]:** This novel indicator is calculated by averaging the differences between the number of predicted and monitored occupied intervals within each hour from 8:00 to 19:45. According to the definition, this statistics captures the asynchronicity of the predicted occupancy profiles (with reference to actual occupancy). A value of 1 for the Asynchronicity Index suggests zero temporal overlap between predicted and actual occupancy duration within a day. A value of zero would suggest full overlap between predicted and actual occupancy duration.
5. **Number of transitions error [-]:** The predicted number of daily occupied-to-vacant transitions minus the monitored number of daily occupied-to-vacant transitions.
Given the stochastic nature of this occupancy model, one cannot evaluate the accuracy of the model predictions by comparing the results of a single run with the measurements. Therefore we conducted a 100-run Monte Carlo simulation in order to analyze the distribution of the errors in predictions. The aforementioned statistics are calculated for each individual day during the validation period. Given the length of the validation period (90 working days) and the number of Monte Carlo simulations, we obtained 9000 values for each statistic.

Note that the current model is not intended to predict periods of long absences due to business trips, sickness, holidays, etc. Such whole-day absences can be presumably communicated to the building management system and reflected in the predictive building systems control. Therefore, in this contribution, we only included the actual working days in the validation process.

3. Results

Figures 2 to 6 illustrate the cumulative distribution functions of the obtained values for the introduced statistics.

FIG 2. Cumulative distribution functions of duration error (left: fixed training interval; right: moving training interval)

FIG 3. Cumulative distribution functions of first arrival time error (left: fixed training interval; right: moving training interval)
FIG 4. Cumulative distribution functions of last departure time error (left: fixed training interval; right: moving training interval)

FIG 5. Cumulative distribution functions of asynchronicity index (left: fixed training interval; right: moving training interval)

FIG 6. Cumulative distribution functions of number of transitions errors (left: fixed training interval; right: moving training interval)
4. Discussion and conclusion

Comparing different training data usage scenarios, models which distinguish between days of the week provide more accurate results in terms of almost all statistics. For these models, little difference in predictive performance could be found between the fixed and moving training modes. However, for models that do not distinguish between weekdays, the moving training mode offers more reliable predictions. Moreover, using longer intervals to train the models generally enhances predictive performance. However, this is much more evident in models with fixed training mode and no distinction between weekdays. In our study, no significant difference amongst the models could be found while predicting the number of transitions.

As noted at the outset of the paper, deployment of stochastic occupancy models in the context of building systems control requires a different standard concerning the evaluation of the models' predictive performance. Thereby, an important question concerns the extent to which short term occupancy prediction errors could be minimized. Table 2 summarizes, for the present study, the highest achieved accuracy in predicting daily occupancy profiles at 80 percent confidence level.

<table>
<thead>
<tr>
<th>Evaluation Statistic</th>
<th>Value at 80% confidence level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration error</td>
<td>2.5 hours</td>
</tr>
<tr>
<td>First arrival time error</td>
<td>1 hour</td>
</tr>
<tr>
<td>Last departure time error</td>
<td>2.5 hours</td>
</tr>
<tr>
<td>Asynchronicity index</td>
<td>0.32</td>
</tr>
<tr>
<td>Number of transitions error</td>
<td>2</td>
</tr>
</tbody>
</table>

The results reported here are derived from a single-occupancy office. Needless to say, using past occupancy data for prediction of future occupancy patterns may yield differing results. The error levels may be higher or lower based on factors such as the duration of the training period and the nature of the occupant's activity. However, the obtained results point out that there may be potentially a limit (lower uncertainty threshold) in predicting the occupants presence by using past data, as in this case, fairly detailed (high-quality) occupancy data was available and the nature of the occupant's task (mostly clerical) displayed a rather regular pattern.

Acknowledgements

The research presented in this paper is supported in part by funds from the project "Control & Automation Management of Buildings & Public Spaces in the 21st Century" (CAMPUS21, Project Number: 285729) as well as the project "Retrofitting Solutions and Services for the enhancement of Energy Efficiency in Public Edification" (RESSEEPE, Project number: 609377) under EU's Seventh Framework Programme.
References


Combining Three Main Modeling Methodologies for Building Physics

A.W.M. (Jos) van Schijndel, Assistant Professor
Eindhoven University of Technology, Netherlands

KEYWORDS: State-Space, FEM, BES, Building, Energy, Modeling

SUMMARY:
An overall objective of energy efficiency in the built environment is to improve building and systems performances in terms of durability, comfort and economics. In order to predict, improve and meet a certain set of performance requirements related to the indoor climate of buildings and the associated energy demand, numerical simulation tools are indispensable. In the paper we consider three types of numerical simulation tools: Finite Element Method (FEM), Building Energy Simulation (BES) and State-Space (SS) together. Commonly used within these tools are zonal approaches of the volumes, assuming uniform temperatures in each zone, and 1D modeling of the walls. Due to the rapid development of Finite Element Method (FEM) software and Multiphysics approaches, it should possible to build and simulate full 3D models of buildings regarding the energy demand. Another application consists of Building Energy Simulation using State space models identified from free floating data. It is concluded that the main benefits of FEM-SS-BES modeling exchange is the possibility to simulate building energy performances with high spatial resolution and low computational duration times.

1. Introduction
An overall objective of energy efficiency in the built environment is to improve building and systems performances in terms of durability, comfort and economics. In order to predict, improve and meet a certain set of performance requirements related to the indoor climate of buildings and the associated energy demand, numerical simulation tools are indispensable. In this paper we consider three types of numerical simulation tools: Finite Element Method (FEM), Building Energy Simulation (BES) and State-Space (SS). For each tool separately, there exist a vast number of references. Also on two tools combined, i.e. FEM-BES, BES-SS, FEM-SS, there is quite a lot of literature. However there is lack of research on an overall evaluation of the three tools FEM-SS-BES together. In this paper we present benefits of the FEM-SS-BES modeling exchange for building physics. The main reasons for converting models in each other are summarized in Table I.

TABLE 1. The main reasons for converting models in each other

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>FEM</th>
<th>BES</th>
<th>SS</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEM</td>
<td></td>
<td>*</td>
<td>Global effects</td>
<td>Lumped results</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Computation Speed</td>
</tr>
<tr>
<td>BES</td>
<td></td>
<td>Local effects</td>
<td></td>
<td>*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>High resolution results</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SS</td>
<td></td>
<td>Inverse Modeling</td>
<td></td>
<td>*</td>
</tr>
</tbody>
</table>
In this work FEM is just a method of solving Partial Differential Equations (PDEs), like Finite Volume methods (FVM) or Finite Difference methods (FDM). We start with two combinations that are quite obvious and already commonly used. 

**BES to FEM** – BES is used to simulate the energy performance of buildings, using lumped parameter modeling. If local effects are important, FEM can be used to obtain high resolution results based on distributed parameter models and using BES simulation results as boundary values. 

**FEM to SS** – FEM based simulations can easily become computational time consuming. One of the methods to improve the computing time is to reduce the mathematical model to a lower order model by using for example a State-Space (SS) approximation. One of the main benefits of SS models is, that very efficient computation algorithms exist, that are able to almost completely reduce the computation time. If such a reduced order SS model is accurate enough, this method can be used for improving computation speed. This paper comprehends an investigation of the two other combinations. Each combination is presented in a separate Section, including background information and case studies. After these Sections a discussion of the results is provided. 


BES using 1D FEM with lumped parameter modeling for air already exist. For example Wufi+ (2013) and HAMBase (de Wit 2006 & HAMLab 2013) are such tools. Commonly used within these tools are zonal approaches of the volumes, assuming uniform temperatures in each zone, and 1D modeling of the walls. Due to the rapid development of Finite Element Method (FEM) software and Multiphysics approaches, it should possible to build and simulate full 3D models of buildings regarding the energy demand. Moreover, the 3D models would also provide detailed (i.e. high resolution) results of the indoor climate and the constructions. The main problem regarding the use of FEM for BES is how to compare a distributed parameter model (FEM) with a lumped parameter model (BES)? Because BES and FEM have quite different approaches, we used the following method: Step 1, start with a simple reference case where both BES and FEM tools provide identical results. Step 2, add complexity and simulate the effects with both tools. Step 3, compare and evaluate the results. For step 1, a suitable reference case was found at the current International Energy Agency Annex 58. It concerns a test box with overall dimension 120x120x120 cm³. Comsol was used to build a 3D model of the test box. In order to compare the Comsol 3D FEM model with the BES lumped model (using HAMBase(de Wit 2006 & HAMLab 2013)), an equivalent heat conduction of the air is used in the FEM model. This provides identical FEM versus BES results.

For step 1, a suitable reference case was found at the current International Energy Agency Annex 58 (2013). It concerns a test box with overall dimension 120x120x120 cm³. Floor, roof and three of the four walls are opaque, one wall contains a window with opening frame. Details of the overall geometry with the exact dimensions can be found in figure 1.

![Figure 1. The reference case.](image-url)
We started to build a 3D model of the opaque test box, heavy weight, air change rate: ACH=0 using Comsol (2013). In order to compare the Comsol 3D FEM model with the HAMBase (de Wit 2006 & HAMLab 2013) lumped model, an equivalent heat conduction of the air is used in Comsol instead of CFD. Equation (1) shows the PDE:

$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T)$$

(1)

where $T$ is temperature (K), $t$ is time (s), $\rho$ is density (kg/m$^3$); $c$ is specific heat (J/kgK) and $k$ is heat conduction coefficient (W/mK). Equation (2) shows the boundary values:

$$q_{\text{boundary}} = h(T - T_e) + q_{\text{irrad}}$$

(2)

where $q_{\text{boundary}}$ is the heat flux at a specific boundary (W/m$^2$), $h$ is the heat transfer coefficient (W/m$^2$K), $T_e$ is the external air temperature (K) and $q_{\text{irrad}}$ is the net radiation from the sun and sky to the surface (W/m$^2$). The temperature distribution in the test box is simulated using Dutch weather data. As mentioned above the model was implemented and solved using Comsol. The default second-order Lagrange element type was used. The mesh contained 4414 tetrahedral elements and with average element quality of 0.7512. The number of degrees of freedom solved for was 6679 using the PARADISO algorithm with absolute and relative tolerances of 0.001. The temporal convergence error was less than $10^{-5}$ for each time step. After the solution was obtained with these settings, the grid dependency was evaluated by a grid refinement study. The latter showed no significant changes in the solution. Figure 2 shows the 3D snapshots of the isosurfaces in simulated by the FEM software.

![Figure 2. 3D snapshots of the temperature isosurfaces.](image-url)
The main challenge now is how to match the high resolution distributed temperature results of Comsol with the lumped temperature results of the BES model. For this reference case (opaque test box, heavy weight, ACH=0) we were able to get a very good match by using a so-called equivalent heat conduction coefficient for the air inside the box in Comsol.

\[ k_{eq} = \frac{d}{R} = \frac{1}{0.34} = 2.9 \]  

(3)

Figure 3 shows the comparison of the simulated mean indoor air temperature using Comsol (thin line) and HAMBase (bold line) during the first month. The verification result is satisfactory.

From figure 3, two important facts can be concluded: Firstly, these results can be used as an additional verification benchmark for both Comsol as well as HAMBase. And secondly, it is seems to be possible to accurately reproduce a BES simulation using a relative simple heat conduction based FEM model with a equivalent heat conduction coefficient for the indoor air, but so far without CFD and internal radiation. The latter is left over for future research.

3. Application 2: State-Space models identified from measured data.

At the IEA Annex (2013) a test box was built to investigate it’s thermal characteristics.

From figure 3, two important facts can be concluded: Firstly, these results can be used as an additional verification benchmark for both Comsol as well as HAMBase. And secondly, it is seems to be possible to accurately reproduce a BES simulation using a relative simple heat conduction based FEM model with a equivalent heat conduction coefficient for the indoor air, but so far without CFD and internal radiation. The latter is left over for future research.

3. Application 2: State-Space models identified from measured data.

At the IEA Annex (2013) a test box was built to investigate it’s thermal characteristics.
The test box was tested at the premises of BBRI in Limelette, Belgium (Lat. 50°41’ N, Long. 4°31’ E). In general, the weather conditions here are temperate, consisting of mild winters and rather cool summers. The experiments extended over a period of one month. Testing was done under real outdoor weather conditions. The following outdoor climate sensors installed near the test box are included in the supplied data: air temperature (with a solar radiation shield and ventilated), vertical global solar radiation (parallel and next to the glazing) and horizontal long wave radiation from the sky. Additional meteorological sensors installed at the test site (200 m from the test box) are also included in the data sets: horizontal global solar radiation, horizontal diffuse solar radiation, vertical long wave radiation from the South direction, wind velocity, wind direction (North 0°, East 90°) and relative humidity. The following experiments have been carried out: Test A: free-floating temperature (with no heating power during 2 weeks) and Test B: co-heating test with constant indoor temperature of 25°C during 2 weeks.

3.1 Free floating experiment

Figure 5 shows the measured indoor and outdoor temperatures of the test box:

![Figure 5: The measured indoor and outdoor temperature are shown. Both temperatures are averages of the two available measurement positions for respectively indoor and outdoor temperature](image)

A model structure that is suitable for a thermal zone is provided by Kramer et al. (2013) and is shown in Figure 6.

![Figure 6: The used lumped thermal model with inputs outdoor temperature (Te) and solar irradiation (Irrad).](image)
The thermal model is a 3rd order model with 7 parameters: \( C_w \) represents the capacitance of the envelope part, \( C_i \) represents the capacitance of the indoor air and \( C_{int} \) represents the capacitance of the interior parts which are not directly connected to the outdoor air. \( G_{fast} \) represents the heat loss due to ventilation and windows. The solar irradiation is placed on the interior node. This model structure proved to be the most suitable amongst several other assessed model structures. For more information see Kramer et al. (2013). The thermal model inputs are: Temperature outdoor and solar irradiation on vertical plane oriented on sooth. For this experiment, the solar input is limited to the global irradiation on the vertical south plane because this has the most influence. The objective is to identify the parameter values of the model by repeatedly trying different parameter values and comparing the simulated output with the measured output (Kramer et al., 2013). The result of the optimization procedure is shown in Figure 7. The measured indoor temperature is reproduced fairly accurately at first sight.

![Figure 7: measured and simulated indoor temperature for the free floating situation using the thermal model from Figure 6 with inputs \( T_e \) and global solar irradiation on vertical South plane (\( G_v \)).](image)

3.2 Co-heating experiment

The state-space (SS) thermal model of the previous section was coupled with an PI controller (see Figure 8) in order to simulate the co-heating experiment.

![Figure 8: the identified thermal model is coupled to a PI-controller maintaining the indoor temperature at 25°C.](image)

The simulation results compared with the experiments are shown in figures 9 and 10.
Figure 9: Simulated and measured indoor temperature for co-heating test. The first 10h (left) and 10 – 320h (right).

Figure 10: the simulated power is scaled by a factor 3.11e5 (Ci) and plotted with the measured power.

The results show a good agreement between simulation and measurement. Moreover, now that the indoor air capacitance Ci has been identified, the other parameters can be isolated. E.g., the individual parameters like Gi can be isolated, see Table 2:

**TABLE 2. The identified parameters are split up by using the identified Ci.**

<table>
<thead>
<tr>
<th>#</th>
<th>Par.</th>
<th>identified</th>
<th>expected</th>
<th>unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G_w</td>
<td>0.86</td>
<td>2.3</td>
<td>W/K</td>
</tr>
<tr>
<td>2</td>
<td>C_m</td>
<td>1.2e-1</td>
<td>41</td>
<td>J/K</td>
</tr>
<tr>
<td>3</td>
<td>G_i</td>
<td>3.11e4</td>
<td>43</td>
<td>W/K</td>
</tr>
<tr>
<td>4</td>
<td>C_i</td>
<td>3.11e5</td>
<td>1.1</td>
<td>J/K</td>
</tr>
<tr>
<td>5</td>
<td>G_fast</td>
<td>3.11</td>
<td>0.3</td>
<td>W/K</td>
</tr>
<tr>
<td>6</td>
<td>G_int</td>
<td>0.31</td>
<td>-</td>
<td>W/K</td>
</tr>
<tr>
<td>7</td>
<td>C_int</td>
<td>2.63e-4</td>
<td>-</td>
<td>J/K</td>
</tr>
<tr>
<td>8</td>
<td>fl-S</td>
<td>0.13</td>
<td>0.27</td>
<td>m²</td>
</tr>
</tbody>
</table>

From Table 2 there it is noted that there is still a discrepancy between identified and expected values. The latter are estimated by hand calculations based on information provided by the IEA Annex 58. This is discussed in the next Section.
4. Discussion and Conclusions

The inverse modeling procedure presented at the previous Section provides a state-space model that is capable of accurately simulating the experiment. The identified parameters should be interpreted as effective parameters. For example the air inside the box has a heat capacity of 1.1 J/K. However, in this experiment it is impossible to heat up the air alone because it immediately affects the construction also. Therefore it could be very difficult if not impossible to get the expected parameters from the inverse modeling method. Nevertheless, the model is a very accurate representation of the dynamics.

It is concluded that one of the main benefits of FEM-SS-BES modeling exchange is the possibility to simulate building energy performances with high spatial resolution and low computational duration times. Regarding FEM to BES – Firstly, these results can be used as an additional verification benchmark for both Comsol as well as HAMBase. Secondly, it is seems to be possible to accurately reproduce a BES simulation using a relative simple heat conduction based FEM model with an equivalent heat conduction coefficient for the indoor air, but so far without CFD and internal radiation. The latter is left over for future research. Regarding BES to SS - The paper presents case studies where SS models are successfully used for reducing computational times for BES models. Regarding SS to BES – Using this so-called inverse modeling approach, it is possible to obtain building energy performances from SS models. The FEM-SS-BES modeling exchange provides two alternative modeling approaches for each other. This may be beneficial if some specific limitations are encountered within one of the single FEM, BES, SS modeling methods.

References

Comsol (2013), www.comcol.com
Wufi+ (2013), http://www.wufi.de/
Empirical and computational assessment of the urban heat island phenomenon and related mitigation measures

Ardeshir Mahdavi
Kristina Kiesel
Milena Vuckovic

Department of Building Physics and Building Ecology, Vienna University of Technology, Austria

KEYWORDS: Urban climate Urban Heat Island, Mitigation Measure, Modeling, Evaluation

SUMMARY:
A central strand of research work in the realm of urban physics aims at a better understanding of the variance in microclimatic conditions due to factors such as building agglomeration density, anthropogenic heat production, traffic intensity, presence and extent of green areas and bodies of water. This research has been motivated in part by phenomena associated with climate change and urban heat islands (UHI) and their implications for the urban microclimate. Note that the characteristics and evolution of the urban microclimate is not only relevant to people's experience of outdoor thermal conditions in the cities. It could be argued that the solid understanding of the temporal and spatial variance of urban microclimate represents a prerequisite for the reliable assessment of the thermal performance of buildings (energy requirements, indoor thermal conditions). In this context, the present paper entails a three-fold contribution. First, the existence and extent of the UHI phenomena are documented for a number of Central-European cities. Second, a number of variables of the urban environment are identified that are hypothesized to influence UHI and the urban microclimate variance. These variables, which pertain to both geometric (morphological) and semantic (material-related) urban features are captured within a formal and systematic framework. Third, to support the process of design and evaluation of UHI mitigation measures, the potential of both numerical (simulation-based) applications and empirically-based urban microclimate models are explored.

1. Introduction
An increasing number of people live in cities and are therefore influenced by the urban microclimate. The microclimate varies significantly within a city depending on factors such as urbanization, presence and density of industrial or commercial buildings, green areas, bodies of water, etc. (Grimmond 2007, Alexandri 2007). Furthermore, the geometry, spacing, and orientation of buildings and surrounding open areas greatly influence the climate in the city (Unger 2004, Kleerekoper et al. 2012, Shishegar 2013). Observations in many cities around the world point to significantly higher urban temperatures than the surrounding rural environment. This circumstance is referred to as the urban heat island (UHI) phenomenon (see, for example, Voogt 2002, Arnfeld 2003, Blazejczyk 2006, Oke 1981, Gaffin et al. 2008). Increase in average temperatures is believed to adversely affect the health of people living in cities (Harlan et al. 2011). Additionally, higher air temperatures have a direct effect on the energy use due to increased deployment of air conditioning (Akbari 2005). In this context, this paper presents the results of an ongoing research project. First the existence and extent of the UHI phenomena are documented for a number of Central-European cities. Thereby, certain features of the urban environment are hypothesized to influence UHI and the urban microclimate variance. The related variables, which pertain to both geometric (morphological) and semantic (material-related) urban features are captured within a systematic framework. Moreover, to support the
process of design and evaluation of UHI mitigation measures, the potential of both numerical (simulation-based) applications and empirically-based urban microclimate models are explored.

2. The Urban heat island in central Europe

2.1 Overview

The UHI is defined as the difference between urban and rural air temperature (Oke 1972). Generally, heat island intensities are quantified in the range of 1 to 3 K, but – under certain atmospheric and surface conditions – can be as high as 12 K (Voogt 2002). Material properties of urban surfaces (Akbari et al. 2001) as well as evapotranspiration, and anthropogenic heat emission (Taha 1997) can result in higher urban temperatures. The present contribution focuses on the frequency, magnitude, and time-dependent (diurnal and nocturnal) UHI intensity distribution (during a reference week) and the long-term development of urban and rural temperatures in eight Central-European cities, namely Budapest, Ljubljana, Modena, Padua, Prague, Stuttgart, Vienna, and Warsaw. The magnitude of the UHI effect can be expressed in terms of UHI intensity $(\Delta \theta)$. This term denotes the temperature difference (in K) between simultaneously measured urban and rural temperatures.

As mentioned before, UHI intensity in observed urban areas was derived for a reference summer week selected by each participating city independently. Specifically the cities were asked to provide climate data recorded at two weather stations for a period of 7 consecutive days during the summer of 2011. The idea was to select a week with considerably high temperatures and relatively low wind velocities (preferably below 5 m/s). The collected information included hourly data on air temperature, wind speed, and precipitation from two representative weather stations (one urban and one rural). The participating cities were asked to select the weather stations according to the following guidelines: i) the urban station should be situated in a central area with a typical urban morphology/setting; ii) the rural station should be situated in a rural surrounding in the vicinity of the city (but not in the suburbs and not near an airport or similar structures). To obtain a long-term impression of the urban and rural temperature development, mean annual (urban and rural) temperatures and UHI values were derived for a period of up to 30 years, namely from 1980 to 2011 (Modena, Prague, Stuttgart, Warsaw), from 1994 to 2011 (Vienna, Padua), from 2000 to 2011 (Budapest).

2.1.1 Short-term (reference week) analyses of the UHI phenomenon

To facilitate the visualization and comprehension of the collected data for the reference week, we further processed it in terms of mean hourly urban temperature and UHI values for a reference day. These values provide thus an insight into the temporal characteristics of both air temperature and UHI.

**FIG 1. Cumulative frequency distribution of UHI intensity for a one week summer period**
Figure 1 shows the cumulative frequency distribution of UHI values for the participating cities for the aforementioned summer reference week. Figure 2 shows the hourly UHI values for a reference summer day. The reference week data clearly demonstrate the existence and significant magnitude of the UHI effect in participating cities, especially during the night hours (Figure 2). However, the time-dependent UHI patterns vary considerably across the participating cities. The UHI pattern differences are also visible in the cumulative frequency distribution curves of Figure 1. In this Figure, a shift to the right denotes a larger UHI magnitude.

2.1.2 Long-term analyses

Figures 3 and 4 show the (mean annual) urban and rural temperatures respectively over 30 years. Figure 5 shows the long-term UHI intensity trend over the same period. The historical temperature records suggest an upward trend concerning both urban and rural temperatures (see Figures 3 and 4). Consistent with regional and global temperature trends, a steady increase in rural temperatures of up to about 2.5 K can be observed in all selected cities (with the exception of Budapest). In the same 30-years period, the mean annual urban temperature rose somewhere between 1 K (Stuttgart) and 3 K (Warsaw). Note that, while both rural and urban temperatures have been increasing, the value of the UHI intensity has been rather steady. Our data suggest increasing UHI intensity trends in Warsaw and Ljubljana, whereas a slight decrease can be discerned from Stuttgart and Prague data (Figure 5).
Within the aforementioned project, a systematic framework was developed (Mahdavi et al. 2013) to assess – for a specific urban location, hereafter referred to as urban unit of observation (U2O) – the urban heat island phenomenon, to specify potential mitigation and adaptation measures, and to evaluate such measures via adequate modelling approaches. The framework involves the following steps: i) Definition of "Urban Units of Observation" (U2O): These are properly bounded areas within an urban setting selected as the target and beneficiary of candidate UHI mitigation measures; ii) Description of the status quo of U2O in terms of a structured set of geometric and physical properties; iii) Specification of the existing UHI intensity; iv) Specification of the candidate mitigation measures in terms of projected changes to the geometric and/or physical properties captured in step ii above; v) Prediction of the effect of mitigation measures using empirically-based and/or numeric models; vi) Expression of the mitigation measures' impact in term of predicted changes in UHI intensity; vii) Overall evaluation of the mitigation measures' effectiveness on the basis of modelling results together with their estimated financial and logistic ramifications.
In this framework, the notion of U2O is applied to systematically address the local variation of the urban climate throughout a city. A spatial dimension (diameter) of approximately 400 to 1000 m has been targeted for U2O, indicating common features in view of geometry, massing, or other aspects of the physical structure. As the urban microclimate is believed to be influenced by different urban morphologies, structures, and material properties, a set of related variables were identified and included in our framework.

3.1.1 The variables

In order to predict, estimate, and verify the effect of urban heat island mitigation actions on reduction of UHI intensity, we need to express such actions in terms of changes that they introduce in an U2O. Toward this end, a set of variables are suggested (Tables 1 and 2) based on past research (Mahdavi et al. 2013, Kiesel et al. 2013) and our own reasoning.

**Table 1: Variables to capture the geometric properties of an U2O**

<table>
<thead>
<tr>
<th>Geometric properties</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sky View Factor</td>
<td>Fraction of sky hemisphere visible from ground level</td>
</tr>
<tr>
<td>Aspect ratio</td>
<td>Mean height-to-width ratio of street canyons</td>
</tr>
<tr>
<td>Built area fraction</td>
<td>The ratio of building plan area to total ground area</td>
</tr>
<tr>
<td>Unbuilt area fraction</td>
<td>The ratio of unbuilt plan area to total ground area</td>
</tr>
<tr>
<td>Impervious surface fraction</td>
<td>The ratio of unbuilt impervious plan area to total ground area</td>
</tr>
<tr>
<td>Pervious surface fraction</td>
<td>The ratio of unbuilt pervious surface area to total ground area</td>
</tr>
<tr>
<td>Mean building compactness</td>
<td>The ratio of built volume (above terrain) to total building plan area</td>
</tr>
<tr>
<td>Built surface fraction</td>
<td>The ratio of total built surface area to total built area</td>
</tr>
<tr>
<td>Wall surface fraction</td>
<td>The total area of vertical surfaces (walls)</td>
</tr>
<tr>
<td>Roof surface fraction</td>
<td>The total area of horizontal surfaces (roofs)</td>
</tr>
<tr>
<td>Mean sea level</td>
<td>Average height above sea level</td>
</tr>
</tbody>
</table>

**Table 2: Variables to capture the surface and material properties of an U2O**

<table>
<thead>
<tr>
<th>Surface/material properties</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflectance/albedo</td>
<td>Fraction of reflected direct and diffuse shortwave radiation</td>
</tr>
<tr>
<td>Emissivity</td>
<td>Ability of a surface to emit energy by radiation (longwave)</td>
</tr>
<tr>
<td>Thermal conductivity</td>
<td>Property of a material's ability to conduct heat, given separately for impervious and pervious materials</td>
</tr>
<tr>
<td>Specific heat capacity</td>
<td>Amount of heat required to change a body's temperature by a given amount, given separately for impervious and pervious materials</td>
</tr>
<tr>
<td>Density</td>
<td>Mass contained per unit volume, given separately for impervious and pervious materials</td>
</tr>
<tr>
<td>Anthropogenic heat output</td>
<td>Heat flux density from fuel combustion and human activity (traffic, industry, heating and cooling of buildings, etc.)</td>
</tr>
</tbody>
</table>

4. Evaluation of UHI mitigation measures

Once U2Os and their respective variables are defined, potential mitigation measures (see Table 3) may be expressed in terms of respective changes to the variable attributes. For example, introduction of green roofs or green facades in an U2O would modify the variables pertaining to surface albedo, emissivity, thermal conductivity, specific heat capacity, and density. Table 3 provides a concise summary of the most common mitigation measures. These measures can be divided into three main realms of interventions: buildings, pavements, and vegetation. Table 3 also includes a detailed description of expected benefits of such measures.
Table 3: A summary of principal mitigation measures

<table>
<thead>
<tr>
<th>Category</th>
<th>Measure</th>
<th>Expected benefit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td>Cool roofs</td>
<td>High solar reflectance and high thermal emissivity</td>
</tr>
<tr>
<td></td>
<td>Green roofs</td>
<td>Shading and evapotranspiration</td>
</tr>
<tr>
<td></td>
<td>Green facades</td>
<td>Reducing ambient air temperature, shading properties, natural cooling, control airborne pollutants, energy efficiency</td>
</tr>
<tr>
<td></td>
<td>Façade construction and retrofit</td>
<td>Reducing cooling/heating load, reducing ambient air temperature, improving building envelope quality</td>
</tr>
<tr>
<td></td>
<td>Geometry of urban canyon (new projects)</td>
<td>Fresh air advection, cool air transport into the city</td>
</tr>
<tr>
<td>Pavements</td>
<td>Cool pavements</td>
<td>Decreasing ambient air temperature</td>
</tr>
<tr>
<td></td>
<td>Pervious pavements</td>
<td>Storm water management</td>
</tr>
<tr>
<td>Green areas</td>
<td>Planting trees within the urban canyon</td>
<td>Shading and evapotranspiration, lower peak summer air temperatures, reducing air pollution</td>
</tr>
<tr>
<td>Parks, green areas</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Finally the impact of those mitigation measures can be estimated based on appropriate calculation tools and modeling methods. For this purpose we considered two principal approaches: statistical analysis of empirical data and numeric (typically CFD-based) computational models. Correlations between measured urban heat island intensity in different locations within an urban environment and the physical features of these locations can be exploited to derive empirically based estimation methods. For numeric computation, different simulation tools can be applied, ranging from regional climate models to single-building models (Mirzaei 2010). To illustrate the application of the framework, a case study from the aforementioned EU project is presented below. The case study concerns a U2O in the center of Vienna, Austria with a total area of roughly half a square kilometer. Figure 6 shows the existing attributes of the variables for this U2O together with the changes in these variables as a consequence of three envisioned mitigation measures: i) Planting the maximum number of trees that could be reasonably accommodated within; ii) Implementing green roofs according to the “Grundachpotentialkataster”, a document provided by the city of Vienna, which specifies roof areas with proper potential for conversion to green roofs (GREEN ROOF 2014); iii) A combination of measures i and ii. In this case, the estimation of the implications of the mitigation measures was conducted using a numeric simulation application (ENVI-met 2014).

**FIG 6. The existing values of the U2O variables for the Vienna case study together with modified values associated with proposed mitigation measures**

Figure 7 shows the modeling results in terms of predicted reduction of UHI index in the course of a reference summer day. These results point to the considerable potential of tree planting toward the reduction of air temperature in the urban canyon. Green roofs, however, did not display a similar degree of effectiveness with regard to street level temperatures. Note that green roofs did not influence shading circumstances in the urban canyon. Nor did they have, in the present scenario, a noteworthy impact on the radiation exchange between (vertical) built surfaces and sky. Based on our current state
of information, we cannot conclude with certainty, if other positive implications of green roofs (e.g., evapotranspiration) are consistently and sufficiently considered in the computational tool deployed.

\[ \Delta \theta \ [^\circ C] \]

**FIG 7. The modeled mean hourly temperature difference ("Innere Stadt", Vienna)**

5. **Conclusion**

We presented the results of an ongoing EU-supported project concerned with the extent of the UHI phenomena in a number of Central European cities. The objectives of this project are to provide a common understanding of the UHI effects and to conceive and evaluate appropriate mitigation and adaptation measures. Short-term and long-term data with regard to urban and rural temperatures demonstrate the existence and significant magnitude of the UHI effect in a number of Central European cities. Furthermore observations based on hourly data display distinguished patterns implying larger UHI intensities during the night hours. To address the need for effective means of evaluating and mitigating UHI effects, a systematic framework was developed and tested within the collaborative context of an EU project. Thereby, a number of geometric (morphological) and semantic (material-related) variables of the urban environment were identified that are hypothesized to influence UHI and the urban microclimate variance. The deployment of this framework and a CFD-based urban climate modeling tool was exemplified using the case of an urban unit of observation in the city of Vienna. Ongoing work further explores and statistically analyses the link between UHI intensity and salient urban variables such as urban density and morphology, block layout, canyon geometry, surface properties, vegetation, bodies of water industrial sites, transportation systems and infrastructures. This work is expected to not only provide empirical data for the validation of numeric models, but also to support the formulation of simplified approaches toward estimation of mitigation measures effectiveness in view of UHI phenomena.

6. **Acknowledgements**

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References


Wind Driven Rain and Climate Change: A Simple Approach for the Impact Assessment and Uncertainty Analysis

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KEYWORDS: Wind Driven Rain, Impact Analysis, Climate Change, Climate Scenarios, Uncertainty Analysis

SUMMARY:
By increasing signs of climate change, growing knowledge about it and the availability of climate data, performing the impact assessment of climate change is becoming more feasible in different fields of science and engineering. However making practical conclusions out of the impact assessment is not easy since there are many climate scenarios for future. This introduces uncertainties in the impact analysis which should be considered. According to different climate scenarios Sweden faces warmer and moister climate. Rain shows strong signals of climate change; more rain in future and stronger and more often extreme raining events, which can increase the risks for buildings and the built environment.

This paper makes a preliminary impact assessment of climate change for wind-driven rain (WDR) on buildings. A simple method from ASHRAE is used to calculate the amount of rain deposition on wall, using the hourly values of rain and wind data from 6 climate scenarios during 1961-2100. Results show that the amount of rain deposition will increase in future, however there are considerable differences in results induced by climate uncertainties. Further research and numerical simulations of WDR is needed to evaluate the preliminary results.

1. Introduction
According to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2007), which is also confirmed by the Fifth Assessment Report (AR5), climate changes induces increase in climate variability and extreme events. Most of the future climate scenarios point to more frequent and extreme rain events in different parts of Europe which make buildings and the built environment more vulnerable. Signs of extreme climatic conditions and the corresponding high levels of precipitation have already appeared in Europe. For example during 2012 heavy rains in southern areas of Sweden caused flooding, many people were affected and buildings needed to be pumped dry (DN.se, 2012; Guibourg, 2012). Impacts of climate change on buildings in Sweden can often be associated with increased moisture stress. More intense precipitation events in future, changes in the timing of seasonal precipitation, rainfall, and the length of time surfaces are wet can result in increased and/or accelerated deterioration of the built environment (Moonen et al., 2012). Not preparing for these future changes increases risks, costs and the severity of damages, which can badly influence living conditions and economy of the country. Sustainability of the built environment depends on its adaptation to future climate. Adaption measures can reduce the risks of climate extremes and disasters, regardless of the degree of certainty around future changes (Field et al., 2012).

Wind-driven rain (WDR) is known as a damaging moisture source; out of all the exterior hygrothermal environmental loads which directly influence the moisture transport, WDR is the main reason for
critical damage to the building performance. WDR affects the hygrothermal performance and durability of building façades enormously. Rainwater is also an agent for most of the physicochemical deterioration processes (Moonen et al., 2012) (Blocken and Carmeliet, 2004). In future climate scenarios, precipitation shows the strongest signals of climate change along with temperature for future climate. Unlike precipitation wind has weak signals of climate change, therefore this study focuses on the rain precipitation in future. To estimate the importance of climate change on the hygrothermal performance of buildings in Sweden and to make the buildings resilient enough it is necessary to perform the impact analysis of climate change for WDR on buildings.

This paper presents a preliminary study about the impacts of climate change for WDR on buildings by using a simple method to calculate the amount of rain striking a vertical surface (ASHRAE, 2009). The main intention is to estimate how much situation for buildings can vary in future by estimating the amount of rain deposition on vertical wall surface. Moreover importance of three climate uncertainties - global climate models (GCMs), initial conditions and spatial resolution - in WDR calculations is considered. An earlier work of the authors looked into WDR and climate change by calculating the Stokes number for the driven rain (Nik et al., 2013). The approach in the present paper differs by using an empirical method which focuses more on characteristics of the wall surface than the driven rain. This study has been performed for the city of Gothenburg in Sweden during the period of 1961-2100.

2. Climate Data

Several climate models and scenarios exist. On a global scale, global climate models (GCMs) are used. GCMs consist of individual model components which describe the atmosphere and the ocean. They also describe the atmosphere-ocean interactions as well as interactions with the land surface, snow and sea ice and some aspects of the biosphere (Persson et al., 2007). Regional climate models (RCMs) are used to downscale results from GCMs dynamically, to achieve a higher spatial resolution over a specific region. The climate data used in this work are mainly results from the RCA3 regional climate model by the Rossby Centre which is the climate modelling unit of the Swedish Meteorological Hydrological Institute (SMHI).

Using the numerically simulated climate data in the building models introduces different uncertainties to the simulations. In this paper three climate uncertainties are considered. The first one concerns the changes in the large-scale circulation determined by the GCM. The second factor relates to the initial conditions which were assumed when running the climate models. The third uncertainty is the spatial resolutions of RCMs, since they can downscale data with different spatial resolutions.

2.1 Global Climate Models

RCA3 has been downscaling three different GCMs to 50km horizontal resolution. The GCMs are: 1) ECHAM5, 2) CNRM and 3) IPSL (for details see (Kjellström et al., 2011)). Different GCMs result in different climate conditions. Based on the previous research the uncertainties induced by GCMs are the most important ones in the hygrothermal simulation of buildings (Nik, 2012).

2.2 Initial Conditions

Climate simulations with global climate models for the 20th and 21st centuries generally start with preindustrial conditions. However the initial conditions are not fully known. Initial conditions are needed for the full three-dimensional fields in the atmosphere and oceans. Also starting conditions for the soil models and sea-ice models are needed. In addition to this there is a need to prescribe the physiography (orography, type of soils, vegetation cover, etc) (Nik, 2010). In this paper three simulations of a climate model (RCA3-ECHAM5-A1B) with three different initial conditions are compared. The evolution of time in these three simulations differs as the initial conditions are not the same. These differences are present throughout the simulations, i.e. both in the 20th and the 21st century.
2.3 Spatial Resolutions

RCMs downscale data from GCMs in different spatial resolutions, down to 5km. Data from two spatial resolutions of RCA3, 50km×50km and 25km×25km, are used in this work. RCA3 is set up so that a 50km grid is covered exactly by four grids in the finer-scale 25km integrations. Considering the availability of very fine spatial resolutions, it is important to investigate the uncertainty induced by different spatial resolutions.

3. Wind-Driven Rain

WDR is known as a potentially damaging moisture source. It especially affects the hygrothermal performance and durability of building façades. Out of all the exterior hygrothermal environmental loads which directly influence the moisture transport, WDR causes more than 90% of critical damage to the building performance (Karagiozis et al., 2003). Consequences of its destructive properties can take many forms. It enhances the dry and wet deposition of pollutants, façade surface soiling and facade erosion. The water layer on the façade can increase collection of pollutants. Rainwater is also an agent for most of the physicochemical deterioration processes, frost damage, moisture-induced salt migration, discoulouration by efflorescence, and structural cracking due to thermal and moisture gradients (Blocken and Carmeliet, 2004; Moonen et al., 2012). More than that, WDR is one of the most important boundary conditions for HAM (heat-air-moisture) simulations of buildings (Blocken et al., 2007).

4. Methodology

For analysing WDR on buildings usually comprehensive models are used. In this work a simple model is used to estimate changes in WDR on buildings (ASHRAE, 2009). In this model the amount of rain striking a vertical surface is calculated using the following equation:

\[ r_{bv} = F_E \cdot F_D \cdot F_L \cdot U \cdot \cos \theta \cdot r_h \]  

Where

- \( F_E \) rain exposure factor [-]
- \( F_D \) rain deposition factor [-]
- \( F_L \) empirical constant, 0.2 [kg.s/m\(^3\)/mm]
- \( U \) hourly average wind speed at 10 m [m/s]
- \( \theta \) angle between wind direction and normal to the wall [deg]
- \( r_h \) rainfall intensity, horizontal surface [mm/h]
- \( r_{bv} \) rain deposition on vertical wall [kg/m\(^2\)/h]

In this work the considered wall is facing west. \( F_E \) is influenced by the surrounding topography of the building and height of the building which is equal to 1.2 in this work, for a medium exposure and the building height between 10 m and 20 m. It is assumed that the wall is subject to rain runoff and therefore \( F_D = 1 \).

By programming in Matlab, the amount of rain deposition on the vertical wall was calculated for 6 climate scenarios in Gothenburg for the period of 1961-2100. Only the west-east component of the wind velocity, \( \pm U_0 \), is considered to simplify the calculations. The west-east component of wind is stronger than the south-north component in Gothenburg. Probable future conditions for WDR and differences induced by the climate scenarios are studied by looking into the distribution of the rain deposition, \( r_{bv} \), during time. For simpler comparison of data sets, the square weighted moving average of the annual mean values is plotted. The dotted line in FIG 1 shows the annual average of precipitation while the black solid line shows the weighted average. The solid line shows the trend of changes with sufficient resolution. Divergence exists in the beginning of the period which occurs due
to the lack of data before 1960 in the calculation of lagging average. However since the focus of the paper is more on the future changes, this divergence can be neglected.

FIG 1. Annual mean precipitation and its square weighted moving average in Gothenburg during 1961-2100. Climate data are from RCA3, downscaling three GCMs with the same emissions scenarios and initial conditions (A1B-3) with the spatial resolution of 50km.

5. Results

As it was mentioned earlier strong signals of climate change are only visible in the rain data and not the wind.

FIG 2 shows the gradual increase in the amount of rain by time, while no considerable changes in the wind velocity are predicted. However climate uncertainties, different GCMs in this case, can affect both the rain and the wind data. Differences are more obvious for rain; although all scenarios point to more precipitation in future there can be differences up to 40% in the annual average of the rain intensity. Differences between scenarios for the WE wind velocity do not follow the same pattern as rain; RCA3-CNRM and RCA3-IPSL show less difference for wind velocity unlike the rain data.

FIG 2. Square weighted moving average graphs for the annual mean value of (left) the rain intensity and (right) the absolute WE wind velocity in Gothenburg. Climate data are from RCA3, downscaling three GCMs with the same emissions scenarios and initial conditions (A1B-3) with the spatial resolution of 50km.

According to relation (1) the amount of rain deposition on vertical wall, \( r_{bp} \), has linear correlation with both the rain intensity and wind velocity. As the distribution of \( r_{bp} \) shows in FIG 3, the amount of rain deposition can increase depending on the climate scenario, which RCA3-IPSL shows the maximum increase by time. There is no considerable change in the amount of deposition for RCA3-
CNRM, however sharp changes happen more often after 2050. A previous work showed that the trend of changes for the Stokes numbers in WDR are mostly affected by the wind data, but differences between scenarios are more influenced by the rain data (Nik et al., 2013). One conclusion was that it might be possible to use one wind scenario for WDR calculations and assess the differences induced by climate scenarios only by looking into the rain data. For the calculated $r_{pv}$ in the present paper, differences between scenarios are still more affected by the rain data, however changes of $r_{pv}$ by time can get equally influenced by wind and rain. Although still there are not considerable changes in the wind data by time, but to avoid underestimating the climate uncertainties in WDR calculations, it might better to use different wind scenarios with large differences. The true assessment of the climate uncertainties and the importance of wind/rain data is available when WDR calculations are performed by numerical simulations.

**FIG 3.** Square weighted moving average graphs for the annual mean value of the rain deposition on vertical wall [kg/m2/h] in Gothenburg. Climate data are from RCA3, downscaling three GCMs with the same emissions scenarios and initial conditions (A1B-3) with the spatial resolution of 50km.

Uncertainties in calculating the rain deposition induced by different initial conditions and spatial resolutions are visualized in figures 4 and 5. Increment of $r_{pv}$ is obvious in FIG 4, specifically for A1B-1 & -2 scenarios. It is interesting to see that using scenarios with different initial conditions can result in considerable differences in calculating WDR. Differences between scenarios are both in the amplitude and the phase of distributions. The patterns of variations are very similar in FIG 5 which compares two scenarios with different spatial resolutions. There is almost no phase shift between the two scenarios since the climate models and the assumptions are unique and the only difference is in RCM downscaling with two different spatial resolutions.

We can get a better image about the influence of climate uncertainties in estimating the amount of rain deposition on a vertical wall by checking FIG 6. It shows the maximum difference due to the climate uncertainties in calculations, for 20-year mean values. For example the GCM graph is the absolute difference between RCA3-CNRM and RCA3-IPSL. Different GCMs can result in differences more than 20%, which cannot be negligible in WDR calculations. For initial conditions the uncertainty decreases to around 15%, which is still high. Difference between the two spatial resolutions of 25km and 50km are less than 7%. These results are in agreement with a previous research which looked into the climate uncertainties in hygrothermal simulation of buildings (Nik, 2012) and calculation of Stokes number (Nik et al., 2013).
FIG 4. Square weighted moving average graphs for the annual mean value of the rain deposition on vertical wall [kg/m$^2$/h] in Gothenburg. Climate data are from RCA3-ECHAM5-A1B with three different initial conditions and the spatial resolution of 50km.

FIG 5. Square weighted moving average graphs for the annual mean value of the rain deposition on vertical wall [kg/m$^2$/h] in Gothenburg. Climate data are from RCA3-ECHAM5-A1B-3 with two spatial resolutions of 25km and 50km.
6. Conclusions

The probable effects of climate change on WDR were considered using a simple method to estimate the amount of rain deposition on a vertical wall. The simple method helps to investigate impacts of climate change on WDR and the importance of climate uncertainties before performing the WDR and CFD calculations. Results were in agreement with a previous research which was done by calculating the Stokes number. However this study is still in the preliminary phase and there is a need to perform numerical simulation of WDR.

Based on the results, the most important factor is the selected GCM. Spatial resolution had the least effect on calculations however further research with finer spatial resolutions should be performed. The importance of climate uncertainties in the wind data and its effects on WDR calculation should be investigated more thoroughly in future. It might be possible to use one reference wind data while different rain data sets are used to consider the climate uncertainties. This will help to decrease the calculation time considerably, especially when the CFD models are used to calculate the wind flow around buildings. However in this work the importance of the wind data and its uncertainties was larger than the case of calculating the Stokes number.

References


Towards efficient numerical modelling of hygrothermal transfers using Proper Generalised Decomposition

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2LOCIE, CNRS UMR 5271, Université de Savoie, Chambéry, France
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KEYWORDS: Model Order Reduction, HAM transfers, Proper Generalised Decomposition

ABSTRACT: This paper proposes a reduced order model to simulate two-dimensional heat and moisture behaviour of material based on Proper Generalised Decomposition (PGD). This innovative method is an a priori method. It proposes an alternative way for computing solutions of the problem by considering a separated representation (for instance time and space) of the solution. PGD allows considerable reduction of numerical cost. In this paper, the PGD solution is first compared with a finite-volume element solution in a 1D-case and then it is applied on a 2 dimensional case.

1 Introduction

Building can be affected by damage due to action of moisture, such as mould growth, corrosion or reduction of thermal resistance of the insulation layers. The development of damage depends on hygrothermal fields in material. To address these issues of durability, detailed modelling exist for precise assessment of hygrothermal transfers in materials. Many 2- or 3-dimensional (2D-3D) heat and moisture (HAM) models are available in literature to assess material behaviour and durability issues (Woloszyn and Rode, 2008). They are used to determine the precise hygrothermal behaviour of complex multi-layered material assemblies. They enable us to take into account different moisture or heat sources. Their integration into whole building simulation tools is an interesting issue to assess durability of building, especially in case of retrofitting. Even if some examples can be found in literature (see for example (Steeman et al., 2009)), this integration is a complex task (Berger et al., 2013b). Such whole integrated building model has a high computational cost.

Thus, innovative and efficient ways of numerical simulation are worth investigation. Reduction techniques seems to be interesting alternatives. This paper proposes a reduced order model to simulate 2D heat and moisture behaviour of material based on Proper Generalised Decomposition (PGD). After a brief state-of-the-art of model reduction techniques, PGD strategy is detailed. Then results of the PGD reduced order model is compared to a finite volume resolution on a 1-dimensional case. In final part, possibility of use PGD on a 2-dimensional test case is investigated.
2 State of the art

For modelling purpose, heat and moisture transfers in layers are generally solved with finite volume or finite elements techniques (in 1, 2 or 3 dimensions). A mesh of M nodes is considered and for transient problems, M values must be computed at each time step. Moreover for non-linear problems, it becomes computationally more expensive when M increases. Reduction techniques aim to approach this kind of highly-dimensional problem with a low-dimensional model. A short review of model reduction methods for non linear models was done in (Berger et al., 2013a). Other details on model reduction methods are given in (Palomo Del Barrio, 2011).

Two families of methods exist. One called \textit{a posteriori}, needs an already-computed or experimental solution to build the reduced order model. Two beneficial approaches belong to this first technique. Firstly, the reduced order model is created with simulations of the large original model on a short time interval. Then the reduced order model is used for simulation on a longer time interval. The second approach is to create the reduced order model with the large original model on a large time interval. Then the reduced order model is used for problems on similar time intervals but with different boundary conditions or material properties.

Such an \textit{a posteriori} method was tested on heat and mass problems in (Berger et al., 2013b). The method gave an interesting reduced order model with a good accuracy. Nevertheless, this kind of methods has important disadvantages. To build the reduced order model, preliminary results, i.e. \textit{snapshots}, of large original model are needed. This requirement is time consuming. In addition, the reduced order model generally works in similar conditions to the ones used to produce the results of the large original models. This point is an important restriction.

The second family of reduction techniques is \textit{a priori} methods. These techniques do not need preliminary informations on the studied problem. The basis of projection is not known \textit{ab initio} and is built by an iterative process or by resolving Lyapunov’s equation. Due to this substantial advantages, this type of method was chosen for the present study. Our works were based on \textit{Proper Generalised Decomposition} (PGD). Many works on PGD done by CHINESTA et all. can be found in literature (Du-mon et al., 2011), (Aghighi et al.), (Chinesta et al., 2011). This method offers an interesting numerical resolution of the problem and is detailed in next section.

3 Methodology

3.1 Heat and moisture transfers in materials

This part presents the hypothesis and equations of heat and mass transfers in building materials considered for PGD resolution in next section. It is assumed that materials are filled with a liquid phase composed of liquid water, and a gaseous phase, considered as a mixture of dry air and water vapour. The mass balance of water depends on moisture flow of the vapour phase \(v\) and of the liquid phase \(l\). The conservation equation of moisture transfer can be expressed as :

\[
\frac{\partial w}{\partial t} = -\nabla \cdot (g_v + g_l) \quad (1)
\]

\(g_v\) is the mass flux of vapour and \(g_l\) is the mass flux of liquid water. Assuming, that air pressure is constant inside the material, the temporal variations of moisture content \(w\) can de expressed in function of vapour pressure :

\[
\frac{\partial w}{\partial t} = \frac{\partial w}{\partial P} \frac{\partial P}{\partial t} + \frac{\partial w}{\partial T} \frac{\partial T}{\partial t} \quad (2)
\]
Temperature variation of moisture content is neglected and $\xi = \frac{9w}{\Theta T}$ describes the moisture storage. Therefore mass conservation in material (1) can be written as:

$$\xi \frac{\partial P}{\partial t} = \nabla (\delta_v + K_l \frac{\rho_l R_c T}{P}) \cdot \nabla P$$ (3)

with $K_l(w)$ liquid permeability and $\delta_v(u)$ the vapour permeability of the material.

The energy balance equation is expressed in function of conductive and convective flux:

$$\frac{\partial E}{\partial t} = -\nabla \cdot (q_{cond} + q_{conv})$$ (4)

where $E$ is the internal energy. Air pressure is assumed as constant. $\{c_a, c_l, c_v\} \ll L_v$ so only latent flux is considered for the study and others flux are neglected. Therefore, energy balance equation is:

$$\rho_0 c \cdot \frac{\partial T}{\partial t} = \nabla \cdot (\Lambda \nabla T + L_v \delta_v \nabla P)$$ (5)

with $c = c(w) = c(P) = c_0 + \frac{\rho_l}{\rho_v} * c_l$, where subscripts 0 and l indicates respectively properties of dry material and water and $\Lambda(w)$ is the thermal conductivity, dependant with moisture. Eventually heat and moisture transport in $\Omega$ can be expressed as the following equation:

$$\begin{bmatrix} \rho_0 c & 0 \\ 0 & \xi \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial T}{\partial t} \\ \frac{\partial P}{\partial t} \end{bmatrix} = \nabla \cdot \begin{bmatrix} \Lambda & L_v \delta_v \\ 0 & \delta_v + K_l \frac{\rho_l R_c T}{P} \end{bmatrix} \nabla \cdot \begin{bmatrix} T \\ P \end{bmatrix}$$ (6)

The problem is a system of two non-linear partial coupled differential equations with temperature $T$ and vapour pressure $P$ as driving potentials.

### 3.2 Proper Generalised Decomposition

A problem is considered in a space of dimension $d$ for the unknown field $u(x_1, x_2, \ldots, x_d)$. $x_i$ can be a spatial coordinate, related to time or a problem parameter such as boundary or initial conditions, source term or material property. The solution is search for $(x_1, x_2, \ldots, x_d) \in \Omega_1 \times \Omega_2 \times \cdots \times \Omega_d$.

With the PGD method, the approximate solution is given by a separated representation:

$$u(x_1, x_2, \ldots, x_d) = \sum_{m=1}^{M} F_m^1(x_1) \otimes F_m^2(x_2) \otimes \cdots \otimes F_m^d(x_d)$$ (7)

The solution is a sum of $M$ functional products involving $d$ separated functions $F_m^i(x_i)$ that are unknown $a$ priori. Functions are built by successive iterative enrichment. At a particular enrichment step $n$, the functions $F_m^i(x_i)$ are known for $i \leq n - 1$ with the previous steps. Unknown functions $F_m^i(x_i)$ are computed using the equations of the considered problems.

The number of terms $M$ required to approximate the solution depends on studied problem but might be between 10 to 100 in building physics application.

In present work, coupled heat and moisture transfers in porous materials, described by equation (6), are considered. For $(x, t) \in \Omega \times \Gamma$, $T(x, t)$ and $P(x, t)$ are search as solutions of the following equation:

$$\begin{bmatrix} c_{11}(T, P) & 0 \\ 0 & c_{22}(T, P) \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial T}{\partial t} \\ \frac{\partial P}{\partial t} \end{bmatrix} = \nabla \cdot \begin{bmatrix} d_{11}(T, P) & d_{12}(T, P) \\ d_{21}(T, P) & d_{22}(T, P) \end{bmatrix} \nabla \cdot \begin{bmatrix} T \\ P \end{bmatrix}$$ (8)
### TAB 1: Wood frame hygrothermal properties

<table>
<thead>
<tr>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sorption curve ( m ) ( [kg/m^3] )</td>
<td>( m = 17.07, \ c = 8.076, \ k = 0.9699 )</td>
</tr>
<tr>
<td>( w = m \cdot \frac{P_m}{P_{sat}} \cdot \frac{1}{\sqrt{1 - k \cdot \frac{P_m}{P_{sat}}}} )</td>
<td></td>
</tr>
<tr>
<td>Liquid permeability ( K_0 ) ( [s] )</td>
<td>( K_0 = 1.17 \cdot 10^{16}, \ a_1 = 0.2449, \ b_1 = 1.339, \ a_2 = -0.2441, \ b_2 = -93.79 )</td>
</tr>
<tr>
<td>Vapour permeability ( D_v ) ( [kg/m/s/Pa] )</td>
<td>( D_v = 2.6 \cdot 10^5 )</td>
</tr>
<tr>
<td>Thermal conductivity ( \lambda_0 ) ( [W/m/K] )</td>
<td>( \lambda_0 = 0.107, \ b = 0.4747 \cdot 10^{-3} )</td>
</tr>
<tr>
<td>Heat storage ( \rho_0 \cdot c_0 ) ( [J/m^3/K] )</td>
<td>( \rho_0 \cdot c_0 = 1551 \cdot 589 )</td>
</tr>
</tbody>
</table>

with coefficient for material properties corresponding to equation (6). Initial conditions are taken into account and Dirichlet or Neumann boundary conditions are associated to the problem. Noting \( \Theta(x, t) \) as the solution, such problems can be expressed with operator \( \mathcal{A} \):

\[
\mathcal{A}(\Theta) = 0 \tag{9}
\]

\( N_x \) and \( N_t \) are assumed to be, respectively, spatial and time discretisation. Operator \( \mathcal{A} \), is discretised by a tensorial product \( A^k_x \) and \( A^k_t \), in space and time directions:

\[
\mathcal{A} = \sum_{k=1}^{N_A} A^k_x \otimes A^k_t \tag{10}
\]

Operator size \( A^k_x \) is \( N_x \times N_x \) and \( A^k_t \) is \( N_t \times N_t \). The PGD solution of this problem is sought in the form:

\[
\Theta(x, t) = \sum_{m=1}^{M} F^m(x) \otimes G^m(t) \tag{11}
\]

with \( (F^i, G^l)_{1 \leq i, l \leq m} \) the modes of PGD basis.

### 4 Proper Generalised Decomposition application on a 1D problem

#### 4.1 Case study

To validate the resolution of heat and moisture transfers in material with PGD, a 1D case study, \( x \in [0; d = 0.08m] \), is chosen. The material is wood fiberboard with hygrothermal properties given in table 1. The initial and Dirichlet boundary conditions for temperature \( T \) and relative humidity \( RH \) are:

\[
T(x, t = 0) = 23^\circ C , \ T(x = 0, t \leq 0) = 23^\circ C , \ T(x = d, t \leq 0) = 15^\circ C \\
RH(x, t = 0) = 0.4 , \ RH(x = 0, t \leq 0) = 0.4 , \ RH(x = d, t \leq 0) = 0.9 
\tag{12}
\]

The problem is solved by PGD and results are compared with a finite volume resolution. Details of the finite volume model are given in (Berger et al., 2013a). It was validated on Hamstad benchmarks. The problem is solved for a time period of 24 hours and a constant time step of 36 seconds. The layer is divided in 81 nodes with a constant spatial discretisation of 1 mm.
4.2 Results

The PGD solution is calculated with 60 modes. Different profiles of temperature and vapour pressure are compared at different moments in figure 2. In addition, the time evolution of temperature and vapour pressure for different nodes is given in figure 1. To compare both resolution of the problem, the maximum relative difference between both model is calculated and plotted in figure 3 according to the number of modes of PGD solution.

FIG 1: Time evolution of temperature and vapour pressure at different nodes for PGD solution (continuous line) and finite volume solution (+ points)

FIG 2: Profiles of temperature and vapour pressure at 1h, 2h and 24h for PGD solution (continuous line) and volume element solution (+ points)

FIG 3: Maximum relative difference between both model for temperature and pressure in function of modes

4.3 Discussion

One can see that there is perfect accuracy of the PGD solution in figures 1 and 2. Absolute differences between the finite-volume model and PGD solution is less than $10^{-4}$ for temperature and pressure. PGD solution of the problem succeeds in representing temperature and vapour pressure inside material. The dynamic and amplitude of the hygrothermal field are well represented.

The choice of number of modes $M$ for the separated representation is a relevant question. A number of 60 modes was chosen to compute the PGD solution in this test case. As shown in figure
3, the relative difference between the finite-volume solution and the PGD solution is less than 0.1% for a number of 40 modes. For the next simulations, a number of 40 modes was assumed sufficient to reach a good accuracy.

The separated representation of the PGD solution enables to have a low computational cost. With PGD techniques, two linear differential equations for $x$ and $t$ has to be solved. The cost of such PGD resolution is lower than solving equation 6 with finite-volume techniques. This point becomes more interesting when problem complexity increases. PGD solution offers interesting outlooks for modelling heat and mass transfers in 2- or 3-dimensional problems.

5 2D heat and mass problem

Results presented in previous section illustrate the possibilities with PGD techniques to solve heat and moisture problems with a good accuracy. The interest of the separated representation is illustrated for solving complex 2D problems. A plate-type decomposition is adopted to compute temperature and vapour pressure (Chinesta et al., 2011):

$$T(x, y, t) = \sum_{i=1}^{N} F_T^i(x, y) \cdot G_T^i(t) \quad \text{and} \quad P(x, y, t) = \sum_{i=1}^{N} F_P^i(x, y) \cdot G_P^i(t)$$  \hspace{1cm} (13)

5.1 Test case

The test case represents composition of an old building walls, associating timber pine filled with mortar. In the context of building retrofitting, this wall assembly should be insulated. Modelling tests with different types of insulations could be performed to assess durability of this type of improved wall assembly. One could be interested in studying the impact of a high or low hygroscopic insulation. In present work, such assembly was modelled with PGD techniques with two different types of insulate: PSE and wood fibre (figure 4. The issue is to study the impact of both insulate on moisture content in wall assembly.

Variations of properties as a function of water content and temperature are taken into account. Material hygrothermal properties were taken from (Kumaran, 1996). Sides ($\forall x, y = 0$) and ($\forall x, y = 0.9m$) are considered as adiabatic. Conditions for the outside and inside faces are given in figure 4 with corresponding surface transfer coefficients given in table 2. Simulation was done for 20 days with a time step of 360 s and a spatial discretisation $d x = d y = 0.02$ m.

<table>
<thead>
<tr>
<th>Inside</th>
<th>Outside</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heat surface transfer coefficient $[W/m^2K]$</td>
<td>8</td>
</tr>
<tr>
<td>Vapour surface transfer coefficient $[s/m]$</td>
<td>$1 \cdot 10^{-7}$</td>
</tr>
</tbody>
</table>
5.2 Results

The solution is calculated using $M = 40$ modes. In figure 5, hygrothermal fields are plotted for modelling considering wood fibre insulation. Figure 6 gives the total moisture content for mortar and wood for both wall assemblies. Figure 7 gives heat and vapour flux exiting insulation for both modelling.

![FIG 5: hygrothermal fields for the wood-fibre wall assembly at $t = 20$ days](image)

![FIG 6: Total moisture content in mortar (left) and wood (right) for both modelling](image)

![FIG 7: Heat and vapour flux exiting insulate for both modelling](image)

5.3 Discussion

One can notice that PGD technique enables us to calculate precise hygrothermal fields in 2D wall assembly as mentioned for wood fibre as example on figure 5. Hygrothermal fields are correctly modelled in 2-dimensions. These hygrothermal results can be used for post-processing. The issue is to analyse which assembly is more efficient for insulating the old wall. As shown in figure 6, the total moisture content in wood and mortar is higher for the wall assembly with wood fibre, for these boundary conditions. Actually, wood fibre is more vapour-permeable than PSE. Dry vapour permeability considered is $8 \cdot 10^{-13}$ kg/(m.s.Pa) for PSE and $9 \cdot 10^{-6}$ kg/(m.s.Pa) for wood fibre. Therefore, for the wall assembly with wood fibre, moisture penetrates from both inside and outside borders. On the other hand, for the PSE wall assembly, moisture only penetrates from outside border. This results can also be seen in figure 7. Vapour flux is really smaller for wall assembly with PSE. In addition, figure 7 shows that heat flux is more important for the wall assembly considering wood fibre. This is due to the effect of vapour flux and to the higher dry thermal conductivity of wood fibre (0.042 W/(m.K) opposed to 0.0251 W/(m.K) for PSE).

With these considerations, one can see that the PSE wall assembly is more efficient for insula-
tion of the wall for these boundary conditions. To go further, the important point is that the PGD resolution enables us to model hygrothermal fields and to observe similar physical aspects as classic resolution (detailed finite-element or -volume resolution etc.). The interesting point is that PGD resolution has a lower computational cost due to the plate-type decomposition. The 2-dimensional problem is replaced by solving 2 differential equation for \((x, y)\) and \(t\). A brief comparison was done with a 2D finite volume resolution and computational gain was divided by 6 (with a AMD Phenom II, processor 2.99 GHz, 3.5 GO RAM). Gain might be increased by parallel computing.

6 Conclusion

This paper proposed a Proper Generalised Decomposition for solving heat and moisture transfers in materials. This technique is based on a space-time separated representation of solution. Comparing PGD solution with finite volume solution, the relative error is less than 0.1 %: This resolution strategy was illustrated on a 2-dimensional test case. PGD is efficient for addressing models defined in high-dimensional spaces with a low computational cost. Future works will concern integration of 2-dimensional PGD model into whole building simulation.

7 Acknowledgements

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References


Road-map for future thermal insulation products and applications

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KEYWORDS: Building envelope, thermal insulation, road map, future materials, energy efficiency

SUMMARY:
The European energy efficiency policy sets challenging objectives both for new buildings and for retrofitting. The thermal performance of the building envelope is one significant part of the energy efficiency of the future buildings. There is ongoing strong development of new insulation materials and also the properties and application systems of conventional insulation are improved.

This paper presents a road-map for research and technology development (RTD) priorities future thermal insulation materials, products and holistic solutions. The objective was to identify and verify the RTD topics and product development priorities and to identify current, emerging and promising technologies and materials that can support the development towards energy and resource efficient targets. The study was focused on Finnish market perspective, being applicable to Northern climate in general.

The study included state-of-the-art, analysis of key performance indicators of thermal insulation products, a patent search, interviews of building sector professionals and analysis forms a survey of the technology development in this field. The interviews revealed the expectations, barriers, trends and hypes that are related to the energy efficient building envelope applications. This paper presents the methodologies and part of the findings of the project.

1. Introduction

Challenges with climate change impacts and natural resources constraints has set multiple energy efficiency targets.

The EU aims to improve energy efficiency by 20% by 20201(from 1990 levels); however, the European Commission estimates that only half of the target can be achieved if new specific measures are not implemented. To attain the objectives of a maximum temperature rise of 2°C by 2050, a reduction of GHG emissions of 80-95% by 2050 will be necessary. Residential and commercial buildings are responsible for about 40% of the EU’s total final energy consumption and 33% of CO2 emissions. Being the largest consumer of energy and the largest CO2 emitter, addressing the building sector is crucial for meeting the ambitious energy and climate objectives.

To achieve these targets requires an integrated approach including the deployment of energy-efficient technologies as well as the engagement of influential stakeholders on the market.

supply and demand for those technologies. A well-insulated building envelope is recognized as key for high energy-efficient performance of buildings (IEA 2013).

Energy efficient and passive structures, in cold climates, typically use high volumes of thermal insulation leading to thick building envelopes. This causes architectural technical challenges, like the placement of windows, and also valuable building space is lost. New improved thermal insulation products and integrated envelope solutions are now emerging in the market. Developments in materials science, for different fields and industries, bring more suitable solutions for use in the construction in order to better manage the building envelope heat flows.

These new solutions are at different development stages from research to commercialization. Along this path their suitability for the building envelopes needs to be analysed against key performance indicators and current legislation (WBCSD 2009). The presented roadmap was created to answer the needs on how building envelope insulation materials and products, at different development stages are positioned in this framework and how changes in the built environment affect existing products and create new emerging ones. This paper presents the highlights of the roadmap. The full report can be found in Ojanen et al. (2014).

The study focused on thermal insulation materials and thermal performance solutions of the building envelope in cold climates. Out of the scope were the technical systems (HVAC), hygrothermal performance of structures and cost-efficiency issues.

Although many promising insulation materials and products solutions are emerging in the market there are many technical and socio-economic barriers to overcome before market upscale and mass production. The main drivers are the building directives and regulations, and the main barriers come often from non-technological issues. Together with the regulations, the market needs and expectations affect the demand for insulation products and envelope systems, performance and technical features. The combination of energy efficiency regulations and the challenge of the renovation of the old Finnish building stock raises demands for adaptable and integrated pre-fabricated products.

2. Roadmap methodology

2.1 State of the art

The state of the art of thermal insulation solutions for building envelopes were analysed through their technical performance and current market environment. The study was done gathering qualitative information through literature surveys on innovation science publications as well as on patents database, product information and statistics and regulatory publications. In addition previous relevant roadmaps were reviewed as the E2BA multiannual roadmap (E2BA 2013); the SET plan materials roadmap (EU 2011) and national ones as the built environment (Airaksinen, M. et. al., 2011). These formed the baseline for the development of roadmap and future recommendations.

2.2 Interviews and workshop

The drivers, barriers and trends were studied through focused interviews and stakeholders feedback in an active workshop discussion. These were analysed and processed through the following steps:
1. Categorization of the main thermal insulation materials, products and systems
2. Identification of solutions that are in different stages of research or already commercialized
3. Evaluation criteria and performance indicators
4. Analysis of demand, potential usage scenarios
5. Description main innovation trends through analysis of main market players patents
6. Stakeholders interviews
7. Roadmaps for short, medium and long-terms
8. Recommendations
Altogether 23 building sector experts from construction industry, insulation material producers, architects, R&D, authorities and industrial associations were interviewed. A workshop for 30 participants was focussed on the most important gaps pointed by stakeholders during the interviews. Four discussion groups were set up based on the dimensions: People, business, processes and technology.

Figure 1 shows the method used in the workshop.

![Method used in the workshop](image)

**FIG 1. A schematic presentation of the method used in the workshop.**

### 2.3 Materials and products analysis

The insulation materials and products were mapped into 3 key segment areas. The definition of these areas was based on market establishment of the main products as conventional versus emerging products. In addition a segment was created to analyse the trend for integrated special products and systems as not just only “thermal insulation solutions for building envelope” but also “energy efficient solutions for proactive envelopes”. These areas are described in figure 2.

### 2.4 Key performance indicators

The CE-marking requires some basic performance indicators for the thermal insulation product. In addition, different performance indicators have to be known and for comparison of the products and their suitability for different building envelope applications. The main indicators are: Thermal conductivity, dimensions and dimensional stability, squareness, tensile strength, fire properties. In addition also properties like sound absorption, air permeability, health issues, sensitivity to moisture, technical lifetime expectancy, embodied energy, and those linked to buildability and recycling are important factors that have to be taken into account. The weight of each performance property depends on the application.
3. Roadmap for future thermal insulation products

Based on the gaps between the state-of-art and the visions, determine by experts and stakeholders the roadmaps were built separately for the industry processes, products and systems, regulations and for the research and development aspects. These form the overall roadmap for the energy efficiency development of the buildings.

The thermal performance of the building envelope couldn’t be separated from the whole building performance and the building couldn’t be separated from the building process. Therefore the result of the roadmapping process is not only an answer for the thermal insulation development or the development of the building as a whole, but it tended to open up the whole building sector. The segments developed in the roadmap were Markets and people, Regulations, Building services, Building products and Research. For this paper only some parts of the results are presented. Figure 3 shows the roadmap summary for the building envelope with target in nearly zero energy buildings and Figure 4 the roadmap for the building products segment.

When developing new thermal insulation materials, or any materials for the building envelope, the performance of the whole system must be taken into account as presented in Figure 5. A new material, even how good technical performance properties it has, is not yet a ready solution for the market. Suitable products have to be developed. If the products do not fit into the existing building systems, a new system has to be developed. Only after that the integration into the building can be done effectively.

This process requires both technical development and improved know-how in production process, design, installation, total performance analysis, etc. The existing products have relatively high level systems already. The new products have to adopted in the building system so that their technical benefits can be utilised in the best way.
FIG 3. Roadmap summary for the building envelope of nZeB

Industry – Building products

FIG 4. Roadmap segment for the building products.
Table 1 presents the summary of recommendation for different stakeholders. The recommendation are aimed to promote for the actions required for the target visions of the future building envelope development. The focus areas are is in the process and application of regulations in practice and also in the information of people in order to have trust and demand for quality of the building. High quality is essential in the nearly zero energy building applications.

4. Discussion and conclusions

The legislation and directives regarding sustainability, in general and energy efficiency in particular are becoming more tight. This is seen as a driver for the insulation products because it increases the market demand. However at the same time many stakeholders indicate it as a barrier because it slows down the business, creates challenges to the processes and creates barriers to the development and market take-up of new products.

The promising potential of new insulations solutions as aerogels, VIPs, bio-based materials and nano-based technologies, is seen as quite important for many of the R&D experts (Jelle 2011, Flynn & Sirén 2012). The industry does recognize these as promising solutions but does not see these as a threat in the near future. This is because the traditional products are well established and the construction industry is a slow adapter of new solutions. The building process is seen as one of the biggest barriers for the adaptation of new solutions.
<table>
<thead>
<tr>
<th>Effect on:</th>
<th>People, Markets</th>
<th>Regulations</th>
<th>Technology</th>
<th>Services</th>
<th>Products</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>People</strong></td>
<td>Quality requirements, demand for safe performance</td>
<td>True info on performance aspects</td>
<td>Supporting systems, possible to choose suitable materials, localized aspect, transparency of reasons for reg.</td>
<td>Show-cases</td>
<td>Adaptable solutions, New products, comparable tech. info, educate sales people</td>
</tr>
<tr>
<td><strong>Research</strong></td>
<td>Impact analysis</td>
<td>Tech.transport and development of new materials, products, applications</td>
<td>Guidelines prepared in good time, update fire regulations, district level</td>
<td>Integration of the building process, Hi-tech industry using pre-fabs</td>
<td>Integrated solutions and smart technologies</td>
</tr>
<tr>
<td><strong>Regulations</strong></td>
<td>Demand</td>
<td>Concept development, safe moisture performance processes</td>
<td>Requirement for quality certificate for buildings, building process and final performance responsibilities</td>
<td>Pre-fabrication concepts, coordination throughout the process, performance of the buildings</td>
<td>Form chain of companies Invest in skilful people, renovation solutions, support for pioneers</td>
</tr>
<tr>
<td><strong>Services</strong></td>
<td>Demand</td>
<td>Performance studies, material and product development</td>
<td>Information, guidelines, localized aspect, embodied energy in CE marking</td>
<td>Performance property matrix</td>
<td>Requirements for building components</td>
</tr>
<tr>
<td><strong>Products</strong></td>
<td>Demand</td>
<td>Research result support system for decision making</td>
<td></td>
<td></td>
<td>Eco efficient, new materials</td>
</tr>
</tbody>
</table>

Promote positive thinking on the performance of buildings and Energy Efficiency, in combination with the correct choice of materials. Good concepts have been developed and significant research has been done. There is now a need to consolidate and invest on more public dissemination and awareness.

The impact of a good insulation cannot be separated from the total performance of the buildings energy performance or building physics. A holistic approach should be taken together with the use of materials. Material efficiency should be taken into account together with other measures as ventilation and automation and energy management systems. It is not only about reducing CO2 emissions or improving energy efficiency.
The forerunner companies and pilot studies should be promoted and supported in order to enhance the release of the good practices and the demand for them. The realization of the new approaches requires investing in education of professionals to design and apply the new systems in practice.

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References


