Applied Energy 116 (2014) 311–321

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

The effect of weather forecast uncertainty on a predictive control concept for building systems operation

Steffen Petersen [a,b,*], Katrine Wieck Bundgaard [b]

[a] Aarhus University, Department of Engineering, Dalgas Avenue 2, DK-8000 Aarhus, Denmark
[b] Alectia A/S, Skanderborgvej 190, DK-8000 Aarhus, Denmark

HIGHLIGHTS

- Effects of weather forecast uncertainty on a predictive control concept is investigated.
- Two different years in a temperate climate are simulated for 24 building scenarios.
- Energy savings demonstrated despite of weather forecast uncertainties.
- Thermal indoor environment improved despite of weather forecast uncertainties.

ARTICLE INFO

Article history:
Received 30 May 2013
Received in revised form 29 October 2013
Accepted 23 November 2013
Available online 20 December 2013

Keywords:
Model-based control
Predictive control
Building systems operation
Energy savings
Building simulation
Weather forecast uncertainty

ABSTRACT

This paper investigates the effects of weather forecast uncertainty on the performance of a concept for predictive control of building systems operation. The concept uses a computational physically-based building model and weather forecasts to predict future heating or cooling requirement. This information enables the building systems to respond proactively to keep the operational temperature within the thermal comfort range with the minimum use of energy. The effect of weather forecast uncertainty was assessed using weather data from two different years in a temperate climate in the simulation of 24 building design scenarios. Despite the uncertainty in the weather forecasts, the predictive control concept demonstrated a potential for energy savings and/or improvements in thermal indoor environment when compared to a conventional rule-based control.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

The recast of the European Performance of Buildings Directive (EPBD) in 2010 states that all new buildings constructed after 2020 should consume "near zero energy" for building operation [1]. Furthermore, it is expected that the demand for better comfort in buildings will continue to increase as it has within the last few decades. This leads to an increasing pressure on the building industry to produce low-energy buildings with a high quality of indoor climate. In this relation, the reduction of energy for heating, ventilation and air conditioning (HVAC) is essential as HVAC currently accounts for approximately half of the energy consumed in buildings corresponding to around 10–20% of the total energy consumption in developed countries [2]. Minimising the energy use for HVAC is a combination of (1) reducing the overall energy needed for building operation using non-energy-consuming means such as building orientation and geometry, insulation, thermal mass and solar shading, (2) designing energy-efficient HVAC plants and routings, and (3) optimizing building systems operation. In the latter case, the current research efforts evolve around the concept of predictive control. The basic idea of predictive control for building systems operation is to use a virtual model of the building and weather forecasts to predict the future evolution of the indoor climate. This information is used to compute control actions which anticipate this evolution by fulfilling indoor climate requirements while minimising utility and energy costs.

There are a number of different approaches to predictive control for building systems operation. The approaches can in general be divided into the use of statistically derived models ("black-box") [3–5], physically-based models ("white-box") [6–8]and combinations hereof ("grey-boxes") [9,10]. However, no matter the modelling technique, the performance of predictive control depends on the accuracy of the weather forecasts, modelled system dynamics and predictions of occupant behaviour. This paper aims at

* Corresponding author at: Aarhus University, Department of Engineering, Dalgas Avenue 2, DK-8000 Aarhus, Denmark. Tel.: +45 41893347; fax: +45 41893001.
E-mail address: stp@iha.dk (S. Petersen).

0306-2619/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.apenergy.2013.11.060

investigating the effect of weather forecast uncertainty in a predictive control concept for building systems operation.

1.1. Literature review

Existing predictive control concepts for building systems operation have shown a theoretical potential for energy savings and improved indoor climate compared to more conventional systems operation. Wittchen et al. [11] identified a theoretical annual energy saving of 5% and thermal indoor climate improvements in a Danish office building by using predictive control. A test case for a predictive control concept developed by Petersen and Svendsen [12] shows a theoretical energy saving of 7% for heating and ventilation while improving the quality of the thermal indoor environment. In the more comprehensive OptiControl project [13], a theoretical energy saving potential of 16% to 41% was identified varying with location, building case, and technical system characteristics [14]. How much of an identified theoretical potential that can be achieved depends on the effect of uncertainty in weather forecasts, predictions about user behaviour and precision in the thermal modelling. The rest of this literature review focuses on the effect of uncertainty in weather forecasts in predictive control concepts for building systems operation.

Henze et al. [15] investigate a number of short-term weather prediction models and test the effect of their uncertainty on the performance of a predictive control concept. The conclusion is that almost the full theoretical potential in the concept is realised despite the uncertainty in the weather predictions. Furthermore, it is highlighted that this can be obtained using very simple short-term weather prediction models. Oldewurtel et al. [16] report on the development and analysis of a stochastic model predictive control (SMPC) strategy for building climate control that takes into account the uncertainty due to the use of weather predictions. The findings suggest that this control strategy outperforms current control practice both in terms of energy usage and comfort violations. It was also shown that SMPC performed clearly better using a complex weather prediction model compared to simple models. The fact that the performance of SMPC depends on the quality of the weather prediction is in contrast to the previously described findings of Henze et al. [15]. There are, however, various reasons that make the two studies incomparable, e.g. different climates, the chosen concept and/or different investigated buildings. Lamoudi et al. [17] use a modification of one of the simple forecast models from Henze et al. [15] in their predictive controller. The result is a maximum increase of 4% in energy invoice due to weather forecast uncertainty.

There are also a number of studies where the effects of weather forecast uncertainty are not investigated directly, but are indirectly represented in the identified savings. An example is Siroky et al. [18] who investigate the heating savings potential of a model predictive control concept with weather forecasts in three different building blocks. The saving for heating was between 15% and 28% compared to a heating curve strategy depending on mainly insulation level and outside temperature. Another example where weather forecast uncertainty is indirectly represented in the savings is in Henze et al. [19] where a saving of 27% in electrical utility costs is identified.

From the literature it can be learned that it is not always clear how significant the effect of uncertainty in weather forecasts is compared to the theoretical potential of predictive control. The effect seems to depend much on the chosen predictive control concept, climatic region and test cases.

1.2. Aim and outline of the paper

The aim of this paper is to investigate how significant the effect of uncertainty in weather forecasts is when a certain deterministic predictive control concept is compared to the performance of a conventional rule-based control and the theoretical potential (i.e. perfect weather forecast). Section 2 explains the investigated concept. Section 3 presents the data and the process used in the investigation. Section 4 presents and discusses the simulation results, and Section 5 gives conclusions.

2. A predictive control concept for building systems operation

The predictive control concept used in this investigation is as described in details in Petersen and Svendsen [12] and summarised in the following. The concept was initially developed for temperate climates, i.e. climates where free cooling is plentiful compared to solar gains. The concept is deterministic, i.e. it determines control decisions under the assumption that weather forecasts are perfect.

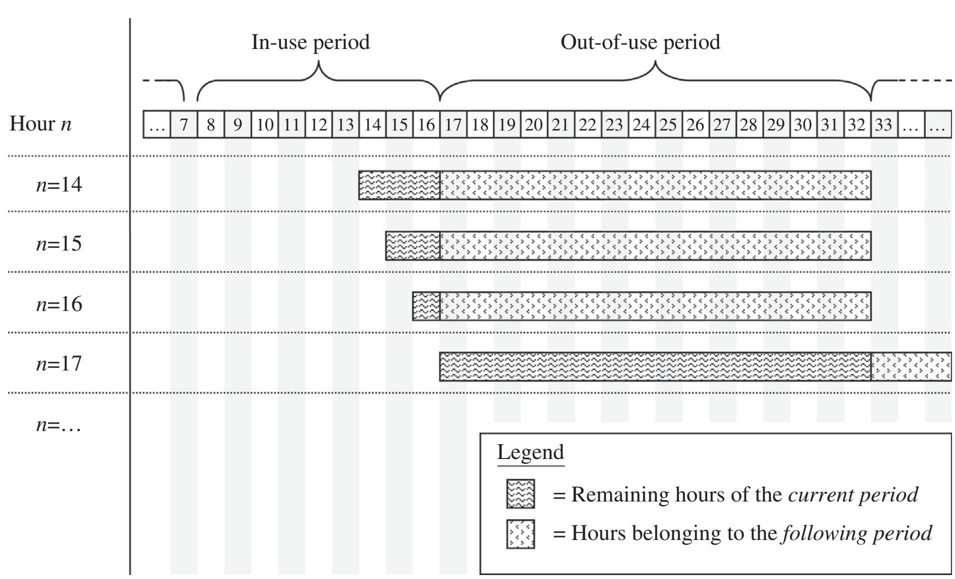


Fig. 1. Illustration of the terminology used in the description of the concept. The prediction horizon for hour n is the sum of the remaining hours in the current period and the hours belonging to the following period.

The concept provides access to a building simulation tool which is able to perform dynamic simulations, i.e. take the time constant of the building into consideration. The tool must as a minimum be able to calculate in hourly steps and provide values for the internal surface temperature of constructions, the air temperature and the energy needed to maintain thermal comfort using (if made available by the user) solar shading, increased venting, increased mechanical ventilation, and/or mechanical cooling.

The concept requires that an in-use period is defined, for example from 8 a.m. to 4 p.m. every day of the week all year, except Saturday and Sunday. All other periods than the defined in-use period will be considered as out-of-use periods. The hours of the year thus shifts between belonging to an in-use period or an out-of-use period. If a certain hour belongs to an out-of-use period then this period is called the current period and the following in-use period is called the following period. However, if the hour belongs to an in-use period then this period becomes the current period and the following out-of-use period becomes the following period. Using these period definitions, the concept operates with a dynamic prediction horizon which always consists of the remaining hours of the current period and the hours of the following period as illustrated in Fig. 1.

The concept also requires a minimum and a maximum acceptance criterion for thermal comfort in the in-use period which applies for the entire year. The premise of a single comfort range covering the entire year requires that occupants are able to adapt their clothing level over the day to maintain thermal comfort. For example, if the building is cooled to 20 °C during the night to

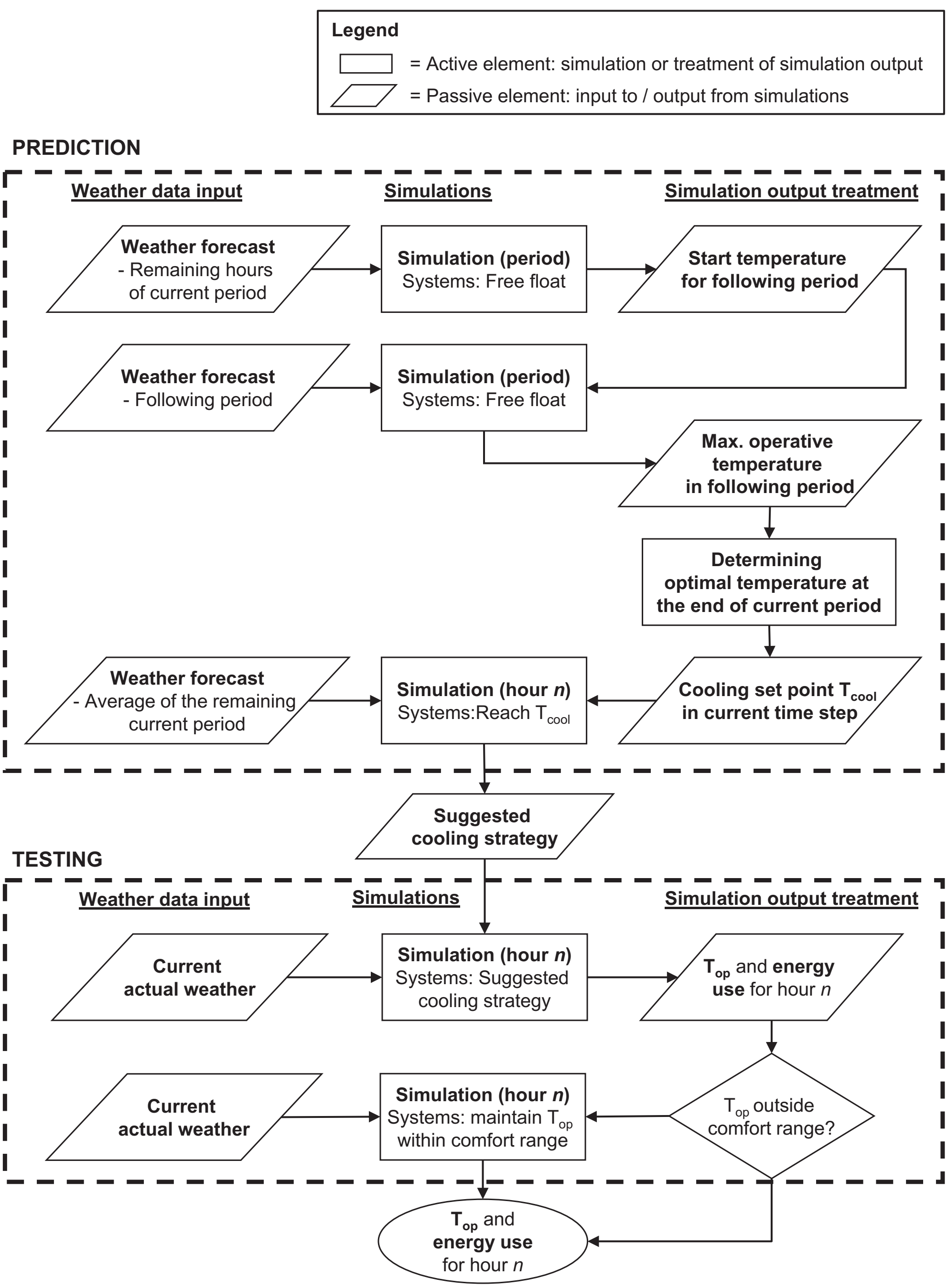


Fig. 2. Flow chart of suggested predictive control concept.

prevent a cooling demand or overheating the next day, occupants can be assumed to have a clothing of 1 clo in the morning, which they are able to change to 0.5 clo if the temperature rises above 24 °C during the day.

A flow chart of the concept is shown in Fig. 2. Overall, the concept is divided in two parts (marked with dotted boxes) with different purposes: Predictions and Testing.

2.1. Prediction

The purpose of the prediction part is to predict the appropriate system control strategy for a time step n (e.g. an hour) to reach certain operative temperature at the end of the period to which n belongs. First, the start temperature of the following period is simulated using weather forecasts for the remaining hours of the current period. The simulation is made with free-floating control systems, i.e. without the intervention of the mechanical heating or cooling systems. The operative temperature is thus only influenced by the weather data, the energy properties of the building constructions, and any user-defined minimum values for ventilation, lighting and internal loads. Next, the maximum temperature in the following period is found in free-float by simulating the following period using weather forecasts. This maximum temperature is used to determine the cooling set point (T_{cool}) for time step n. The appropriate T_{cool} is found within an operative temperature range constituted by the minimum and maximum acceptance criterion for thermal comfort. Bearing the assumption of adaptive thermal comfort in mind, the setting of T_{cool} is based on the following assumptions:

1. There is a heating requirement if the operative temperature at some point in the future period becomes lower than the lower value of the thermal comfort range. The cooling systems are deactivated.
2. There is most probably a heating requirement rather than a cooling requirement if the maximum operative temperature at some point in the future period is between $T_{c,min}$ and $T_{c,av}$, where $T_{c,av}$ is $0.5 \cdot (T_{c,max} + T_{c,min})$. The potential solar heat gain is fully used to minimise the heating requirement by setting T_{cool} to $T_{c,max}$.
3. There is a predominant need for cooling in time step n to prevent overheating in the future period if the maximum operative temperature at some point in the future period is between $T_{c,av}$ and $T_{c,max}$. However, to avoid generating a heating requirement due to excessive cooling, T_{cool} is set to $T_{c,av}$.
4. There is a need for cooling in time step n to prevent overheating in the future period if the maximum operative temperature at some point in the future period is above $T_{c,max}$. In this case T_{cool} is set to $T_{c,min}$.

Now the overall cooling strategy is to reach T_{cool} at the end of the current period by gradually cooling down the building in the remaining hours of the current period. The purpose of the gradual cooling strategy is to prevent that the operative temperature becomes less than $T_{c,min}$ in the remaining hours of the current period and thereby create a heating demand. The next simulation therefore suggests a cooling strategy for time step n based on the average value of the weather forecasts for the remaining hours of the current period. The cooling strategy is formed by activating cooling systems, if they are made available in the model, in the following predefined order: (1) solar shading, (2) increased venting, (3) increased mechanical ventilation, and (4) mechanical cooling. This simulation marks the end of the prediction part of the suggested concept. The output is a cooling set point and a suggested cooling strategy for time step n.

2.2. Testing

The purpose of the testing part is to test the predicted cooling set point and system control strategy to ensure that it maintains the operative temperature within the thermal comfort range in time step n. If so, the predicted strategy is applied. If not, the predicted system control strategy is revised using actual weather

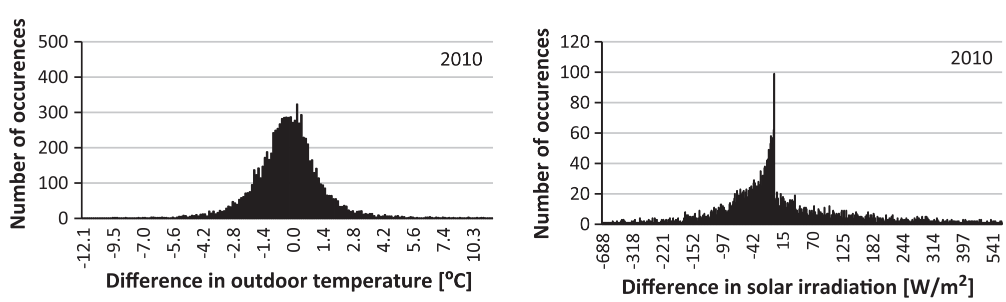


Fig. 3. Distribution of difference between weather forecast data and actual weather data (difference equals forecasted value minus actual value) for the year 2010. The solar forecast has 168 occurrences where the difference is -1 W/m^2 which is not plotted for graphical reasons.

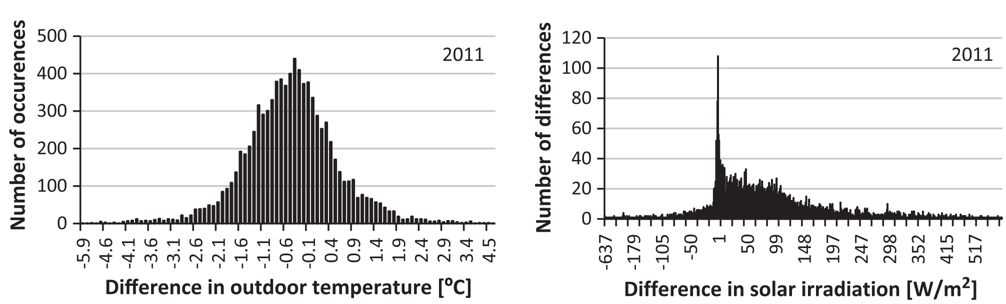


Fig. 4. Distribution of difference between weather forecast data and actual weather data (difference equals forecasted value minus actual value) for the year 2011. The solar forecast has 340 occurrences where the difference is -1 W/m^2 which is not plotted for graphical reasons.

Table 1
Overview of the four variants in the differential sensitivity analysis.

Variant	Name	Description
Façade orientation	South	
	North	
	West[a]	
Construction type	Lightweight	Specific effective heat capacity 144 kJ/K per m^2 floor area.
	Heavyweight	Specific effective heat capacity 432 kJ/K per m^2 floor area.
Window area fraction	Medium	Height 1.5 m, width 1.8 m, offset is symmetrical, 0.8 m from floor.
	Fully	Height 2.0 m, width 2.8 m, offset is symmetrical, 0.8 m from floor.
Glazing system	3-layer glazing with external blinds	Glazing: U/g/LT = 0.76/0.49/0.68. Solar shading is activated when the operative temperature exceeds the cooling set point.
	Solar-coated glazing	Glazing: U/g/LT = 0.73/0.34/0.58

[a] This variant also represents the performance of east-oriented rooms as east-oriented and west-oriented rooms virtually have the same annual performance in Danish weather conditions.

data for time step n to reach the predicted set point and then applied.

2.3. Implementation

The suggested concept is implemented in an existing simplified building simulation tool for integrated daylight and thermal analysis called iDbuild [20] which is based on the simulation routines described in Refs. [21,22]. The tool calculates daylight levels, energy demand and the operative temperature in discrete hourly values on a yearly basis based on hourly weather data.

3. Investigating the effect of weather forecast uncertainty on predictive control concept

A case study featuring a single-sided, single-zone two-person office with a one window located in Aarhus, Denmark is used to investigate the effect of weather forecast uncertainty on the suggested concept. The investigative concept is to analyse performance data generated by a differential sensitivity analysis of building design parameters in the tool iDbuild. Each parameter variation is simulated with three different control strategies: a rule-based control, the suggested concept taking into consideration the imperfect weather forecasts and the suggested concept assuming perfect weather forecasts. The purpose of the different control strategies is benchmarking. Details about weather forecasts, the control strategies and their purpose as benchmarks, as well as details about the sensitivity analysis are explained in the following sections.

3.1. Weather forecast data

The analysis is performed using annual weather forecast data and corresponding actual weather data sets for the year 2010 for a location north of Aarhus, Denmark (coordinates: 56.3°N 10.7°E, elevation 61 m), and the year 2011 for a location north of Copenhagen, Denmark (coordinates: 55.9°N 12.4°E, elevation 38 m). Both data sets contain hourly outdoor temperature and global solar irradiation for the entire year. The forecasts have a range of 72 h and are updated every 12th h in 2010, and every 6th h in 2011. Figs. 3 and 4 show the normal distribution of differences between forecasted and actual weather data for temperature and solar irradiation for year 2010 and 2011, respectively. In these figures, the actual data is always compared with data from the most recent forecast update.

In 2010, the temperature differences have a mean value of −0.2 °C and a standard deviation of 1.8 °C. The differences in solar irradiation have a mean value of 4.5 W/m^2 and a standard deviation of 102 W/m^2. In average, the forecasted temperature and solar irradiation is almost the same as the actual solar irradiation. However, in both cases the standard deviations indicates the presence of a significant amount of overestimated and underestimated values. The distribution graphs illustrate an almost normal distribution for temperature but for solar irradiation the values are mainly underestimated.

In 2011, the temperature differences have a mean value of −0.5 °C and a standard deviation of 1.0 °C. The differences in solar irradiation have a mean value of 46 W/m^2 and a standard deviation of 103 W/m^2. In average, the forecasted temperature is a bit underestimated compared to the actual temperature and solar irradiation is somewhat overestimated. The distribution graphs illustrate an almost normal distribution for temperature but for solar irradiation the values are mainly overestimated.

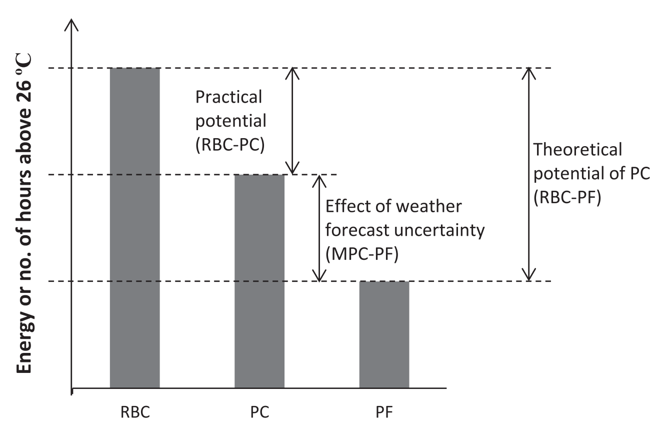


Fig. 5. Concept for determining the theoretical and practical potential of MPC, and the effect of weather forecast uncertainties. Modified from [14].

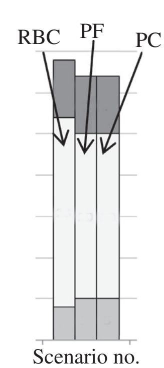


Fig. 6. Illustration of how the simulation results are presented in Fig. 5, this figure, and Figs. 7–10. RBC is Rule-based Control, PF is Perfect Forecast, and PC is the Predictive Control.

3.2. Control strategies and benchmarks

The impending investigation of data requires the formulation of benchmarks to quantify the effect of weather forecast uncertainty on the predictive control concept. One benchmark is found by running simulations assuming perfect weather forecasts, i.e. the forecasted weather is the same as the actual weather. The result of such a simulation is called *perfect forecast* (PF). A *rule-based control* (RBC) is also formulated. The chosen RBC accommodate the long transitional periods in the Danish climate by dividing the year into four seasons: a heating season from 16th October to 15th April, a transitional period from 16th April to 31st May (spring), a cooling season from 1st June to 15th September, and a transitional period from 16th September to 15th October (autumn). In the RBC, the night ventilation is only available in the cooling season with a set point of 20 °C, and in the transitional periods with a set point of 23 °C. Fig. 5 illustrates how the PF simulations and the simulations with RBC can be used as benchmarks to identify the theoretical and practical potential of the suggested concept, as well as the effect of weather forecasts uncertainty (see Fig. 12).

Table 2
Data assumptions for test case.

	Parameter	Description
Room dimensions	Height × width × depth	2.8 m × 3 m × 6 m
Window	Frame	Standard wooden frame, U = 1.6 W/m^2 K, width = 0.08 m, ψ = 0.05 W/m K
Constructions	Façade	U = 0.15 W/m^2 K
Systems	Infiltration	0.10 l/s m^2, always active
	Mechanical ventilation in occupied hours	Min. ventilation rate 1.48 l/s m^2 corresponding to class II in EN 15251:2007. Max. ventilation rate is 2.96 l/s m^2. Average specific fan power of 1.0 kJ/m^3 air. No mechanical cooling available
	Mechanical ventilation in unoccupied hours	Min. ventilation rate is 0 l/s m^2, max. ventilation rate 2.96 l/s m^2
	Heat exchanger	Efficiency of 85%
	General lighting	Dimming control, set point 200 lux, min. power 0.5 W/m^2, max. power 6 W/m^2, 3 W/m^2/100 lux. Only active in occupied hours
	Task lighting	On/off control, set point 500 lux, min. power 0 W/m^2, max. power 1 W/m^2. Only available in occupied hours
	Internal load	300 W in occupied hours, 0 W in unoccupied hours
External conditions	Shadows from surroundings	None
	Weather data	Danish design reference year [23]

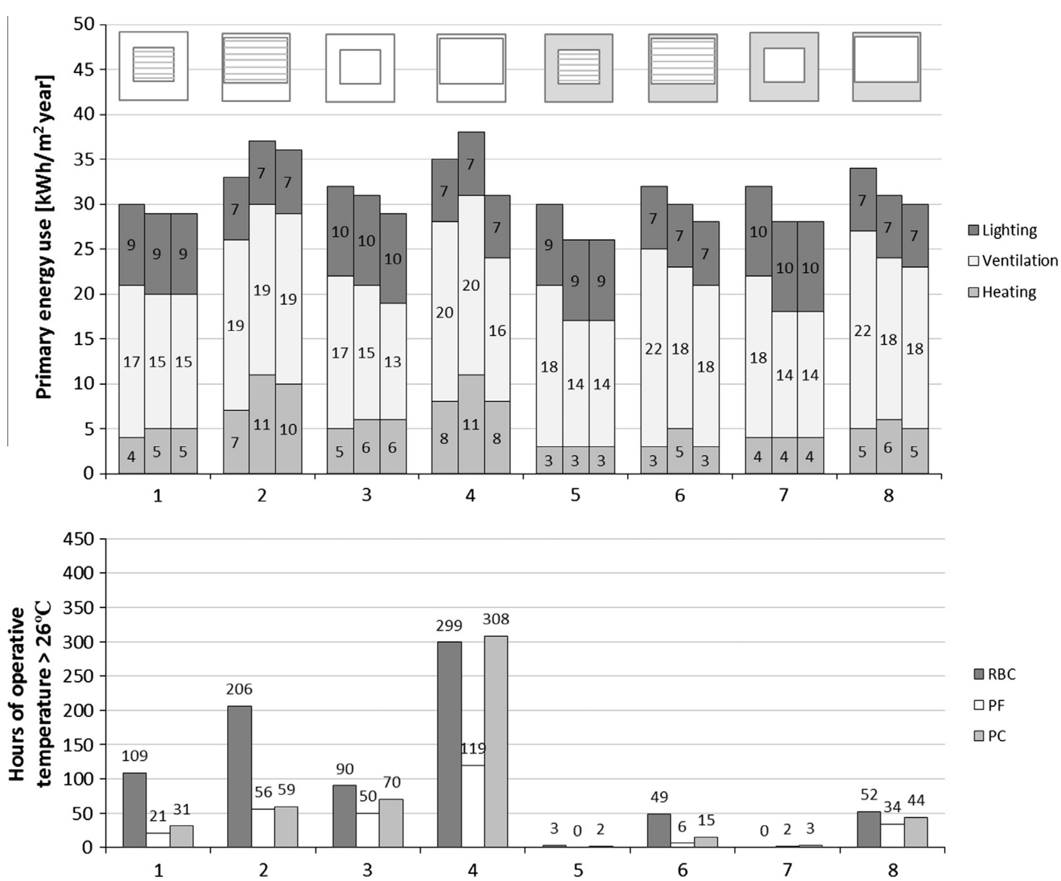


Fig. 7. Result from sensitivity analysis. Orientation: South. Year: 2010.

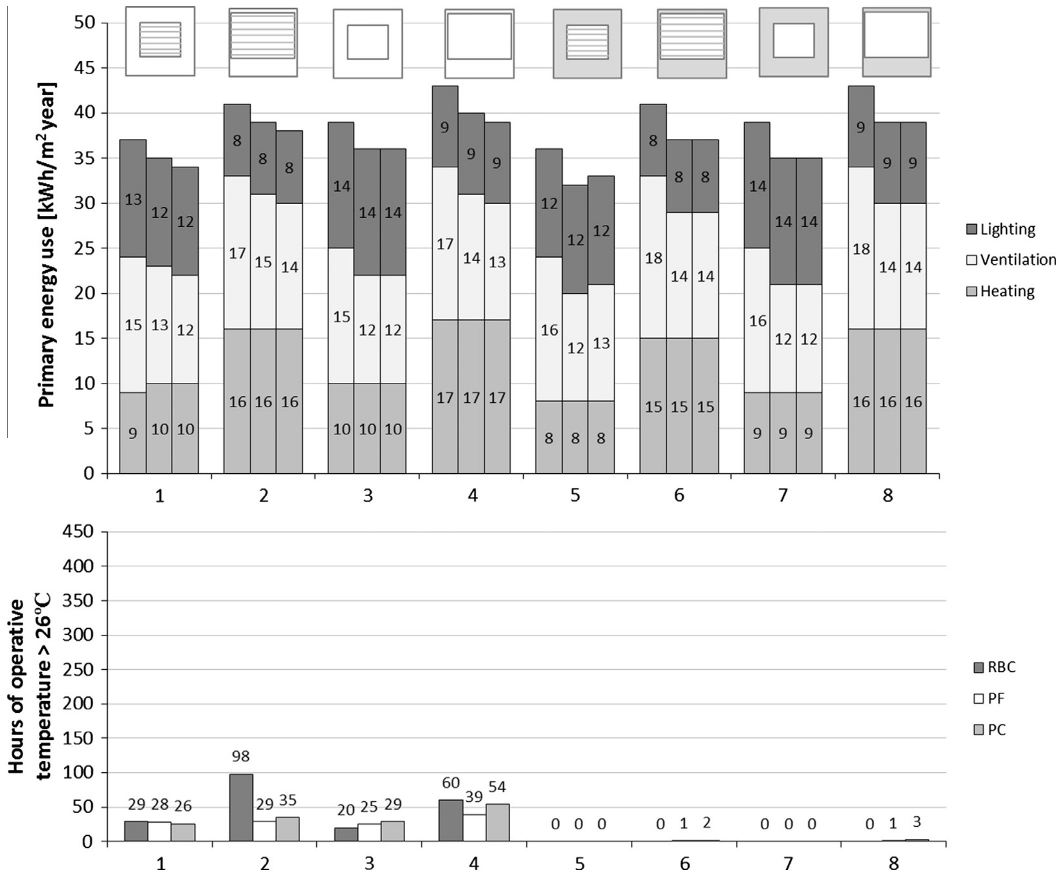


Fig. 8. Result from sensitivity analysis. Orientation: South. Year: 2011.

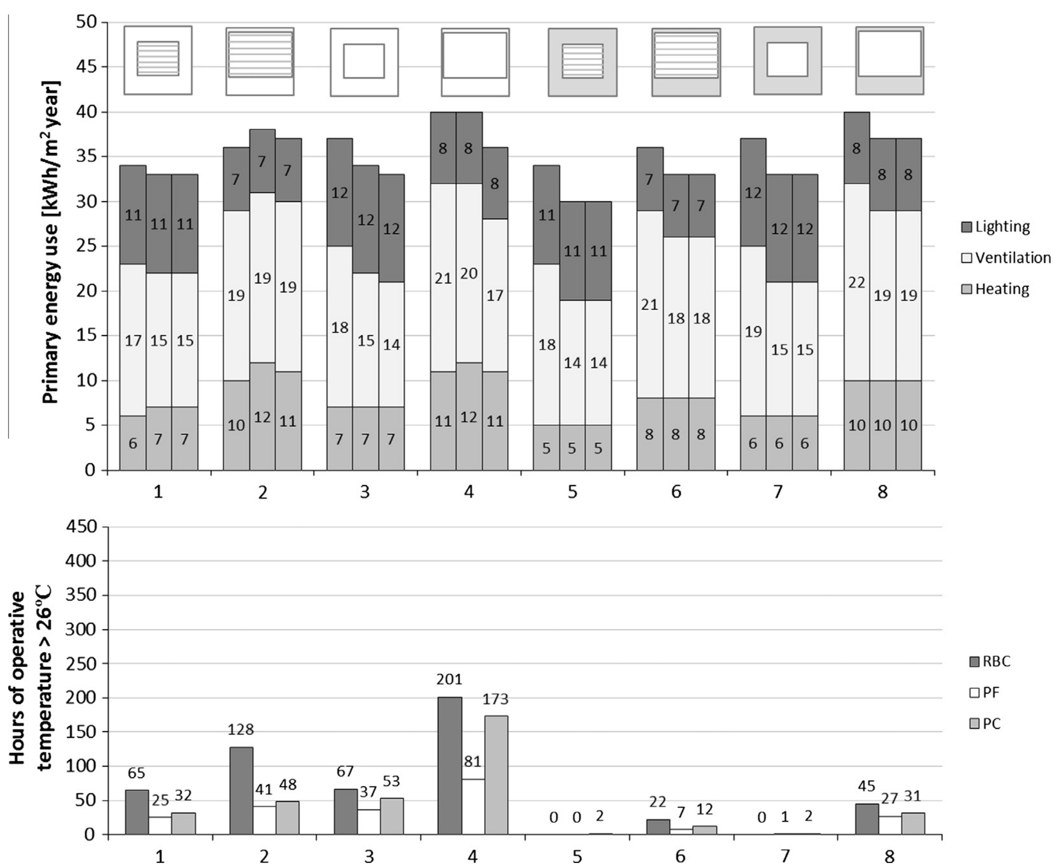


Fig. 9. Result from sensitivity analysis. Orientation: North. Year: 2010.

3.3. Sensitivity analysis

The purpose of the sensitivity analysis is to assess how sensitive various building design parameters are to weather forecast uncertainty in terms of building energy performance (heating, ventilation and lighting) and thermal indoor climate (hours above 26 °C during time-in-use). The sensitivity analysis is performed as a one-at-the-time analysis [24] and encompasses four variants: orientation, thermal mass, solar shading and window area. An overview of the variant is shown in Table 1.

The combination of all variants makes in total 24 cases. The sensitivity analysis is performed for the two different weather data sets with different weather forecast uncertainty as described in Section 3.1 making a total of 48 simulations in the investigation. The global assumptions for the simulation model are:

- The occupied period from 8 a.m. to 4 p.m. every weekday.
- The lower limit for thermal comfort is 20 °C and the upper limit is 26 °C.
- It is assumed that the occupants use clothing for adaptive thermal control throughout the entire year.
- The thermal response of the room is perfectly represented by the building model, i.e., there is no mismatch between the modelled and actual building dynamics and user behaviour.

All other parameters defining the model are fixed as shown in Table 2.

4. Results

The results from sensitivity analysis are presented for each year (2010 and 2011) and grouped for each orientation (south, north and west) in Figs. 6–11. Thus, eight scenarios are presented in each figure and for each of these eight simulations the results from the three control strategies are presented. Table 3 and Fig. 6 explain how to read Figs. 6–11.

Results for the light thermal mass scenarios (1–4) in the south-oriented room, Figs. 7 and 8, show that the RBC simulations have the lowest heating demand compared to predictive control but a high amount of hours above 26 °C in both years. When compared to RBC results, the PF results show potential for overall energy savings and improvement of thermal indoor climate for offices with moderate window size (1 and 3) but not for fully glazed facades (2 and 4). This applies for both years and for both of the investigated solar shading types. However, when comparing the simulations for year 2010 and 2011, the realisation of the PF potential in predictive control in terms of energy use depends on the accuracy of the weather forecasts.

In the year 2010, the predictive control often performs better than the PF in terms of energy use. The reason is that energy use for heating is lower in predictive control than in PF primarily due to underestimations in the outdoor temperature prediction in the heating season. In scenario 3 and 4, the energy for ventilation in the occupied hours is lower in predictive control than in PF because the solar irradiation prediction (and thereby the cooling need) is overestimated.

In the year 2011, the predictive control for the offices with external venetian blinds (1 and 2) exceeds the energy use of RBC and PF due to a higher heating demand, but in comparison with RBC, the thermal indoor climate is improved significantly. The main reason is overestimations in the solar irradiation predictions which result in excessive use of ventilation and solar shading to compensate for future solar heat gain and thereby avoid future overheating. Instead, this system control leads to a heating

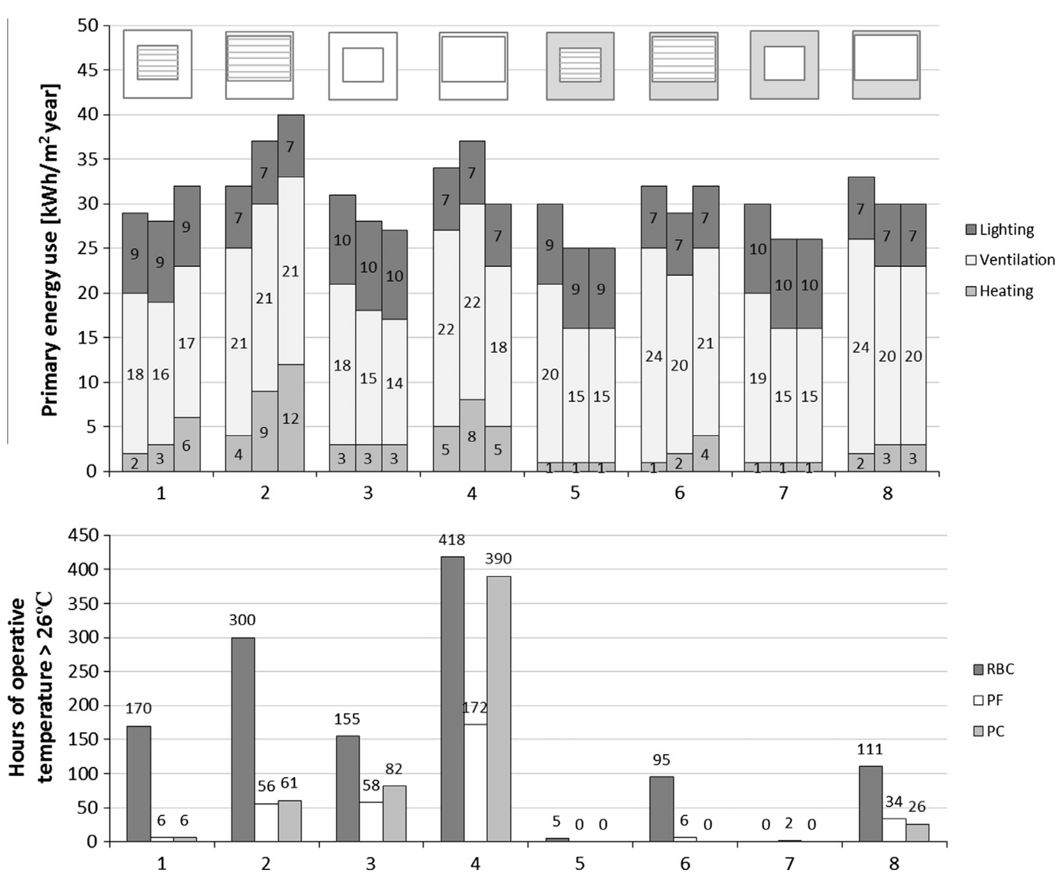


Fig. 10. Result from sensitivity analysis. Orientation: North. Year: 2011.

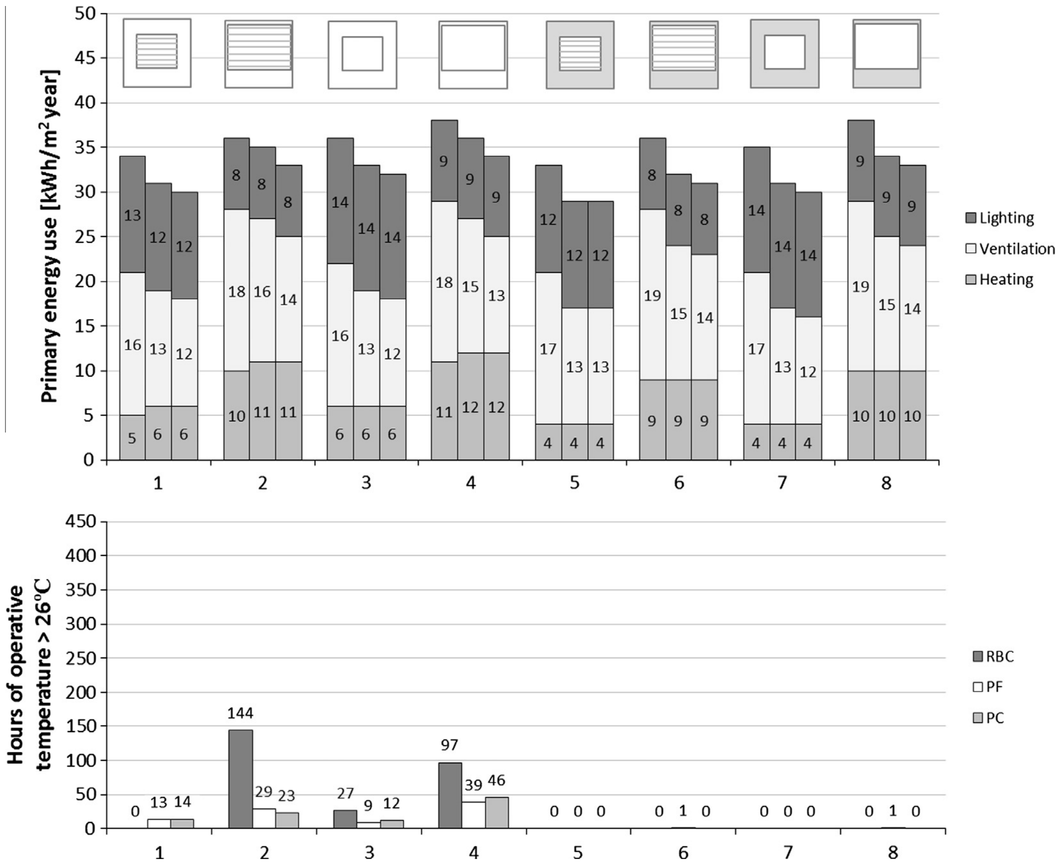


Fig. 11. Result from sensitivity analysis. Orientation: West. Year: 2010.

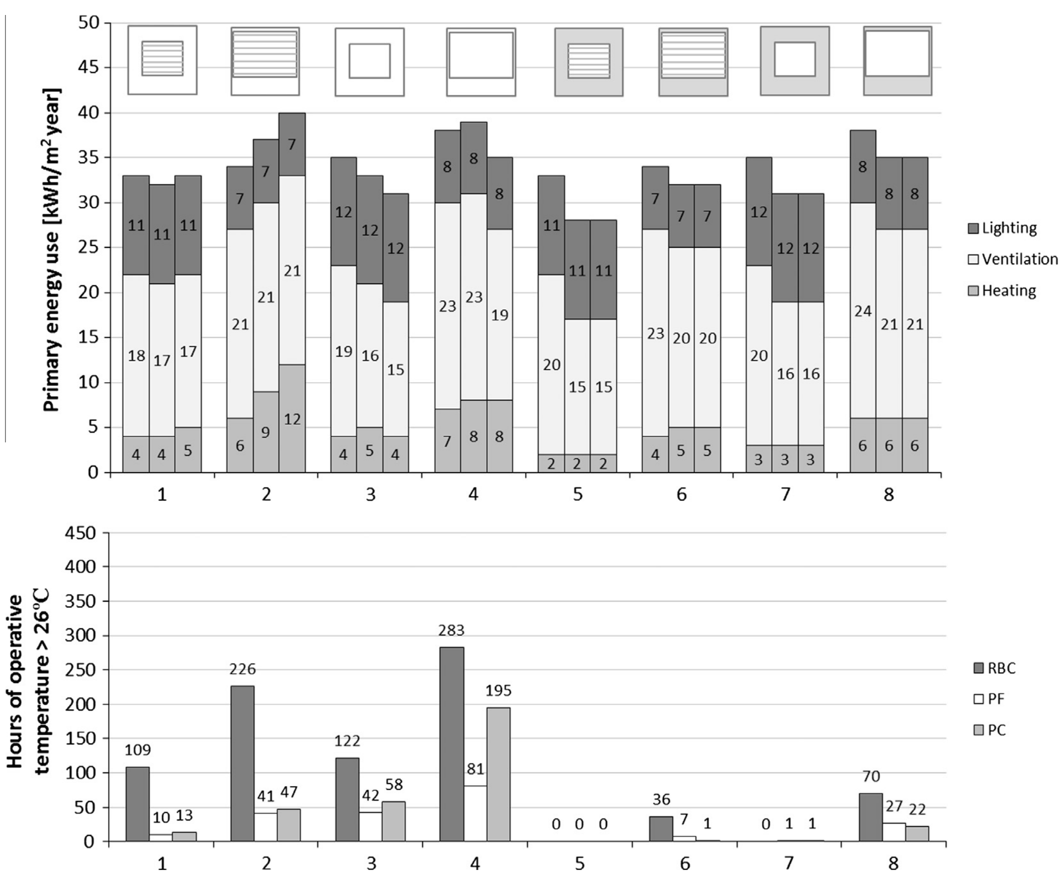
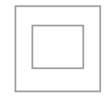
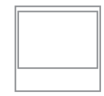
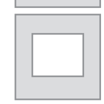
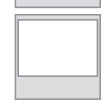


Fig. 12. Result from sensitivity analysis. Orientation: West. Year: 2011.

Table 3
Description of the scenarios presented with the numbering and signatures used in Figs. 6–10.

Scenario No.	Thermal mass	Solar shading	Window area	Signature
1	Lightweight	External venetian blind	Moderate	
2	Lightweight	External venetian blind	Fully	
3	Lightweight	Coating	Moderate	
4	Lightweight	Coating	Fully	
5	Heavyweight	External venetian blind	Moderate	
6	Heavyweight	External venetian blind	Fully	
7	Heavyweight	Coating	Moderate	
8	Heavyweight	Coating	Fully	

demand because the expected solar gain is absent in the actual weather. As special case in both years is scenario 4 (fully glazed façade with solar coated glass) which has a lower energy use but a lot more hours above 26 °C compared to the PF. The reason is that the fully glazed façade with no possibility of regulating solar heat gain and the low thermal mass makes the energy use and operative temperature very sensitive to differences between weather forecast and actual weather. Periods with underestimation in the solar irradiation prediction is therefore very quickly leading to operative temperatures above 26 °C.

Results for the scenarios with heavy thermal mass (5–8) show that the predictive control is outperforming RBC in both years if not in energy use then in hours above 26 °C. One exception is scenario 6 in Fig. 8 (fully glazed façade with external blinds) which has a higher energy use for heating and ventilation than PF because the solar shading is activated too often and night ventilation is too excessive due to overestimations of solar irradiance prediction. In scenario 6 and 8 in Fig. 7, the predictive control performs even better than the PF which is primarily due to many instances of underestimations in the outdoor temperature prediction and solar irradiation in winter time.

Results for the north-oriented room, Figs. 9 and 10, show that the predictive control is outperforming RBC in energy use and hours above 26 °C for all scenarios in both years. Compared to RBC results, the PF results show potential for energy savings and/or improvement of thermal indoor climate for all scenarios in both years. The realisation of the PF potential in predictive control in terms of energy use only slightly depends on the accuracy of the weather forecasts.

In the year 2010, the PF potential is taken up by the predictive control in all cases (except case 5 in 2010). In the cases with very light thermal mass, the predictive control performs better than the PF due to the overestimation of the solar irradiation prediction which leads to lower need for ventilation in the daytime.

In the year 2011, the predictive control performs better than the PF in all cases because of lower needs for ventilation in the daytime due to the overestimation of the solar irradiation prediction which is somewhat higher and more frequent in 2011 compared to 2010.

Results for the west-oriented room, Figs. 11 and 12, show the same tendencies with the same reasons as explained for the south-oriented scenarios.

5. Conclusion

This paper presents an analysis of the effects of weather forecast uncertainty on energy use and indoor climate of a building which uses a deterministic predictive control concept for building systems operation. The effects are quantified by comparing the performance of the concept including any differences in forecasted and actual weather data with a rule-based control (RBC) and with a theoretical simulation where perfect forecasts (PF) are assumed in the predictive control concept. The effects were identified through a differential sensitivity analysis of four building design parameters: orientation, thermal mass, solar shading and window area. The analysis was performed using Danish weather data (temperate climate) from two different years, i.e. a variation of weather forecast uncertainty resulting in 48 scenarios. The results from this large-scale simulation study showed, with a few exceptions, a potential for energy savings and/or improvements in thermal indoor environment when using the suggested concept compared to RBC despite the uncertainty in the weather forecasts. In the scenarios with heavy thermal mass, the concept realisation of the PF potential was less dependent on the accuracy of the weather forecasts compared to the scenarios with very light thermal mass. The performances of the scenarios with very light thermal mass were especially sensitive to the precision of solar irradiance forecasts. It is noticed that predictive control concept might outperform the PF depending on the compositions of variants and uncertainty in the weather forecasts.

Conclusions have been made regarding the effect of weather forecast uncertainty on the performance of the concept in a temperate climate. Future studies could test the concept in other types of climates. The study in this paper used fixed weather data update intervals. Studies investigating the effect of the update interval of the weather forecast are therefore relevant. The performance of the concept in real applications can also be expected to vary due to deviations between modelled and actual conditions and deviations between the user pattern of the real building and the user patterns assumed in the simulation model. Further work is required to assess the effect of these issues. Finally, it is desirable to implement the concept in a more sophisticated building simulation tool to assess the effect of a more detailed modelling of the building energy management systems.

References

[1] EPBD recast – Directive 2010/31/EU of the European Parliament and of the Council of 19 December 2010 on the energy consumption of buildings (recast).
[2] Pérez-Lombar L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy Buil. 2008;40:394–8.
[3] Loveday DL, Virk GS. Artificial Intelligence for Buildings. Appl. Energy 1992;41:201–21.
[4] Loveday DL, Craggs C. Stochastic Modelling of Temperatures for a Full-Scale Occupied Building Zone Subject to Natural Random Influences. Appl. Energy 1993;45:295–312.
[5] Bhavani RG, Khan MA. An intelligent simulation model for blind position control in daylighting schemes in buildings. Buil. Simul. 2009;2:253–62.
[6] Clarke JA, Cockroft J, Conner S, Hand JW, Kelly NJ, Moore R, et al. Simulation-assisted control in building energy management systems. Energy Buil. 2002;34:933–40.
[7] Mahdavi A. Simulation-based control of building systems operation. Buil. Environ. 2001;36:789–96.
[8] Henze GP, Felsmann C, Knabe G. Evaluation of optimal control for active and passive building thermal storage. International Journal of Thermal Sciences 2004;43:173–83.
[9] Sourbron M, Verhelst C, Helsen L. Building models for model predictive control of office buildings with concrete core activation. Journal of Building Performance Simulation 2013;6:175–98.
[10] Braun J, Chaturvedi N. An inverse grey-box model for transient building load prediction. HVAC&R Research 2002;8:72–99.
[11] Wittchen KB, Løgberg E, Pedersen S, Djurtoft R, Thiesen J. Use of weather forecasts to control night cooling. in: Proc. of Building Simulation '05, 9th international IBPSA conference, Montreal; 2005, p. 1347–1353.
[12] Petersen S, Svendsen S. Method for simulating predictive control of building systems operation in the design phase. Appl Energy 2011;88:4597–606.
[13] OptiControl Project, <http://www.opticontrol.ethz.ch> [accessed 07.03.12].
[14] D Gyalistras. Use of weather and occupancy forecasts for optimal building climate control (OptiControl). ETH Zurich 2010.
[15] Henze GP, Felsmann C, Knabe G. Impact of forecasting accuracy on predictive optimal control of active and passive building thermal storage inventory. Int J HVAC & Res 2004;10:153–78.
[16] Oldewurtel F, Parisio A, Jones CN, Gyalistras D, Gwerder M, Stauch V, et al. Use of model predictive control and weather forecasts for energy efficient building climate control. Energy and Buildings 2012;45:15–27.
[17] Lamoudi MY, Beguery P, Alamir M. Use of simulation for the validation of a model predictive control strategy for energy management in buildings. in: Proc. of Building Simulation 2011, 11th international IBPSA conference, Sydney; 2011, p. 2703–2710.
[18] Siroky J, Oldewurtel F, Cigler J, Privara S. Experimental analysis of model predictive control for an energy efficient building heating system. Appl Energy 2011;88:3079–87.
[19] Henze G, Kalz D, Liu S, Felsmann C. Experimental analysis of model-based predictive optimal control for active and passive building thermal storage inventory. Int J HVAC & Res 2005;11:189–214.
[20] Petersen S, Svendsen S. Method and simulation program informed decisions in the early stages of building design. Energy and Buildings 2010;42:1113–9.
[21] Hviid CA, Nielsen TR, Svendsen S. Simple tool to evaluate the impact of daylight on building energy consumption. Solar Energy 2008;82:787–98.
[22] Nielsen TR. Simple tool to evaluate energy demand and indoor environment in the early stages of building design. Solar Energy 2005;78:73–83.
[23] Jensen JM, Lund H. Design reference year – a new Danish reference year (in Danish). Technical University of Denmark, LFV announcement no. 281; 1995.
[24] Lomas KJ, Eppel H. Sensitivity analysis techniques for building thermal simulation programs. Energy and Buildings 1992;19:21–44.