PERFORMANCE PREDICTION OF ADVANCED BUILDING CONTROLS IN THE DESIGN PHASE USING ESP-R, BCVTB AND MATLAB

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ABSTRACT

In this paper, we present a new simulation-based approach with capabilities for analysing the impact of advanced control strategies on building performance during the building design phase. This environment consists of ESP-r as building simulation tool, Matlab as software for advanced building controllers and BCVTB as middleware for data exchange per time step between the two programs.
After describing the implementation details, we illustrate usability of the design support environment in a case study. This application example demonstrates model predictive control of a building with a thermally activated floor and solar shading. Furthermore, we show the use of explicit state initialization in ESP-r and a method to include uncertain weather predictions in the controller.

INTRODUCTION

On our way towards nearly zero-energy buildings, there is increasing attention for integrated building and systems designs. Among the most popular concepts are the use of thermally activated building systems (Lehman et al., 2007), dynamic daylighting and shading systems (Jelle et al., 2011), and onsite energy generation and storage with renewable technologies (Arteconi et al., 2012).
These concepts aim to take advantage of the multiple interactions between the building's shape and structure, ambient conditions, occupants' behaviour, and building services, for achieving high levels of indoor environmental quality while saving energy for space conditioning. Although this high degree of complex, dynamic and non-linear interactions, serves as basic working principle for the integrated building and systems concepts, it also introduces extra challenges in the design process (Kolokotsa et al., 2010). Some of these may be attributed to the stronger mutual dependence between design decisions and operational performance of integrated concepts compared to 'conventional' buildings.

The performance space that can be traversed by operational strategies after construction is to a large extent confined by choices for building-specific design attributes (e.g. orientation, glazing percentage, system sizes). Well-informed design decisions may increase opportunities for successful building operation. Similarly, there is also a risk that unfavourable design decisions, based on e.g. intuition and rules of thumb, limit the scope for further control optimization, and result in performance lower than expected (Torcellini et al., 2004).
It is therefore important to take realistic control aspects into account already in the design phase. Due to the strong dependency between their design and operation, this is especially important for integrated building and system concepts. Experimentation with different controller configurations helps in gaining better understanding of the challenges that are met in design of these concepts. In turn, this may help in refining the design for achieving the prospective higher levels of performance during operation.
In addition, there is also a need to analyse the potential of advanced supervisory control strategies. Recent studies show that conventional rule-based strategies can only partially capture the complexities encountered in integrated building and systems control, and that more advanced operation strategies are needed to achieve the higher levels of performance as intended (Oldewurtel et al., 2012).
Currently, however, there is a lack of design support tools that can provide such insights (Trcka and Hensen, 2010; Treado et al., 2011).
In this paper, we introduce a virtual environment for performance evaluation of integrated building design and advanced control aspects, by using ESP-r, BCVTB and Matlab. This simulation-based approach enables users to experiment with different controller settings and configurations, in order to get more realistic information about operational performance already during the building design phase.
In the next section, we provide more details on the software environment and its implementation. After that, these principles are illustrated in an application example.

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ADVANCED DESIGN AND CONTROL ENVIRONMENT

For effective and realistic performance prediction of advanced control strategies in the building design phase, we identified the following requirements:

- All physical principles and their interactions, which are necessary to study the impact of design decisions on performance during operation, are preserved in the simulation process.
- The method is scalable, and can be applied to many building types and climates.
- The method does not rely on availability of training data or system identification procedures.
- Energy performance and comfort evaluation can be studied at a high level of detail.
- The method offers sufficient flexibility for modelling innovative building energy concepts.
- The building model allows the user to manipulate a large number of sensor and actuator variables.
- Relevant uncertainties, including weather forecasts and occupants' behaviour can be taken into account for assessment of robustness.

Using these requirements, we consider whole building simulation as the favourable tool to use as basis for the design support environment.

Tool selection

ESP-r is amongst the building performance simulation (BPS) tools that offer the widest range of modelling capabilities (Crawley et al., 2008); therefore, it is an interesting candidate for studying advanced building controls. Its open-source structure is an additional advantage. ESP-r has been under continuous development for more than three decades, and has currently a number of strategies available for both local and supervisory control of building integrated energy systems (Clarke, 2001). However, considering the ongoing trend of increasing diversity and complexity of building controls (Dounis and Caraiscos, 2009), this predefined set of options does likely not offer the level of flexibility that is needed to continue fulfilling the demand. Moreover, other software programs are more suitable for this task. One of the most popular control-oriented tools is Matlab.

To take advantage of the complementary aspects of ESP-r for design, and Matlab for control aspects, interprocess communication between the two tools during simulation run-time is needed. To this end, we use BCVTB as middleware (Figure 1). BCVTB is a software environment that enables users to couple different simulations programs for co-simulation (Wetter, 2011). Matlab is one of the clients that is available for coupling in the standard BCVTB release, however, ESP-r is not. In the next subsection, we show how we implemented the connection between BCVTB and ESP-r.

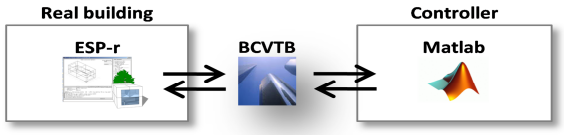

Figure 1: Design support environment for buildings with advanced building controls; BCVTB provides data exchange of sensor and actuator values between the building (ESP-r) and the controller (Matlab) during simulation run-time.

The coupling of ESP-r to Matlab through BCVTB is modular, and results in a co-simulation approach that offers several advantages compared to implementation of advanced controllers directly in ESP-r, including:

- It is relatively straightforward to implement new controller concepts, or to change controller settings; the latter does not require recompilation of ESP-r.
- It requires only limited knowledge of ESP-r's source code structure and users do not need to be experts in FORTRAN programming.
- It enables efficient use of Matlab's toolboxes with powerful capabilities for controller development.
- It is reusable and extensible, and can therefore accommodate newest developments in building controls research.

Extension of ESP-r with BCVTB subroutines

We used the existing BCVTB library functions to add ESP-r as a new client to BCVTB. Figure 2 shows a schematic overview of the code modifications we made to introduce BCVTB functionality in ESP-r. We added subroutines to establish and close communication with BCVTB, and for exchange of initial values. Furthermore, a subroutine was added for the exchange of control variables at each time step. This subroutine is currently implemented in a generic way for ESP-r's 'basic' heating and cooling controller. However, it is relatively easy to place these functions anywhere in the ESP-r code where exchange of data is needed. Some typical use cases of the new possibilities in ESP-r include, adaptive-window opening behaviour, comfort-driven heating and cooling control, and external coupling to other simulation packages for simulation of selected physical phenomena at higher resolution. In the application example presented in the next section, it is used in the ESP-r complex fenestration facility (CFC) to control solar shading.

A version of ESP-r with BCVTB functionality is available for download from the ESP-r developers branch `'ESP-r_BCVTB'`. Example projects and instructions are available in the standard BCVTB release.

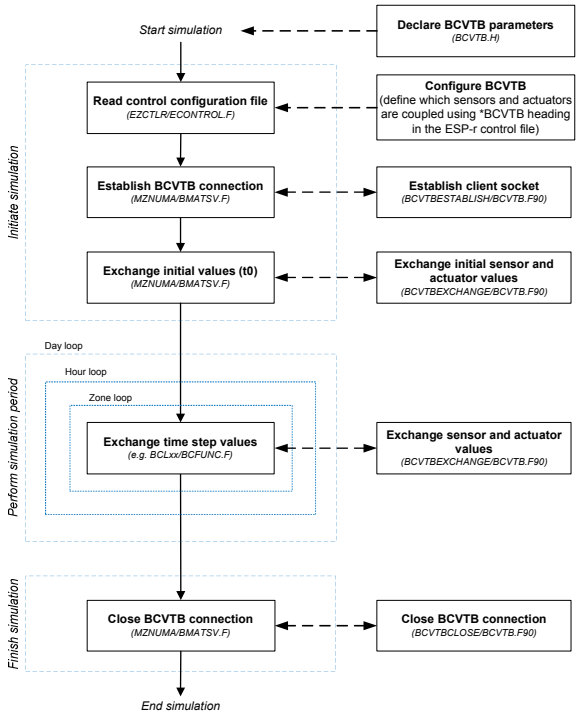

Figure 2: New ESP-r subroutines for communication with BCVTB (in BCVTB.F90) and adapted existing subroutines.

APPLICATION EXAMPLE: MODEL PREDICTIVE CONTROL OF TABS AND SOLAR SHADING

In this section, we show an application example of the control and design environment. We use it to study the behaviour of a building with a thermally activated floor and solar shading. Since thermally activated building systems (TABS) are slow responding, we need a controller which is able to anticipate on future events to assure optimal performance. Therefore, the potential of operating the coupled system of TABS and solar shading with a model predictive controller (MPC) is investigated.

MPC uses models to predict future events, so it can anticipate to these events with an appropriate control strategy. In Figure 3 we show the basic principles of a MPC (Braun, 1990; Henze et al., 2004).

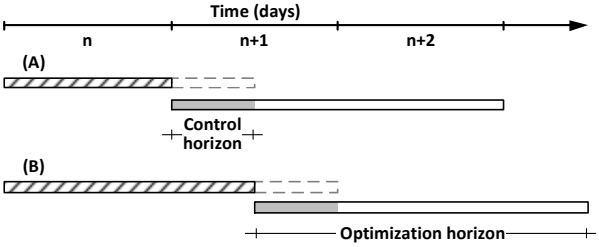

Figure 3: Schematic overview of the MPC controller for two consecutive horizons (A and B). In both horizons, the upper bar represents the real building; the lower bar the controller-embedded model with moving horizons.

First, the MPC searches for the most optimal control sequence for the optimization horizon. Next, the MPC implements the first control signals of this optimized sequence. After this, the optimization starts again with a shifted optimization horizon and updated predictions of boundary conditions.

Design environment set-up

As discussed in the previous section, in our design support environment the 'real' building is emulated with an ESP-r building model, and the controller is programmed in Matlab. As mentioned, a MPC uses models to predict future events. In literature, two main methods are described for these embedded models, using (i) reduced order or statistical, data-driven models, or (ii) detailed first principle models. An analysis of literature (Clarke et al., 2002; Coffey et al., 2010) suggests that the latter approach matches best with our requirements (see previous section). Therefore, in this application example, we use instances of the same ESP-r building model for both the 'real' building and the embedded MPC model (from here on referred to as the embedded building model). Figure 4 shows the design support environment with the MPC.

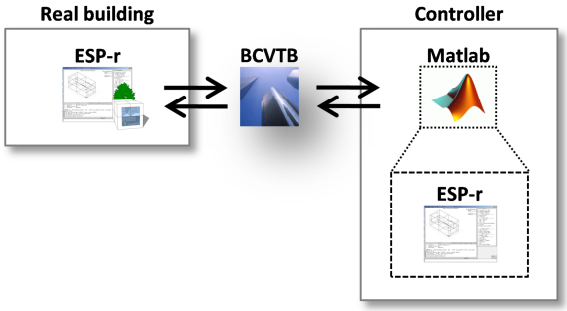

Figure 4: Overview of the design support environment with the model predictive controller. BCVTB facilitates the data exchange between ESP-r (building) and Matlab (controller) during simulation runtime. Communication inside the controller is based on scripts.

To simulate performance of MPC under realistic conditions, we have to take into account disturbances or uncertainties. These effects are introduced for two reasons:

- Without disturbances, the performance of the MPC would be overestimated, since control actions would be based on hypothetical perfect predictions from the embedded building model.
- The goal is to ensure robust performance in accordance with the degree of uncertainty that is present in the real world application.

Later, we show the method that we used to introduce weather uncertainties to the controller. But before we focus on these MPC related issues, we first discuss the 'real' building model.

Building case study

The ESP-r building model is based on the residential houses of the Zonne-entrée project (Tata Steel Star-Frame and Courage Architecten bna) in Apeldoorn (The Netherlands). The Dutch reference climate data of NEN5060:2008 are used. The building consists of five zones: zone A (south orientated) and B (north orientated) on the ground floor and zone C, D (south orientated) and E (north orientated) on the first floor. In Figure 5 the building is shown with additional details. The building is heated using a thermally activated layer in the (concrete) floor. Controllable external horizontal venetian blinds are installed on the South façade.

The dwelling is occupied by two persons during evenings (18h to 24h) and nights (24h to 8h) with average internal heat gains of 4 W/m^2.

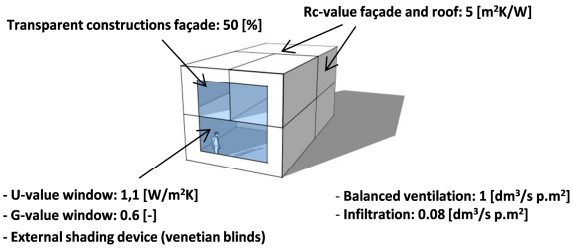

Figure 5: Case study based on Zonne-entrée Apeldoorn, facing the south façade.

The MPC controller is able to operate the TABS and blinds simultaneously. The controller is set-up to change the heating control signal every 4 hours from 0 (no heating) to 1 (full capacity) with three intermediate steps. The controller can set the blinds to three different states: 0 (fully retracted), 0.5 (lowered with slat angle of 0^o) and 1.0 (lowered with slat angle of 80^o). For comparison, we also defined a basic feedback controller. This controller operates the TABS by changing the heating control signal from 0 to 1 (continuous) for every 12 minutes (which is one simulation time step). During summer months, the blinds are lowered with slats set to 80 degrees (horizontal position) when the solar irradiance on the façade is higher than 300 W/m^2.

The objective of both controllers is to keep the PPD in the rooms below 10% during occupied hours, while minimising the heating energy demand.

Uncertainties using a weather generator

As mentioned, we use different uncertainty scenarios in the building controller to resemble the degree of uncertainty inherent in weather predictions. Therefore, the controller requires a method that is able to generate variability in daily weather forecasts depending on 'observed' weather variables (here the reference year used in ESP-r). This method should consider the following when generating weather forecasts (Wilks and Wilby, 1999):

- **Cross-correlation:** The statistical correlation of weather variables with each other.
- **Persistence:** The weather state of previous days.

Rajagopalan and Lall (1999) introduce a weather generator with these features, which is based on historically recorded observed data at a specific location. Their weather generator is used to generate daily weather sequences for weather erosion prediction models. Basically, the weather generator searches for weather patterns in the historical data which are similar to the observed weather at the day of interest. The search is limited to a time window of several days around the day of interest to account for seasonal effects.

Searching for similar weather patterns is done using a *k*-Nearest Neighbour approach. The nearest neighbours are historical days which show the 'closest' statistical similarities with the observed weather data on day *n*. Three of these nearest neighbours are then selected, and the observed values for the subsequent days are adopted as predicted values for days after day *n* (*n*+1 and *n*+2 for horizon *a* in Figure 3).

In our case study, we use historical weather data (1953-2011) recorded in De Bilt (The Netherlands), as input dataset to the *k*-Nearest Neighbor algorithm. We use hourly values of diffuse and direct solar intensity, dry bulb temperature and relative humidity to represent the daily weather state. In Figure 6 we show an example of a weather forecast generated for the 20th of May of the reference year. We show this day, because it is in an intermediate season and therefore is more likely to show uncertainties in predictions. In the figure, the neighbours show good agreement with the observed weather. Furthermore, realistic uncertainties are observed in the predicted weather variables.

This method seems useful for our purpose and will therefore be used in the MPC controller.

State initialization in ESP-r

Another MPC issue we address here is the state initialization of BPS tools. According to literature (Wetter and Haugstetter, 2006; Coffey et al., 2009), one of the main drawbacks of using detailed BPS tools for MPC applications are the time-consuming preconditioning periods which are necessary to guarantee stability in starting conditions. Depending on operational schedules, and thermal time constants of constructions, this initialization period may consume up to 80% or more of the actual simulation time (Nghiem and Pappas, 2011; Corbin et al., 2012). In earlier MPC studies with BPS as embedded building model, it was not, or only partly (Coffey, 2011) possible to remove this initialization period, because the programs they used (e.g. TRNSYS and EnergyPlus) did not allow access to the state

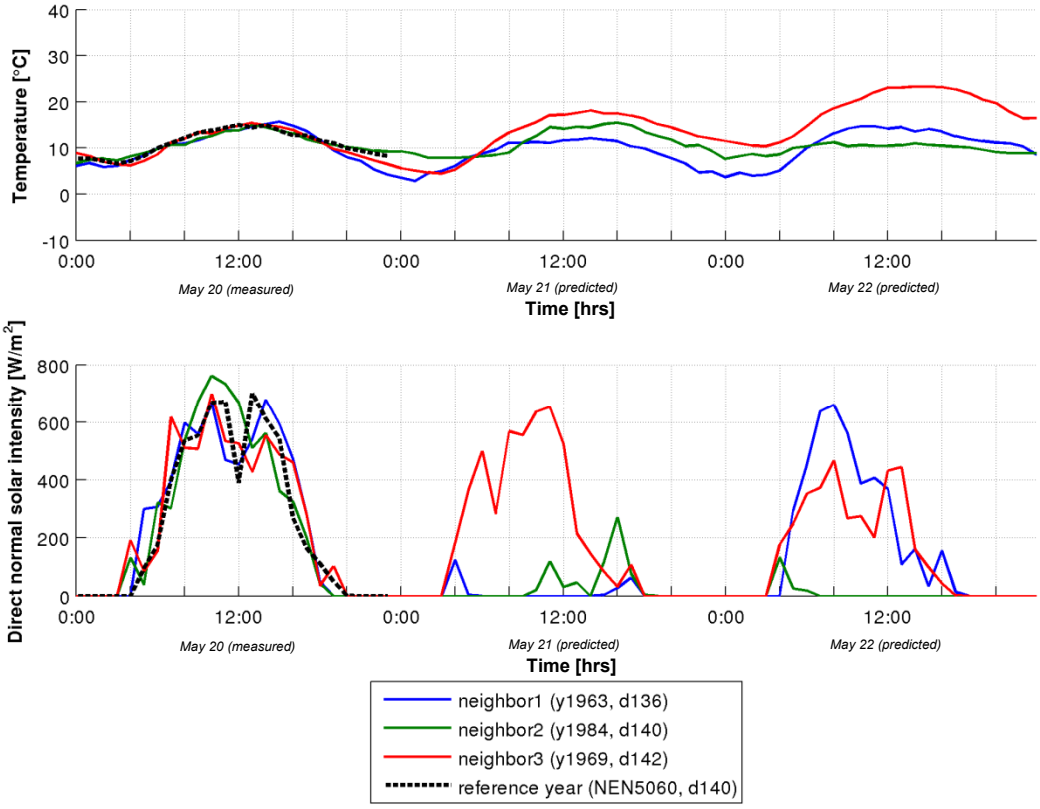

Figure 6: Temperatures and direct normal solar intensity of a day in the reference year (May 20; dashed line) and its three 'nearest neighbours' (May 16 of 1963, May 20 of 1984 and May 22 of 1969; resp. solid blue, green and red lines). The neighbours are selected from the historical data with a time window of 10 days around the reference day. A weather forecast of two days is generated using the historical data of these neighbours.

variables. An advantage of ESP-r is that it does give the user access to the building and system's state variables. We used this flexibility to circumvent the need for repeatedly running initialization periods. For that purpose, we added a subroutine, which stores all state variable values in a text file before the start of a new control horizon. At the first time step of the MPC optimization horizon, these state variables are used to explicitly overwrite ESP-r's default initialization values (while setting the start-up period to zero days).

Control sequence optimization

The final MPC feature we discuss, is the optimization procedure that is used to search for the optimal control strategy. We use the Matlab genetic algorithm (single objective) to optimize each optimization horizon. In this case study, the length of the optimization horizon is 48 hours, to account for the system's slow response time (Candanedo and Athienitis, 2011). The control sequence of this optimization horizon consists of 12 signals for the TABS (every four hours) and 4 signals for the blinds (two in the morning and two in the afternoon). The objective of the algorithm is to minimize the average energy demand of the uncertainty scenarios, while maintaining the average PPD < 10% during occupation.

The following settings are used for the genetic algorithm: cross-over fraction of 0.8, population of 30 and 2000 iterations per optimization horizon. To aid convergence, the previously optimized control sequence (shifted with one control horizon length) is added to the initial population.

As an example, we show the optimized control sequence for zone A (Figure 7) and the resulting thermal comfort (Figure 8) for the previously generated weather scenarios. The figures show that the algorithm chooses to heat the building during the first day, this is caused by the high probability of relatively low temperatures and almost no solar gains (two out of three uncertainty scenarios). On the third day, the algorithm choses to close the blinds, since it predicts a high probability of high solar gains (two out of three uncertainty scenarios).

Comparison of controller strategies

For three winter days (December 9, 10 and 11), we tested the performance of the MPC and compared the results with the basic controller. The period covers two sunny days and one day with overcast sky (Figure 9).

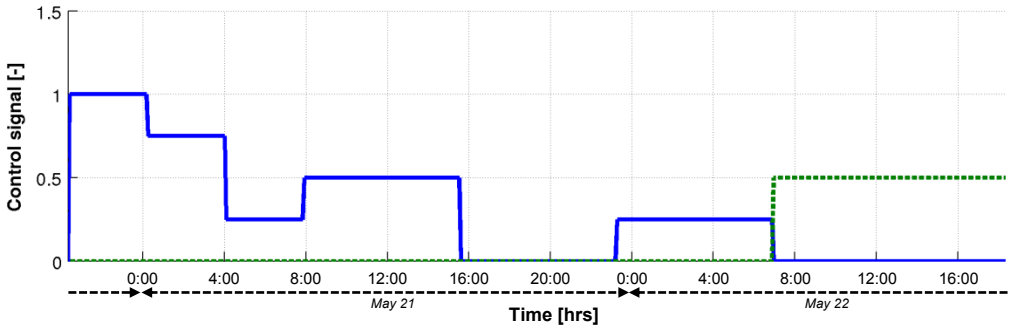

*Figure 7: Optimized control signal. Solid line is control signal for the heat injection (signal*1kW). Dashed line is signal for the blinds (0 is retracted, 0.5 is lowered with angle of 0° (horizontal), 1.0 is lowered with angle of 80°).*

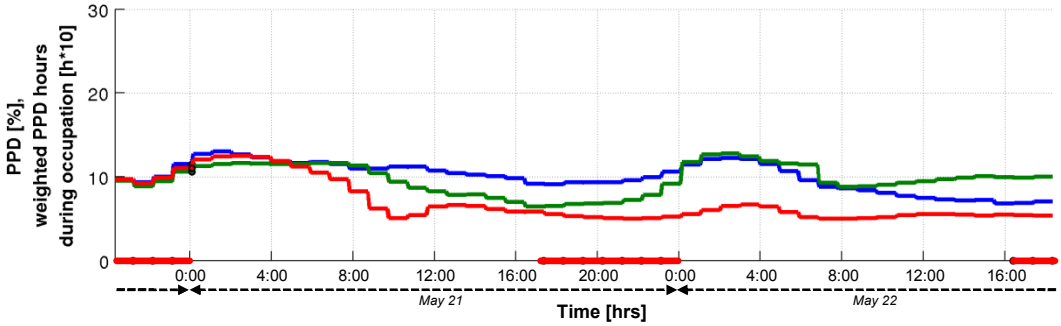

Figure 8: Thermal comfort for each weather scenario using the optimized control sequence. The average PPD per hour is indicated with the solid lines. Occupied hours are indicated with the red bars on the x-axis.

The resulting thermal comfort and control sequences for both controllers are shown in Figures 10 and 11 respectively. The behaviour of both controllers shows clear differences during the first two days. The basic controller heats up the room with maximum capacity directly when the PPD rises above 10%. The MPC predicts the direct solar gains that occur later during the day, and anticipates by using these gains to heat the building in a passive way. This results in lower heating loads, and also produces less fluctuations in PPD compared to the basic controller.

On the third day (no direct solar gains), the basic controller starts heating the building early in the day, whereas the MPC uses an optimized starting time for heating. Furthermore, the MPC demands less energy, since it maintained more constant temperatures during the previous days.

Over the three days period in December, the MPC

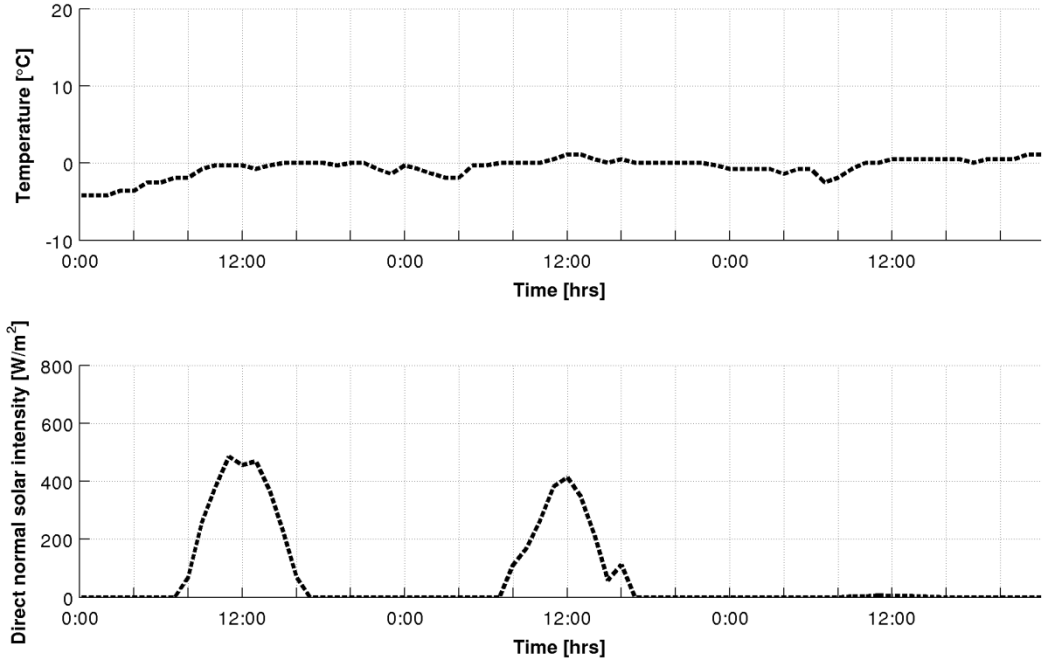

Figure 9: Temperature and direct solar gains on December 9, 10 and 11 of the reference year.

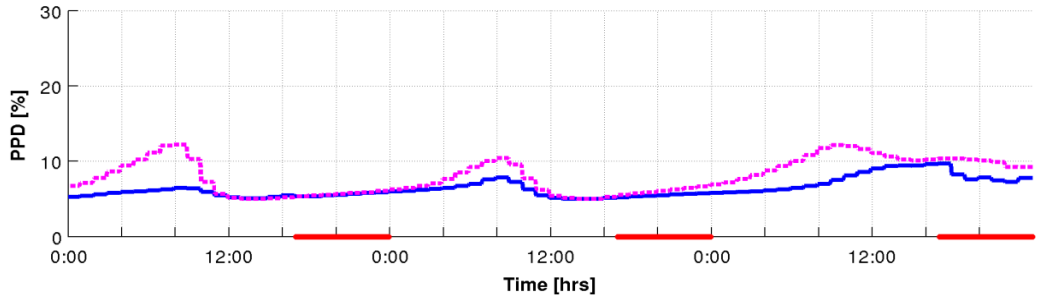

Figure 10: Resulting thermal comfort for the MPC (solid blue line) and basic controller (dashed purple line). Red bars indicate the period when occupants are present.

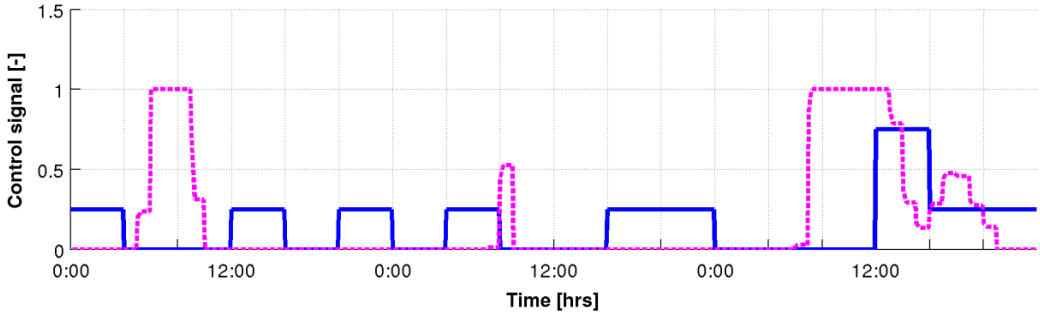

Figure 11: Resulting control sequences for the MPC (solid blue line) and basic controller (dashed purple line). Blinds are not used in this winter week.

strategy reduces the energy demand for heating with 15% (MPC demands 11kWh for the simulated period and the basic controller 13kWh). At the same time, thermal comfort conditions in the room are improved.

DISCUSSION

The focus in the application example is on the demonstration of proof of principle, and to comment on the details of the ESP-r to Matlab coupling with the MPC implementation. In future work, this controller implementation will be used to study the influence of the building design and MPC controller configuration on the performance of the TABS. In such a study, the influence of the following MPC parameters should be investigated in more detail:

- Choice of optimization algorithm;
- Control horizon length;
- Optimization horizon length;
- Number of uncertainty scenarios;
- Formulation of the objective function.

Nevertheless, it is encouraging that our preliminary results show the potential benefits of a MPC that takes uncertainties into account. In follow-up studies, it would be worthwhile to demonstrate that the concepts presented in this paper also work in supervisory control of actual buildings.

CONCLUSIONS

This article presented a tool based on ESP-r, BCVTB and MATLAB, for performance prediction of advanced supervisory control in the building design phase. By using this tool, it is possible to analyse the mutual impacts of advanced building controls and integrated building and systems designs. As a result, it may help as a decision support tool to enable more effective design and operation of such complex systems.

An application study of MPC for a building with TABS and solar shading showed the principles of this new way of performance prediction of advanced building controls in more detail. Furthermore, we showed the use of explicit state initialization and uncertain weather predictions with a *k*-Nearest Neighbour approach as useful additions to the growing body of research that focuses on investigating the potential of offline MPC.

ACKNOWLEDGEMENTS

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