Quality requirements for forecasts in HVAC operation optimization

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Abstract. Optimizing HVAC operation by taking into account predictions for presence, occupancy and inner loads, weather (mainly air temperature and solar irradiation) and thermal behaviour of the room or building can lead to significant energy savings while maintaining thermal comfort for the occupants. However, the quality of forecasts plays an important role for the success: High prediction qualities are essential for achieving the objectives in energy saving and thermal comfort. In the present paper, a simulation study is presented for the example of an office room with up to three occupants. Perfect and real (non-perfect) forecasts are applied for simulating predictive HVAC control in the course of one year. For evaluating the impact of forecast quality, the annual reduction of cooling energy demand and the decrease of thermal comfort are considered. Results show that there is a complex interaction between the different forecasts: The combined quality of all forecasts determines the benefit which can be reached from predictive control. If forecasts are not good enough, thermal comfort decreases significantly compared to perfect forecasts or the reference case without predictive control. Here, especially the forecast of room temperature development (thermal behaviour of the room) was found to be very important. If the forecasts are good, the annual cooling energy demand can be decreased by 19 % in the example while maintaining high thermal comfort.

Keywords. building model, machine learning, thermal comfort, energy saving
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1. Introduction

The operation of HVAC systems can be optimized by considering forecasts for the control system. Control actions might be tested in advance by means of simulating the system behaviour for the next time range (model-predictive control, MPC). Thus, different advantages are provided: For example, oscillations in the system (e.g. alternating heating and cooling) are avoided, room heating is deactivated or reduced when solar heat gains are expected for the next time, offices are cooled only if they are really used. Improvements in both energy savings and thermal comfort can be achieved by operating HVAC systems based on appropriate forecasts. Machine learning algorithms can be applied for approaching optimal control [1, 2]. Different concepts and methods were proposed which consider forecasts of weather and occupancy [3, 4] and achieve for example 18 % savings in cooling energy demand [5]. Some studies took into account the uncertainty of weather predictions [6, 7] and showed the influence on MPC performance. It was also shown that reliable cooling load predictions are required for MPC [8].

Thus, the performance of predictive HVAC control strongly depends on the quality of the forecasts which are required for the optimization. If the quality of such forecasts is not sufficient, lower thermal comfort and higher energy consumption may occur than without using forecasts. Well performed predictions are an important basis for successful optimization of operation. In the present paper, a simulation study is presented which compares the application of perfect and real (non-perfect) forecasts. It is shown which forecasts are required for HVAC predictive control in offices and how their quality influences energy savings and thermal comfort.

Here, an office room is modelled numerically as a basis for the study. An operation in the course of one year is simulated with predictive HVAC control applying varied prediction models for presence, occupancy, weather and thermal behaviour of the room. For evaluating the performance, cooling energy savings and thermal comfort are analysed.

2. Research Methods

2.1 Example room

The study is based on the numerical model of a theoretical office room with the dimensions 3.92 m x 8.00 m x 3.16 m (volume 99 m^3) situated in Potsdam, Germany. The room can be occupied by up to three people. The outer walls contain windows with a total area of 22.4 m^2. For the sake of simplicity, horizontal orientation of the windows is assumed. For non-horizontal windows, the sun's position determines the irradiation to the room for a given irradiation measured on the horizontal surface. For starting with a basic model for room temperature forecast, this dependency has not been considered yet. Therefore, the influence of solar altitude on the irradiation to the room is neglected in this stage of research.

For modelling the transient thermal behaviour of the room, the room model described in VDI 6007 Part 1 [9-11] is used as a basis. This is a second-order model which divides the building mass into two thermal capacitors. One capacitor subsumes all non-adiabatic components (e.g. outer walls), the other one represents the adiabatic components (e.g. wall to neighbour rooms with the same thermal conditions). The transient solution for the system of capacitors and resistances is found by analogy to electric circuits. The model is based on a time step of 1 h, but can be adopted to smaller time steps. Here, some simplifications for thermal radiation were made to decrease the calculation duration for a small time step of 1 min (no absorption or emission on opaque outer surfaces, no emission from inner surfaces).

Thermal loads within the room are the following:

- base heat source: 200 W (50 % convective, 50 % radiative)
- heat source per occupant: 75 W (person) + 200 W (IT), 50 % radiative
- lighting: 150 W (50 % radiative)

These are practical values for different kinds of offices, e.g. with CAD-workstations. For the HVAC system, the following typical parameters are assumed:

- air supply per person: 40 m^3/h
- supply air temperature: 24 °C for heating, 18 °C for cooling
- setpoint value for room air temperature during active operation time: 21 °C
- minimal and maximal room air temperature during passive operation time (night, weekend): 18 °C/27 °C
- active operation time: 6:30 to 18:30 on weekdays (if not derived from occupancy forecast)
- start-up time before active operation: 1 h
- decay time before end of active operation: 1 h (During decay time, heating/cooling is reduced and the room air temperature is allowed to deviate from the set-point value because a slight increase or decrease is acceptable for the occupants before they leave the office.)

2.2 Forecasts

For predictive HVAC control, different forecasts are required. These are described in the following and details on the machine learning models are given in Table 1.

(1) Presence forecast (PF): For optimal control, information is required on when there are people in the room or building and when not. For an office room, especially the arrival time of the first occupant in the morning and the time when the last occupant left the room in the afternoon (departure time) are relevant, because these times define the period when comfort requirements are to be met. If a forecast predicts the presence of people in a room or building, the room temperature can be kept at the required value and restricted to this time for the sake of energy savings.

The target values in presence forecasting are for example the arrival time of the first person and the departure time of the last person on a specific day. Relevant features (influence parameters) can include the weekday, the month, school holidays yes/no, working day yes/no. Here, a random forest model is used. Alternatively, presence forecast can be derived from occupancy forecast (see below): When the predicted occupancy is at least one, somebody is present in the room.

(2) Occupancy forecast (OF): The occupancy (number of people in a room or building) predicted for a certain time horizon allows for optimal operation of the HVAC system both with regard to user comfort and reaction to inner thermal loads (heat emission of people, devices, machines and lighting). This allows for example to avoid overshooting of the room temperature. The occupancy can be predicted based on the same features as used for presence forecast. Additionally, the time is an important parameter.

For the study described here, synthetic occupancy data were created for an office room with three desks and flexible work time. 5 min values were generated for a total period of two years. They take into account the individual holiday and working time preferences of the people being modelled. The particular times of arrival, lunch break and departure at each day are

Tab. 1 – Models applied for forecasts. Machine learning models are taken from scikit-learn [12]; validation performance given as root mean square error (MSE)

Forecast	ML model	Details	Performance
Presence (PF)	random forest regression	arrival time of first person in seconds at day based on features weekday, working day departure time: same method as for arrival time	arrival time: MSE = 2743 s departure time: MSE = 2806 s
Occupancy (OF)	random forest regression	number of people being present at current time step based on features weekday, working day, time, occupancy in previous time step	MSE = 0.1
Weather (WF)	none	simple model: ambient temperature and global solar irradiation from same time at previous day	temperature: MSE = 3.4 K irradiation: MSE = 115 W/m^2
Room temperature (RF)	linear regression	room air temperature based on features ambient temperature, solar irradiation, convective and radiative inner heat sources (including heating/cooling systems), temperature in previous time step	MSE = 0.2 K

subject to random distribution within the respective typical time windows. A random forest model has been trained and validated with the data for the first year while the second year data are used for the application in the predictive HVAC control study.

(3) Weather forecast (WF): If it is known that high solar irradiation will affect the room within the next hours, heating can be deactivated anticipatorily. Weather companies provide forecast data for air temperature, solar irradiation and other parameters. Solar irradiation data might be split into direct and diffuse irradiation or consolidate these parts into global irradiation. Generally, provided irradiation data are related to one square meter of horizontal surface. As the effect of solar irradiation on the room or the building depends on the current solar position and thus e.g. on calendar day and time, conversion by an analytical or numerical model (could also be a machine learning model) is necessary. For limiting the complexity of the study presented here, this conversion has been avoided by assuming horizontal windows.
For the most cases studied here, a perfect weather forecast was applied because the focus was on the building-specific predictions (presence, occupancy, thermal behaviour). In the case with weather prediction, a simple model using the values from the same time at the previous day was applied.

(4) Thermal behaviour of the building (room temperature forecast RF): For finding the optimal HVAC control, the development of the room air temperature depending on thermal loads, room or building properties and HVAC system operation needs to be predicted. This forecast can be conducted by means of an analytical or numerical room/building model or with a machine learning model. Here, a linear regression model is used which was trained and validated with data from the room model.

2.3 Predictive HVAC control

For optimizing HVAC operation, the active operation time of the system is not fixed but depending on the presence forecast. At the beginning of each day (0:00), this forecast is generated for the present day and the active operation time is derived from the result. At the defined start-up time before the (predicted) active operation (see Figure 1; here: 1 h), the system starts to heat or cool in order to reach the setpoint value when the first occupant arrives.

The predicted departure time of the last occupant defines the end of the active operation time. As a slight decrease or increase of temperature might be acceptable for the user before leaving the room, a decay time (here: 1 h) is assumed before the end of the active operation time. During this time, heating or cooling is reduced or deactivated.

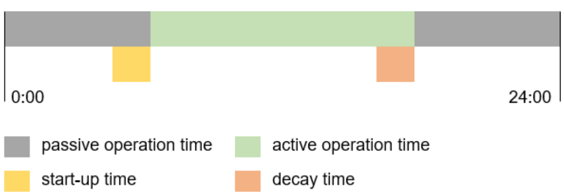

Fig. 1 – Nomenclature of time periods.

Heating the room when cooling would be required shortly afterwards or vice versa should be avoided. To this end, a defined "preview time" is considered here. The preview time is a defined time horizon from the current real time to the future which is considered for predictive control. This means that forecasts are conducted e.g. for the following hour to check if a change from cooling to heating or from heating to cooling becomes necessary. If this is the case, cooling or heating will already be stopped at the current time. For the preview time, inner and outer thermal loads are estimated based on the occupancy forecast and the weather forecast, respectively. The development of the room temperature is predicted by the forecast model for the thermal behaviour as described in section 2.2.

In the optimized operation, the air change/the air supply to the room is set according to the real occupancy.

The predictive HVAC control modelled here is only a basic example because the main focus was to investigate the influence of forecast quality. Much more advanced strategies and optimization algorithms are possible and desirable.

2.4 Metrics

The aim of predictive HVAC control is to reduce energy demand while ensuring thermal comfort for the occupants. Here, the following metrics are used for evaluating energy demand and thermal comfort, respectively:

- Cooling energy reduction: The relative change of cooling energy in the room during one year compared to the reference case without predictive control shows the energetic advantage. Heating energy was studied as well, but is not shown here because it follows the same trends.

- Temperature deviation hours: A temperature deviation hour of 1 Kh means that during the presence of at least one person the room air temperature deviates from the setpoint value plus tolerance (here 1 K) by 1 K for one hour. The summarized value for one year is used here as an indicator for thermal comfort.

2.5 Cases

Perfect and real predictions are used in the cases. “Perfect” means that the real value, e.g. the number of people being present in the next time step, is known in advance. “Real” predictions are the forecasts made by the machine learning models named in section 2.2.

The following cases are investigated:

- Case 0: Reference case without any predictions. The HVAC system runs with fixed active operation time and start-up time as given in section 2.1. There is no decay time, air supply is constant at 120 m^3/h during active operation time. Thus, the setpoint temperature is met during all times when people are present.
- Case 1: As case 0, but air supply is controlled according to a perfect occupancy prediction. That means that the air supply is adjusted to the real number of persons at each time.
- Case 2: As case 1, but with a decay time of 1 h before the fixed end of active operation time.
- Case 3: As case 2, but with a preview time of 1 h for predictive HVAC control. For simulating the preview time, perfect predictions for occupancy, weather and thermal behaviour of the room are used. The active operation time remains fixed, no presence forecast is used.
- Case 4: As case 3, but with real occupancy forecast.
- Case 5: As case 4, but with real presence forecast used during preview time simulation.
- Case 6: As case 5, but with active operation time based on real presence forecast.
- Case 7: As case 6, but with real forecast of thermal behaviour and perfect forecast for presence, occupancy and weather.
- Case 8: As case 7, but with real occupancy forecast.
- Case 9: As case 7, but with real presence forecast.
- Case 10: As case 9, but with real occupancy forecast.
- Case 11: As case 10, but with real weather forecast- Thus, no perfect forecasts are used in this case.

The case configurations are summarized in Table 2. One year of operation is simulated for each case, the simulation time step is 1 minute.

3. Results and discussion

The resulting metrics for the 11 cases are shown in Figure 2.

For case 1, there is no temperature deviation because the setpoint of the room temperature is maintained during the fixed active operation time. However, cooling energy demand can be reduced by 9 % compared to the reference case (case 0) by adjusting the air supply to the number of people being present.

Cases 2 to 6 show cooling energy reductions between 15 and 20 %. These reductions are accompanied by deviations between the setpoint and the real room air temperature during certain hours. For the whole year, temperature deviation hours are below 50 Kh and might thus be acceptable.

Tab. 2 – Case overview: Forecasts for presence (PF), occupancy (OF), weather (WF) and thermal behaviour of the room (RF); p = perfect, r = real; n.d. = no decay time; n.a. = active operation time not based on forecast.

	Forecast			
Case	PF	OF	WF	RF
1	-	p (n.d.)	-	-
2	-	p	-	-
3	-	p	p	p
4	-	r	p	p
5	r (n.a.)	r	p	p
6	r	r	p	p
7	p	p	p	r
8	p	r	p	r
9	r	p	p	r
10	r	r	p	r
11	r	r	r	r

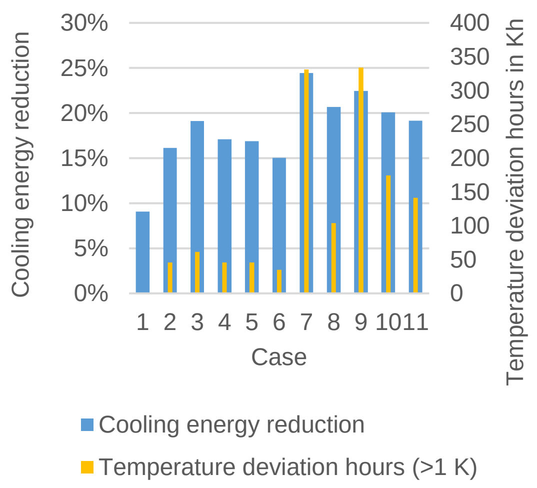

Fig. 2 – Cooling energy reduction and temperature deviation hours for one year depending on the case.

The cases up to 6 have in common that a perfect forecast for the thermal behaviour of the room is used. Switching to a real prediction (cases 7 to 11) leads to significant increase of temperature deviation hours and thus a loss in thermal comfort. The reason is that in certain hours the forecast says that no cooling is required for example, but the real temperature development is different and the room gets too warm.

From case 3 to 6, further perfect forecasts are replaced by real forecasts. Cooling energy reduction decreases, but temperature deviation hours decrease as well. Thus, the real forecasts lead to less success in energy savings, but no comfort problems are produced by the real forecasts compared to the perfect forecasts in the example considered here.

Cases 7 to 11 show that the success of predictive HVAC control depends on the combination of forecast qualities: Case 7 with real forecast of thermal behaviour and perfect forecasts for all other parameters shows poor thermal comfort (temperature deviation hours: 330 Kh). Replacing the perfect occupancy forecast by the real one (case 8) leads to significant comfort improvement (104 Kh). Case 9 with real presence forecast, but perfect occupancy forecast is much worse again. Tis shows the complex interaction of the different forecasts.

Basing the predictive HVAC control only on real forecasts (case 11) provides cooling energy savings of 19 % compared to the reference case while there are 141 Kh temperature deviation hours. This might be acceptable, but could be improved by increasing forecast accuracy (see case 3 with the same cooling energy savings, but less than half of the temperature deviation hours due to perfect forecasts).

In the cases presented here, preview time is set to 1 h. Figure 3 shows for the example of case 3 what happens if this value is varied.

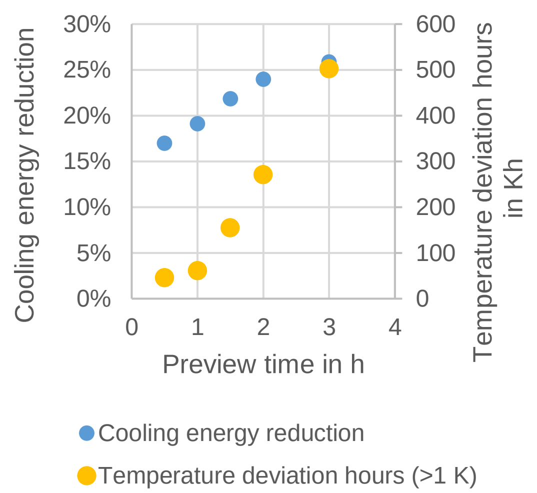

Fig. 3 – Influence of the preview time length on cooling energy reduction and temperature deviation hours (based on case 3)

With more than one hour of preview time, thermal comfort decreases significantly. The relative increase of cooling energy reduction is much smaller and does not justify the loss of thermal comfort. Thus, preview time length needs to be chosen carefully.

4. Conclusions

For the example of an office room with three occupants, the influence of the forecast quality on the performance of predictive HVAC control was investigated. Results show that the complex interactions of the different forecasts (presence, occupancy, weather, thermal behaviour of the building/room) have a strong influence on the energy savings which can be achieved while maintaining an acceptable level of thermal comfort. If forecasts are not reliable, thermal comfort decreases significantly compared to perfect forecasts or the reference case without predictive control. Here, especially the forecast of room temperature development (thermal behaviour of the room) was found to be very important. A machine learning model applied for this forecast needs to be well-suited to the room or building. Alternatively, an analytical or numerical building/room model could be applied. Modelling and parametrization effort might be higher than for a machine learning model, but the forecast quality is expected to be better as well if the analytical or numerical model is an appropriate representation of reality.

The example studied here cannot be generalized. The thermal behaviour of buildings and rooms is very individual and depends on many parameters as for example thermal capacity of the envelope, ratio of transparent to opaque areas, etc. Thus, the results shown here are supposed to give an impression on the effects that can be expected depending on the forecasts which are available, but further studies are required. The room model will be improved by taking into account the orientation of windows and the sun's position. Furthermore, other room types (e.g. meeting rooms) will be studied and experimental validation of the findings needs to be conducted.

5. Acknowledgements

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Data Statement

The datasets generated during or analysed during the current study are not publicly available but will be available upon direct request to the author.