Investigation of the resiliency of passive and natural cooling solutions through uncertainty analysis in a NZEB residential building in Denmark.

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Abstract
The current research of resilient cooling technologies mainly focuses on the thermal comfort and energy use reduction aspects. The existing studies evaluating the resiliency of passive and natural cooling technologies consider only a limited number of associated uncertainties, which results in significant knowledge gaps. This study analyses the resiliency of PCM, shading and natural ventilation in a Danish NZEB family house, through uncertainty analysis. The considered uncertainties include the performance of the technologies, future climate and occupational time. By comparing the technologies' robustness and indoor overheating degree, it was discovered that the application of automated natural ventilation proved to be the most resilient technology, when compared to PCM and automated external shading. The proposed workflow to assess the resiliency of the passive and natural cooling technologies makes it possible to consider the most important uncertainties associated with the performance of these technologies.

Key Innovations
This research paper documents several contributions made to the area of resilient cooling assessment. The proposed workflow to assess the resiliency of the passive and natural cooling technologies includes:

• validation of the thermal model
• local sensitivity analysis to determine the most significant technology-related input parameters
• uncertainty analysis to quantify the robustness of the passive and natural cooling technologies.

The following variables were considered in the uncertainty analysis:

• increasing occupant loads: considering the number of occupants and their schedule
• predicted and extremely warm weather data
• technology related uncertainties

Practical Implications
The currently available, ready-to-use software where it is possible to conduct uncertainty analysis are limited in the possible input variables and output KPI. This creates the need to develop dedicated computational solutions to appropriately assess the resiliency of passive and natural cooling technologies. This limits the possibility for such investigation to the research community, which might hamper the proliferation of the resilient cooling technologies.

Introduction
Resilient cooling
Overheating becomes an increasing problem in Danish low-energy houses, especially during summer periods. The phenomenon is driven by multiple factors, including climate change, oversimplified design processes, tight energy codes and more electrical equipment introduced in the living spaces. Excessive heating affects health, wellbeing, and productivity of the occupants. It can lead to lowered performance of the building systems, increased maintenance costs and alarming CO₂ emissions (Hamdy, et al., 2017). Therefore, introduction of resilient cooling solutions becomes inevitable. In Annex 80 of the EBC programme (2019) resilient cooling is defined as a low energy and low carbon method, which strengthens the ability to withstand and prevent thermal impacts including increased outside temperatures, increased severity and frequency of extreme events, changed internal loads and occupancy profiles, while at the same time preventing changes to the global and local climates. The primary aim of a resilient technology is to reduce external heat gains, improve personal comfort, remove sensible heat and control latent heat, without creating additional emissions from a building.

When considering resilient cooling technologies, most of the researchers focus on the thermal comfort and energy-related aspects. Sakka et al. (2012) studied the indoor temperatures occurring in several residential buildings in Athens during summer heat waves. He suggested that passive cooling techniques could improve the indoor environmental conditions. Psomas (2017) investigated the indoor environment in renovated dwellings and found that automated window openings and external shading systems are effective in reducing the overheating risk in colder temperate climates. Zhang et al. (2010) studied the indoor thermal comfort conditions in naturally ventilated buildings in China. Guo et al. (2019) investigated the performance of night ventilation and determined the most influential design parameters. Santamouris et al. (2013) collected research results regarding ground cooling, evaporative cooling and night ventilation and reports substantial energy saving possibilities compared to traditional air-conditioned buildings. Oropeza-Perez and Østergaard (2018) reviewed the operation, energy needs, economic and technical feasibility of passive cooling
methods in dwellings and determined the most suitable methods for Mexico. Campaniço et al. (2019) analysed the impact of climate change on the performance of direct ventilation, and found that even considering climate change this method will considerably reduce the cooling demand in the Iberian Peninsula.

Parys et al. (2012) analysed the performance of several resilient cooling technologies, also considering the uncertainties in the inputs. This way he was able to determine the robustness of the passive cooling technologies. Hamdy et al. (2017) assessed the risk of overheating in Dutch dwellings, considering 9216 combinations of design and operation options, and developed a methodology to evaluate the impact of climate change. Although this research considered predicted weather data and varying heat gains, it examined only two cooling technologies and occupant profiles.

The authors of this document aim to provide a workflow to analyse the resiliency of cooling technologies that makes it possible to consider the most influential uncertainties. The proposed workflow is demonstrated analysing three passive and natural cooling technologies: PCM panels, automated natural ventilation and automated external shading.

The article begins with the description of the examined building and definition of resiliency based on IEA EBC Annex 80. A detailed description of the analyses conducted is given in the methods section explaining the chosen key performance indicators and the calculation procedures behind local sensitivity analysis and uncertainty analysis. Next, the results of these investigations are provided, separately for each of the technology and in combined cases. The last section of this research document includes the discussion on the outcomes and proposals for further design development.

Case building

The examined building is a single-level family house located in Ry (Denmark), completed in 2017. The house is part of an EUDP project, which aims at creating a new housing generation that would fulfil the 2020 requirements, and solve problems associated with standard requirements for nearly zero energy buildings. The structure is made of heavyweight construction with concrete-brick external walls and concrete partition walls.

The building envelope was designed according to the maximum allowed heat requirement stated for building class 2020 (3.7 W/m² heat loss through the external surfaces for one-story building). The case house is presented in Figure 1.

Methods

Investigation workflow

The investigation started with the qualitative analysis of the natural and passive cooling technologies. In the next step, validation of the thermal model and determination of the most influential technology-related parameters using local sensitivity analysis was performed. The investigation started with the validation of the thermal model and determination of the most influential technology-related parameters by conducting a local sensitivity analysis. Then, an uncertainty analysis (UA) was performed, to determine the robustness of the examined passive and natural cooling technologies. The uncertainty of the following parameters was considered: occupancy time, extremely warm weather, and technology-related uncertainties. The original thermal model was created using EnergyPlus 8.9 in the DesignBuilder 6.1.3 interface. The sampling of the uncertain parameters was performed with SimLab 2.2.1. The input definition files used in the uncertainty analysis were created applying a Python script using the Eppy library. To post-process the UA results, a Python script was used. In this research paper only natural and passive solutions were examined, as those are the most sustainable. Additionally, the technologies were not meant to cause any significant change to the building's core design and be applicable in the Danish climate. Based on that criteria, the chosen cooling solutions were delimited to phase change materials (PCM), automated external shading and natural ventilation.

Cooling technologies - qualitative analysis

For a technology to be examined in this research paper, the following criteria had to be met:

- The solution had to comply with the definition of resiliency provided in Annex 80 of the EBC programme.
- To be able to validate the thermal model of the case building using the available measured data, no significant change to the core building design shall be caused by the technology.
- The cooling solution must be applicable in a residential building located in the Danish climate.
- Abstract solutions, which are not in accordance with the Danish building practice shall not be considered.

Based on the above criteria, the chosen technologies were PCM, shading and natural ventilation.

It is important to mention that since the PCM technology was applied to a building with a high thermal mass, this is expected to lower its impact. To assess the full potential of this technology, it would be recommended to analyse it in a building with lower thermal mass – however, in this case this was not possible because measured data (and
thus the possibility to validate the thermal model was available only for the examined case building.

**Model Validation**

The base thermal model of the examined building was originally created as part of an Aalborg University project (Loukou, et al., 2019) using the DesignBuilder 6.1.3 interface of the EnergyPlus 8.9 calculation engine (see Figure 2).

![Figure 2: Case-house zone division.](image)

This model was validated for electricity and heating use only and therefore the model’s thermal performance still had to be verified. This was accomplished using measured indoor environment, system and weather data. During the validation, the authors followed the approach of Strachan et. al. (2016) which aimed at eliminating the occupant effect as much as possible. Therefore, the focus was on the two weeks long period between 10/07/2018 and 24/07/2018 when the occupants were on holidays. The achieved Spearman’s correlation coefficients were 0.89 and 0.91 for the examined thermal zones, with the average absolute operative temperature difference of 0.62 and 0.68 K. These values were found appropriate according to the literature (Strachan, et al., 2016), therefore, the thermal model of the building was deemed to be suitable for the analysis of passive and natural cooling technologies.

**Local sensitivity analysis**

During the uncertainty analysis, the uncertainty of the following inputs was considered: the length of the occupancy, the weather, and the uncertainty in the performance of the cooling technologies. In order to limit the computation time, only the most influential parameter of each technology was selected. To determine which parameter of the examined cooling techniques is the most significant, a local sensitivity analysis was conducted. For each technology, a separate investigation was performed. In the local sensitivity analysis, the method of Spitz (2012) was adopted. In this method the distance of the sensitivity index is determined for each examined parameter, where the higher value indicates greater influence. The distance of sensitivity index is determined as in Equation (1).

\[ S_{i,d} = \sqrt{S_{i,m}^2 + S_{i,std}^2} \]  

(1)

where:

- \( S_{i,m} \) : mean of the sensitivity index
- \( S_{i,std} \) : standard deviation of the sensitivity index

The sensitivity index in Equation (1) is calculated in the following way - see Equation (2).

\[ S_i(t) = X_i \cdot \frac{\partial y(t)}{\partial X_i} \]  

(2)

where:

- \( S_i \): sensitivity index, -
- \( X_i \): nominal value of input “i”
- \( \partial X_i \): a small perturbation of the input “i”
- \( \partial y(t) \): change in the output as a result of the change in the input (compared to the baseline output)

To determine the sensitivity index, the indoor operative temperature was used as an output. In order to analyse the effect of changing inputs during the summer season only, the distance of the sensitivity index was calculated considering only the operative temperatures that are higher than 25 °C.

The change that was applied to each input – as in Equation (2) - was determined the following way: an uncertainty range was applied to each input parameter, based on a literature review, and the change was the difference between the highest value, that was possible based on the uncertainty range and the baseline value (i.e. the mean value of the uncertainty range).

The inputs considered in the local sensitivity analysis of each technology are summarized in Tables 1-3.

**Table 1: PCM properties considered during the local sensitivity analysis of the PCM technology.**

<table>
<thead>
<tr>
<th>Inputs and their baseline value</th>
<th>Uncertainty range</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conductivity, 0.2 W/mK</td>
<td>+/- 10%</td>
<td>(Delgado, et al., 2014)</td>
</tr>
<tr>
<td>Thickness, 15 mm</td>
<td>+/- 10%</td>
<td>(Delgado, et al., 2012)</td>
</tr>
<tr>
<td>Specific heat capacity, 1970 J/kg/K</td>
<td>+/- 5%</td>
<td>(Rudtsch, 2002)</td>
</tr>
<tr>
<td>Density, 1000 kg/m3</td>
<td>+/- 2%</td>
<td>(Mazo, et al., 2015)</td>
</tr>
<tr>
<td>Melting point, 23 °C</td>
<td>+/- 1 K</td>
<td>(Mazo, et al., 2015)</td>
</tr>
<tr>
<td>Specific phase change enthalpy, 201.9 kJ/kg</td>
<td>+/- 10%</td>
<td>(Günther, et al., 2009)</td>
</tr>
</tbody>
</table>
Proceedings of the 17th IBPSA Conference
Bruges, Belgium, Sept. 1-3, 2021
https://doi.org/10.26868/25222708.2021.30372

Table 2: Technology-related inputs considered during the local sensitivity analysis of the natural ventilation technology.

<table>
<thead>
<tr>
<th>Inputs and their baseline value</th>
<th>Uncertainty range</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inside air temperature setpoint, 25 °C</td>
<td>+/- 0.5 K</td>
<td>(Parys, et al., 2012)</td>
</tr>
<tr>
<td>Percentage of time during the day when the main external door is open, 10%</td>
<td>+/- 10%</td>
<td>(Marr, et al., 2012)</td>
</tr>
<tr>
<td>Window discharge coefficient, 0.675</td>
<td>+/- 9%</td>
<td>(Park, et al., 2007)</td>
</tr>
</tbody>
</table>

Table 3: Technology-related inputs considered when applying external shading.

<table>
<thead>
<tr>
<th>Inputs and their baseline value</th>
<th>Uncertainty range</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shading control setpoint, 25 °C</td>
<td>+/- 0.5 K</td>
<td>(Parys, et al., 2012)</td>
</tr>
<tr>
<td>Shading slat width, 4.5 cm</td>
<td>+/-0.04%</td>
<td>(Takebayashi &amp; Kyogoku, 2017)</td>
</tr>
<tr>
<td>Slat separation, 3.96 cm</td>
<td>+/-0.05%</td>
<td>(Lee, et al., 1998)</td>
</tr>
<tr>
<td>Slat thickness, 0.4 cm</td>
<td>+/-0.5%</td>
<td>(Lee, et al., 1998)</td>
</tr>
<tr>
<td>Slat distance from glass, 10 cm</td>
<td>+/-0.2%</td>
<td>(Lee, et al., 1998)</td>
</tr>
</tbody>
</table>

Uncertainty analysis

Uncertainty analysis was used to determine the robustness of the analysed cooling technologies. Separate UA was conducted for each technology and the case where the cooling technologies were applied together. The original thermal model was created using EnergyPlus 8.9 in the DesignBuilder 6.1.3 interface. During the uncertainty analysis, the sampling of the parameters was performed using SimLab 2.2.1. The sample size was ten times the number of inputs considered for an UA. The input definition files used in the uncertainty analysis were created applying a Python script using the Eppy library. To post-process the UA results, a Python script was used. In this section, first the inputs considered in the UA and their corresponding probability distributions are described, followed by the KPIs used in the analysis.

In the uncertainty analysis, the uncertainty of the following inputs was considered:

- The most significant technology-related parameters (see the “Local sensitivity analysis” section and Table 4). This was based on which technology was applied at the specific uncertainty analysis.
- Weather data
- The length of the occupancy

To consider the uncertainty in the weather, two weather data sets were developed using Meteonorm version 7.3.3 software: extremely warm P10 weather data sets were assigned 10% probability, while typical weather data sets were considered with 90% probability.

The uncertainty in the length of the occupancy was based on statistical data. The study conducted by Keiding (2003) shows the number of hours spent indoors in Denmark during weekdays (see Figure 3). The weekend occupancy time was based on the research of Knudsen et al (2010).

Figure 3: Distribution of the number of hours spent indoors during weekdays by an average Danish citizen.

During an uncertainty analysis, the application of correct probability density functions is a crucial step. These are summarized for the technology-related uncertain parameters in Table 4.

Table 4: Technology-related inputs and their probability distributions considered during the uncertainty analyses.

<table>
<thead>
<tr>
<th>Inputs and their mean value</th>
<th>Probability distribution</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCM melting point, 23 °C</td>
<td>Normal distribution, mean=23 °C, standard deviation: 0.5 K</td>
<td>(Parys, et al., 2012)</td>
</tr>
<tr>
<td>Natural ventilation and shading control setpoint, 25 °C</td>
<td>Normal distribution, mean=25 °C, standard deviation: 0.25 K</td>
<td>(Parys, et al., 2012)</td>
</tr>
</tbody>
</table>

The assumptions regarding the probability distributions in Table 4 are based on the uncertainty ranges of the variables and were determined using the approach by Parys (2012)

Since this study examines the resiliency of cooling technologies, it was important to select a KPI that shows the degree of overheating in the building. Based on a literature review, the indoor overheating degree (IOD) was chosen, as this reflects both the severity and frequency of the overheating (Hamdy, et al., 2017), see Equation (3).

\[ IOD = \frac{\sum_{i=1}^{Z} \sum_{l,z=1}^{N_{occ}(z)} \left( T_{fr,i,z} - T_{comf,i,z} \right) \cdot t_{i,z}}{\sum_{i=1}^{Z} \sum_{l,z=1}^{N_{occ}(z)} t_{i,z}} \]  

where:

- \( Z \): building zone counter
- \( i \): occupied hour counter
- \( t \): time step
- \( Z \): the total number of zones in a building,
- \( N_{occ}(z) \): total occupied hours in a given calculation period
- \( T_{fr,i,z} \): free running indoor operative temperature at the time step \( i \) in the zone \( z \)
- \( T_{comf,i,z} \): the comfort temperature limits at the time step \( i \) in the zone \( z \).
The comfort temperature limits were based on comfort category II and the adaptive comfort model given in DS/EN 15251 (European Committee for Standardization [CEN], 2007).

Following the method from Parys (2012), to determine the robustness of the examined passive and natural cooling technologies, uncertainty analyses and corresponding deterministic analyses were conducted, and the IOD results were compared. In the deterministic simulations, the mean input values were used (see Table 4) – in case of the weather, the typical weather data, while for occupancy length, 16 hours were considered as a mean case. To quantify the robustness, the probability, that the deterministic analysis results are achieved based on the uncertainty analysis was determined. This was achieved calculating the percentile rank of the deterministic IOD result compared to the IOD results of the uncertainty analysis - see Equation (4). If the deterministic IOD falls between two values, linear interpolation was used to determine the percentile rank.

\[
\text{Percentile rank} = \frac{N_{IOD,UA}}{T_{IOD,UA} + 1} \times 100
\]  

(4)

where:

- \(N_{IOD,UA}\): number of uncertainty analysis IOD results smaller than the deterministic IOD result
- \(T_{IOD,UA}\): total number of UA results

This research paper presents three distinct robustness analyses, considering the following uncertainties:

1. technology, weather (extremely warm weather) and the occupant schedule
2. climate change (predicted weather data)
3. increased number of occupants

To determine the robustness of the cooling technologies against climate change, the previously described uncertainty analyses were conducted also using predicted weather data for the year of 2060 and 2100. These datasets represent typical years around this period (Remund, et al., 2019). Meteonorm version 7.3.3 was used to generate the predicted weather data sets, based on the A1B scenario of the 4th IPCC report. The robustness against climate change was then determined the following way: the baseline deterministic analysis results of the case considering present weather data were compared to the UA results considering predicted weather data as described in Equation (4).

A similar approach was followed to determine the robustness against increased occupant loads. In this case, separate uncertainty analysis was conducted considering 2 and 5 occupants. According to statistical data, 2 occupants are the most common in Danish detached houses (39.8%), while the cases with more than 5 occupants are rare (<1.7%). When assuming two occupants, only the living room and the master bedroom was considered as an occupied space, the IOD was not calculated for the other zones. However, for the simulations with five occupants, also the remaining three bedrooms were taken as occupied spaces. For the robustness against the occupant loads calculation, 2 cases were used. In the 2-people case, the examined rooms included the master bedroom and the living room. For the 5-people case the above-mentioned rooms were examined together with the remaining three bedrooms.

The robustness against increased occupant loads was then determined the following way: the baseline deterministic analysis results of the 2-person case were compared to the UA results considering 5 occupants – see Equation (4). This calculation was performed for the results of the three considered weather data sets, then the average value was considered as the technology’s robustness against increased occupant loads.

To determine the resiliency of an examined cooling technology, both the robustness and the IOD results were considered.

**Results**

**Local sensitivity analysis**

During the local sensitivity analysis, the most influential parameters for each of the technology were determined, using the distance of sensitivity index for the examined inputs. The results are presented on Figures 4-6.

The analysis indicated the most significant factors for each of the cooling technologies that were later considered in the uncertainty analysis. For PCM the most influential input was the melting point. Both for the external shading and the natural ventilation, the temperature set point controlling these technologies appeared to be the most significant.

![Figure 4: Results of the local sensitivity analysis for the PCM technology.](https://doi.org/10.26868/25222708.2021.30372)

![Figure 5: Results of the local sensitivity analysis when applying external shading.](https://doi.org/10.26868/25222708.2021.30372)
It might be surprising to see Brotas and Nicol (2015) and García et al. 2019 on this topic. The increased occupant time, extremely warm climates, and occupant comfort result in lower IOD values of natural ventilation scenarios compared to those with automated natural ventilation.

The PCM technology shows low robustness against climate change of increased occupant time, warm years, and technology-related uncertainties, when compared to the robustness against climate change or increased number of occupants.

The PCM technology shows low robustness against climate change of increased occupant time, warm years, and technology-related uncertainties. The external shading clearly outperforms the other examined technologies considering its robustness against climate change, and the same is true for the automated natural ventilation in case of increased occupant load.

Since the model combining all three cooling technologies did not result in any indoor overheating degrees, its robustness based on Equation (4) would be 100%, and thus significantly outperforms the application of individual technologies.

**Discussion**

Overheating is an increasing problem in the Danish residential building sector. In this study, resilience and robustness of PCM panels, automated external shading, and automated natural ventilation were applied to a NZEB building in Denmark. The building was investigated using uncertainty analysis, the case house was examined against technology-related uncertainties, climate change and occupational loads based on the adaptive comfort model criteria from DS/EN 15251. The KPIs used in the analysis were IOD and robustness.

Based on the indoor overheating degree calculations, it can be concluded that the natural ventilation provides the best comfort (least IOD). Considering the low IOD results using predicted climate data to simulate the performance of natural ventilation, it might be surprising to see low robustness against climate change (Figure 7). The reason for this outcome is a very good baseline (present weather data) IOD value, compared to which even a slight rise of overheating - when applying predicted weather data - causes a decrease in robustness - see Equation (4).

The IOD results summarized in Table 5. show some interesting trends. In case of natural ventilation and shading, higher IOD results were simulated using 2060 predicted weather data, compared to 2100 weather data. These phenomena could be caused by the behaviour of the applied adaptive temperature model. To give an example, even though in one of the simulation cases the operative temperature was 0.1 K higher on average based on 2100 weather data, the IOD resulted in lower values, since the upper limit temperature of the adaptive comfort criteria was on average 1.3 K higher when compared to the case using 2060 weather data. Results with a similar pattern were reported by Brotas and Nicol (2015) and Sánchez-Garcia et al. (2018).

**Table 5. Outcomes of the uncertainty analyses: highest and average IOD.** When applying the three analysed technologies parallelly, no overheating was simulated in any cases.

<table>
<thead>
<tr>
<th>Applied technology</th>
<th>Weather data set</th>
<th>Present weather data</th>
<th>Predicted weather data for 2060</th>
<th>Predicted weather data for 2100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of occupants</td>
<td>2</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>PCM</td>
<td>Maximum IOD</td>
<td>18.8</td>
<td>231.9</td>
<td>22.9</td>
</tr>
<tr>
<td></td>
<td>Average IOD</td>
<td>1.8</td>
<td>32.9</td>
<td>6.1</td>
</tr>
<tr>
<td>External automated shading</td>
<td>Maximum IOD</td>
<td>3.2</td>
<td>47.1</td>
<td>17.0</td>
</tr>
<tr>
<td></td>
<td>Average IOD</td>
<td>0.6</td>
<td>5.7</td>
<td>2.5</td>
</tr>
<tr>
<td>Automated natural</td>
<td>Maximum IOD</td>
<td>0.0</td>
<td>0.0</td>
<td>11.8</td>
</tr>
<tr>
<td>ventilation</td>
<td>Average IOD</td>
<td>0.0</td>
<td>0.0</td>
<td>1.4</td>
</tr>
</tbody>
</table>
Conclusion

The results of the resiliency investigation are summarized below:

- Considering the robustness of the examined technologies, the automated natural ventilation and automated shading outperforms the PCM panels (Figure 7).
- The robustness results of the external shading and natural ventilation were on a same level, however, the latter surpassed the shading in terms of IOD results, thus proved to be the most resilient out of the examined three technologies.
- Modeling the combination of the three cooling technologies resulted in no overheating in any of the analysed cases, therefore this approach shows the highest resiliency.

For the future investigation regarding resilient cooling technologies, the following directions could prove valuable:

- Investigation of not only the thermal comfort KPI-s but also indicators that consider other aspects of sustainability (energy, carbon, etc.).
- Reviewing of other kinds of passive and natural cooling technologies.
- Investigation of residential buildings with different layout (e.g. multi-storey) or buildings with functions other than residential.
- The robustness against uncertainties related to occupancy time, extreme weather and technologies were investigated together in this report. However, these uncertainties could be examined separately, with separate uncertainty analyses, this way providing clearer results regarding the behaviour of the examined technologies.
- In this work, when considering the rise in occupant loads, only the sensible and latent loads from the persons were considered. Adding to this the potential rise in other internal loads (lighting, equipment) may result in more precise outcomes.
- Considering additional uncertainties in the performance of the technologies, especially in the calculated natural ventilation rates would be an interesting future research direction.

Acknowledgements

The research paper is based on the master thesis work written in collaboration with the lecturers from Aalborg University, Per Kvols Heiselberg and Chen Zhang, to whom we would like to express our gratitude and thankfulness for their guidance and for constructive criticism.

Furthermore, we would like to thank Anais Machard for providing us with detailed information on future weather data analysis and for introducing us to new tools, which gave us a better overview of the future climate changes.

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