A PREDICTIVE APPROACH TO INTELLIGENT BUILDING SYSTEMS CONTROL

ARDESHIR MAHDAVI[1]

ABSTRACT

This keynote presents the implementation of a novel predictive approach to intelligent building systems control. The implementation specifically pertains to the utilization of passive cooling in buildings. Thereby, numeric simulation is deployed as an integral part of the control logic to predict future implications of alternative control options (alternative positions of windows, shades, etc.) and identify the best performing control option. A genetic algorithm was developed to generate a manageable set of alternative options from the corpus of all possible control actions at any given time. Five rooms in two office buildings in Austria were used to test this method. The paper describes the approach and implementation in detail and presents the results.

Key words: building systems, predictive control, performance simulation, passive cooling, genetic algorithms

1. INTRODUCTION

The cooling energy demand in middle Europe is rapidly increasing, due in part to developments regarding climate change and urban heat islands. Conventional cooling systems are energy-intensive and problematic from the environmental point of view. Development of alternative energy-efficient alternatives for space cooling in new and existing buildings is thus of paramount importance both environmentally and economically. One innovative possibility to address this challenge is to explore the potential of technologically revisited and updated passive cooling techniques, which are primarily based on outdoor day-night temperature amplitudes and buildings' inherent thermal inertia. The intelligent use of passive control methods combined with innovative building systems as well as advanced sensory and actuating components have the potential to significantly decrease the energy use for space cooling (Lomas 2006, Garça et al. 2003, Krausse el al. 2007, Salmeron et al.

[1] Prof. Dr., Department of Building Physics and Building Ecology, VIENNA

2009, Mahdavi and Pröglhöf 2004, 2005, 2006, Mahdavi et al. 2009). This possibility was explored within the framework of a number of recent research projects. Thereby, the primary ingredients of passive cooling (thermal mass and amplitudinal variation of outdoor temperature) were optimally harnessed via a sensor-supported simulation-assisted predictive system control strategy. To evaluate this method, it was implemented and tested in five offices in two office buildings in Vienna and Stallhofen, Austria.

2. A PREDICTIVE SIMULATION-POWERED CONTROL APPROACH

2.1. General structure

The aforementioned novel predictive simulation-assisted control method was deployed toward intelligent passive cooling in office buildings. The application of the underlying concept in the building performance domain was introduced in (Mahdavi 1997) and further elaborated, amongst others, in Mahdavi 2001. This concept, which should not be confused with model-predictive control (García et al. 1989), involves the incorporation of explicit numeric performance simulation in the control core of buildings' environmental systems (in this case for window ventilation and shading controls). Thereby, candidate control options (i.e., alternative combination of the possible state of different control devices) for a future time instance are proactively evaluated via performance simulation. The simulation results for these alternative control constellations are compared with regard to the control objective. Thus, better performing control actions are identified and instantiated, either directly by the building's control unit, or through informed occupants' actions. A number of virtual and prototypical implementations of this concept have been introduced in the past, especially in the field of lighting and shading controls (see, for example, Mahdavi et al. 2000, Mahdavi 2008). Further studies augmented the simulation-based predictive building systems strategy with agent-based technologies and machine-learning methods (Chang and Mahdavi 2002, Mo and Mahdavi 2003). More recently, we have explored the application of simulation-powered control systems to the natural ventilation and passive cooling domains (Mahdavi et al. 2009, Schuss et al. 2010).

In the present implementation, the control method generates and evaluates alternative operation possibilities using genetic algorithms and the multi-domain simulation results. Figure 1 illustrates the basic sequence involved in the approach, which is typically instantiated on a regular basis (e.g. once every hour). The control procedure was implemented in the matlab environment (Matlab 2010) and uses HAMbase (van Schijndel 2007) and (Radiance 2010) as embedded simulation tools. Services for data monitoring, communication, and weather forecast were programmed in C and run independently. Monitoring data (internal and external sensors) together with the web-based weather forecasts data were stored in a SQLite database.

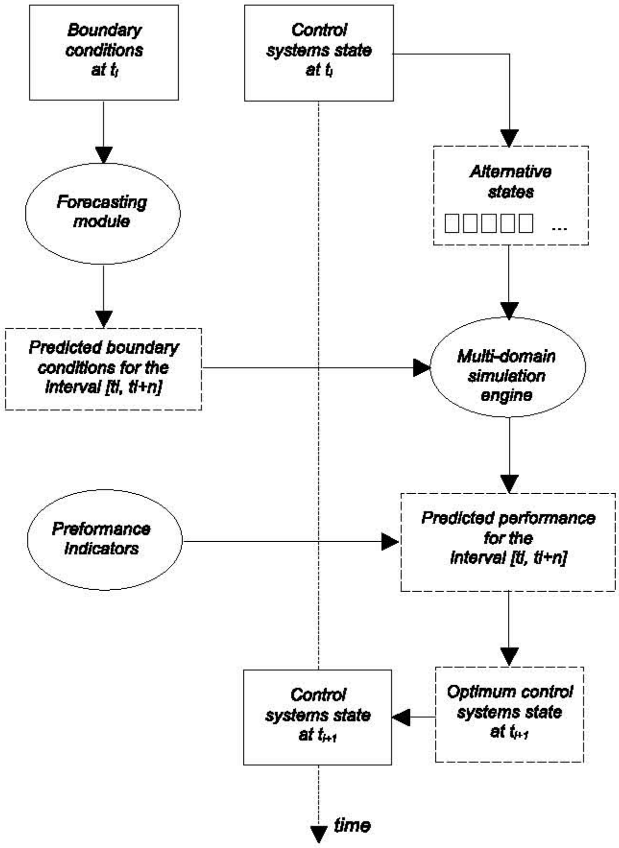

Figure 1. Illustration of the multi-domain simulation-assisted control method

2.2. Performance indicators

To guide the operation of the control system, a number of performance functions and indicators were defined and applied to evaluate the multi-domain simulation results. The overall performance indicator i (Equation 1) is the weighted sum of all individual indicators i_x. The value of each indicator and the sum of the weighting factors w_x is in the range of 0 to 1. Hence i must be in the same range. The ranking of the alternative control possibilities is done by maximum to minimum sorting.

$$i = \sum i_x \times w_x \qquad (1)$$

$i, i_x, w_x \in [0,1]$ and $\sum_x w_x = 1$

The calculation of each indicator is based on the simulated predictive trend of the related system parameter (e.g., room air temperature). For each parameter, the sum of deviations d_{period} is calculated for the future n time steps shown in Equation 2.

$$d_{period} = \sum_{k=t_i}^{t_i+n} d(k) \tag{2}$$

The calculation of each deviation depends on a fixed set point (Equation 3) or an acceptable parameter range as shown in Equation 4 and Figure 2. The general indicator i_x could be derived either linearly (Equation 5), or exponentially (Equation 6).

$$d(t) = \left| p(t) - p_{SP}(t) \right| \tag{3}$$

$$d(t) = \begin{cases} p_{\min} - p(t) & if \quad p(t) < p_{\min} \\ 0 & if \quad p_{\min} \le p(t) \le p_{\max} \\ p(t) - p_{\max} & if \quad p(t) > p_{\max} \end{cases} \tag{4}$$

$$i_x = \begin{cases} 1 - \dfrac{d_{period}}{d_{period\max}} & if \quad d_{period} < d_{period\max} \\ 0 & if \quad d_{period} \ge d_{period\max} \end{cases} \tag{5}$$

$$i_x = 1 - e^{-c.d_{period}} \tag{6}$$

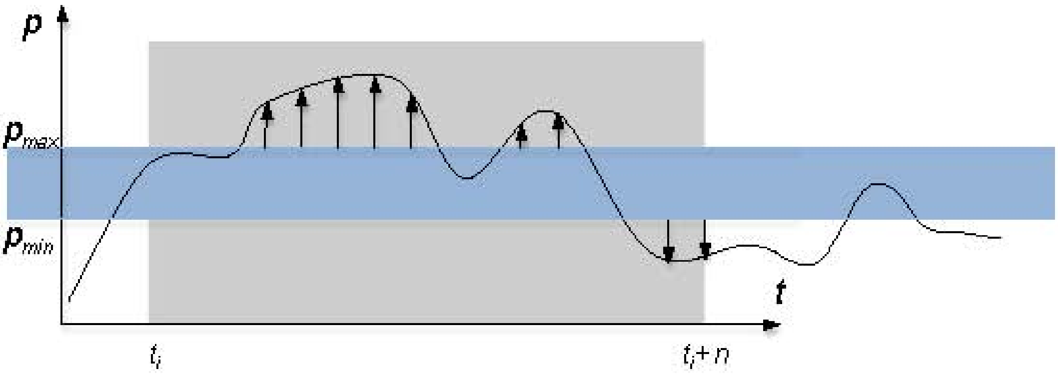

Figure 2. Deviation calculation for a general system parameter p

The principle calculation procedure for HVAC and lighting power use are expressed in equations 7 and 8 respectively.

$$i_{PHVAC} = \frac{1}{n}\sum_{t=t_i}^{t_i+n} 1 - \frac{P_{HVAC}(t)}{P_{HVAC_{\max}}} \tag{7}$$

$$i_{PL} = \frac{1}{n}\sum_{t=t_i}^{t_i+n} 1 - \frac{P_{Lighting}(t)}{P_{Lighting_{\max}}} \tag{8}$$

2.3. Generation of alternative control schedules

The predictive control method needs a set of alternative operation states in terms of the relevant device control schedules. These schedules have to be produced to run the multi-domain simulations. Using all possible combinations over the whole forecast interval would lead to an unmanageable number of possibilities. An approach using genetic algorithms (see Figure 3) provides a possibility to handle this challenge.

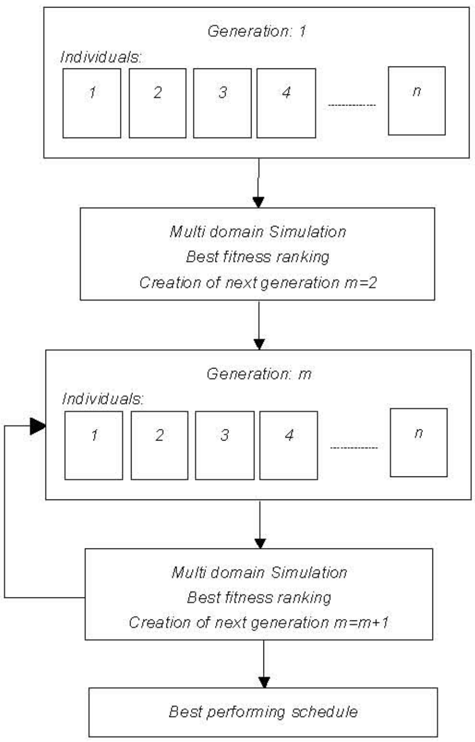

Figure 3. Illustration of the genetic generation of the desired operation schedules

Thereby, a number of default operation schedules were used together with randomized schedules as the initial setup. Needed state definitions and device attributes were stored in a predefined data structure to generate the schedules automatically. Based on the first generation simulation, the best-ranked schedules were selected to generate new child schedules in a random multipoint crossover reproduction process. For this purpose, the high-ranked schedules were crossed with themselves as well as with additional randomly selected schedules as parent elements. The selection of the fittest alternative (schedule) was done by the use of performance indicators (discussed before).

3. IMPLEMENTATION

Two office buildings in Austria were selected to implement and systematically test and evaluate the aforementioned approach. The first object (VUT) consists of three adjacent office rooms in an old office building of Vienna University of Technology. The second test facility (FIBAG) consists of two rooms (identical in layout but located on two adjacent floors) in an office building in Stallhofen, Styria. Note that the offices in VUT were actively used during the test period. This provided the opportunity to test the method's operation under realistic conditions. The corollary was, however, a few instances of user interference with the system's operation. In contrast, tests in FIBAG were conducted under unoccupied conditions.

3.1. VUT

Three occupied nearly identical south-oriented office spaces (R1, R2, and R3) were specifically targeted for our study (see Figure 4). The office R1, which has manually operated windows and internal venetian blinds, was kept as is and used as a reference. The other two offices were equipped with window actuators (for automated operation), as well as internal (R2) and external (R3) window shades. Additionally, PCM elements as well as a ceiling fan were installed in R3. All rooms were equipped with sensors for measuring indoor parameters such as air, surface, and globe temperature, relative humidity, occupancy, illuminance at the ceiling and at the workplace, air velocity, and carbon dioxide concentration (Figure 5). In addition, outdoor environmental data was collected (Figure 6) in front of the offices (air temperature, relative humidity, wind speed, and precipitation) and on the rooftop (global horizontal radiation, and diffuse horizontal radiation). Shade position and door/window status were also monitored. An overview of the deployed hardware equipment is provided in Table 1 and the hardware system schema is illustrated in Figure 7.

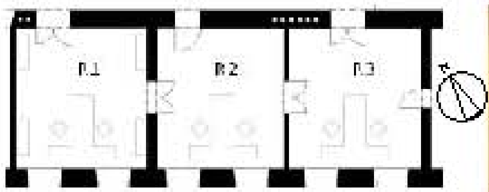

Figure 4. VUT - office layout

Figure 5. VUT – Internal climate sensors

Figure 6. VUT – Façade with climate sensors

Table 1. Summary of deployed hardware components

Hardware	Description
Indoor climate sensors	Compact indoor climate stations to measure air temperature, relative humidity, and velocity as well as carbon dioxide and illuminance at the workplace.
Outdoor climate sensors	Weather station for air temperature, relative humidity, precipitation, global irradiance, wind speed, and wind direction
User action and presence sensor	Presence: PIR - Sensor with adjustable threshold time; Door opening: magnetic contact sensors
Window automation	Two synchronized adjustable drives for each window to control the window opening position continuous.
Shading automation	Single drives with a special gear unit for height and angle positioning
Lighting control	The room controller can adjust dimming levels between 10 to 100% of the total lighting power
Backbone and communication network	IP base communication with access to building data points and data history

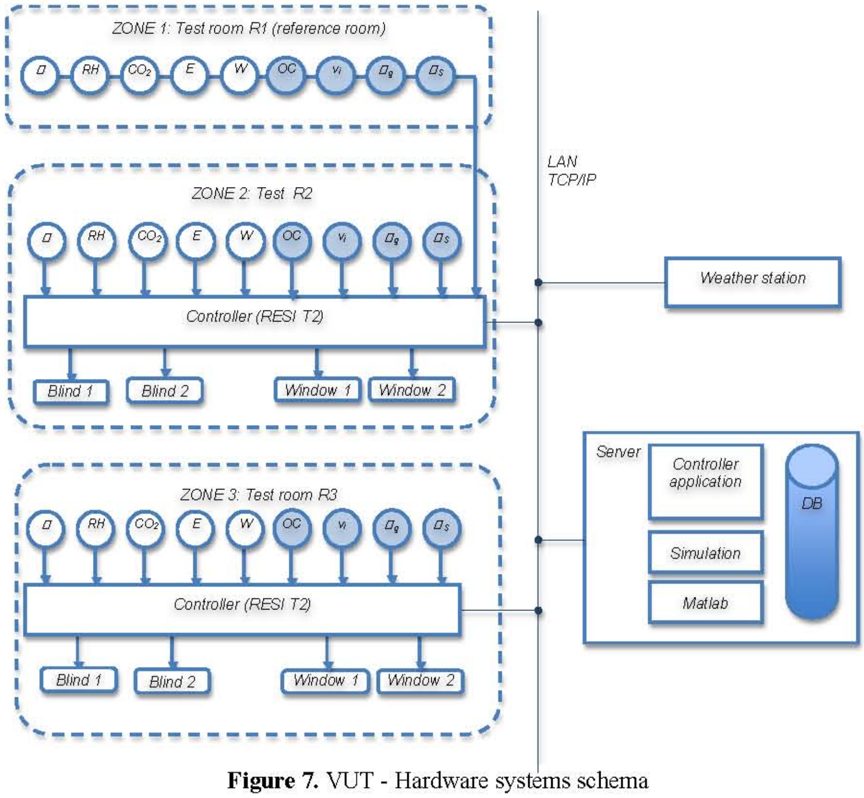

Figure 7. VUT - Hardware systems schema

3.2. FIBAG

A second implementation of the predictive control approach was done in a new office building in Styria, Austria (see Figure 8). For this purpose, two rooms in this office building were selected. The building structure with a concrete skeleton (ceilings and staircases) and the lightweight internal and external walls is typical for new office buildings in Austria. This circumstance, combined with the glass and aluminum façade, results in a reduced useable thermal storage mass and thus aggravates the impact of solar gains.

The two rooms are identical in terms of layout (Figure 9 and 10) and are located in the first and second floor on the northwest corner of the building. The offices were equipped with actuators for lighting, shading, and window operation. Indoor conditions in both rooms as well as the external climate were monitored with sensors for thermal and lighting parameters. One room was controlled with an implementation of the proposed predictive simulation-based control method. The second room was used as a reference.

Figure 8. FIBAG - Office building with two test rooms (marked)

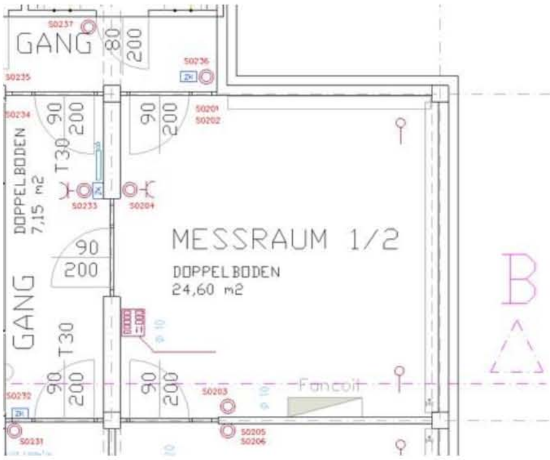

Figure 9. FIBAG - Test room layout

Figure 10. FIBAG - internal view of test room

3.3. Evaluation period

The developed control method was deployed in the operation of two test facilities during two months in summer 2010. However, parts of July were used for initial testing of the control setup. Thus full operational data is not available for all days in July. In August the system operated continuously. Hence, the present treatment focuses (with the exception of Figure 9), on August data. The control cycle was executed on a regular basis – once every hour. Figure 11 illustrates a typical outcome of such a cycle. The left side of the plot represents the history trends of the room air temperature (grey) and the outdoor air temperature (red). The predicted outside temperature is plotted on the right sight together with multiple simulation-based predictions of air temperature trends due to the virtual enactment of candidate control options. The best performing option is marked in black.

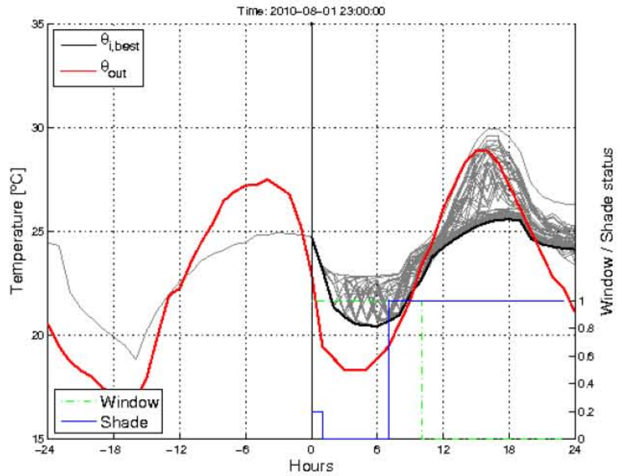

Figure 11. Indoor and outdoor (red) temperature history (left) and multiple predictions (right) with the best performing course (thick black) in the test room for a day in August 2010

To identify the preferable control option, two performance indicators (i) were used. One was related to the air temperature (θ_{air}) and the second related to mean interior surface temperatures of the room (θ_s). These two indicators were equally weighted (w_{air} , w_s).

$$i = i_{\theta_{air}} \times w_{\theta_{air}} + i_{\theta_s} \times w_{\theta_s} = \frac{1}{2} \times i_{\theta_{air}} + \frac{1}{2} \times i_{\theta_s} \quad (1)$$

To derive the indicator values, a negative exponential formulation was used based on corresponding time-dependent aggregate deviations (Equation 10 and 11). In these equations, c represents a calibration factor.

$$i_{\theta_{air}} = 1 - e^{-c \cdot d_{\theta_{air}}} \tag{2}$$

$$i_{\theta_s} = 1 - e^{-c \cdot d_{\theta_s}} \tag{3}$$

In case of the storage temperature indicator, aggregated deviations are calculated as a sum of all discrete time deviations *m(t)* in the forecast interval (Equation 12). In case of air temperature (Equation 13), only the occupancy hours (08:00-17:00) are considered, as represented by *g(t)*. Figures 12 and 13 illustrate this circumstance.

$$d_{\theta_s} = \sum_{t=t_i}^{t_i+n} m_{\theta_s}(t) \tag{4}$$

$$d_{\theta_{air}} = \sum_{t=t_i}^{t_i+n} m_{\theta_{air}}(t) \times g(t). \tag{5}$$

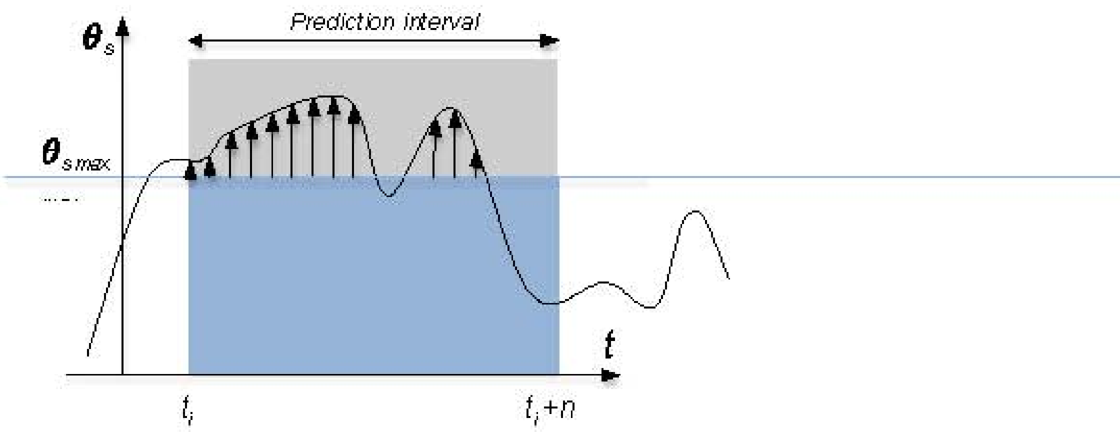

Figure 12. Deviation calculation for the surface temperature performance indicator

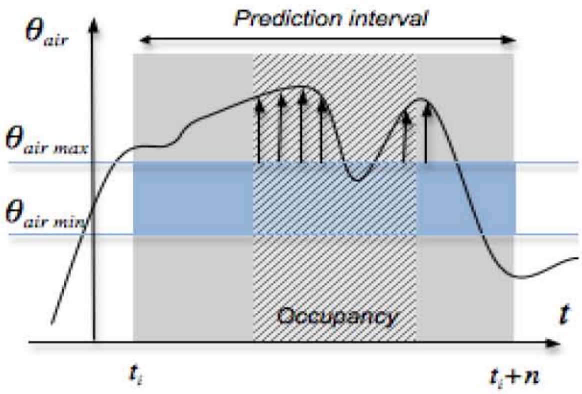

Figure 13. Deviation calculation for the air temperature performance indicator.

4. RESULTES

The test results point to the potential of the proposed predictive control: as compared to the reference rooms, the rooms with the predictive control systems demonstrated preferable indoor climate conditions

4.1. VUT

To illustrate the performance of the method, Figure 14 shows the indoor and outdoor air temperature trends for three successive days in July 2010. The better thermal performance of the controlled rooms is obvious. The peak temperature readings in R3 and R2 were 4 K and 2 K lower respectively compared to the reference room R1. To evaluate the system's performance in more detail, Predicted Mean Vote values (PMV) as well as mean overheating was calculated for August (during working hours, i.e. from 8:00 to 17:00). Note that, strictly speaking, PMV is not applicable to free-running buildings. Nonetheless, given its familiarity, it is used here to document the relative differences between the reference and controlled rooms. Figure 15 depicts the monthly mean PMVs and the mean overheating (computed for a reference overheating temperature of 26°C) for R1 (reference room), R2, and R3. As compared to the reference room, rooms R2 and R3 show better results. The difference between R1 and R3 is about 0.5 points in terms of PMV and 1.1 K in terms of mean overheating. The collected data was also processed in terms of psychometric charts (Figures 16 to 18). The (red) dots represent mean hourly values during working hours (08:00-17:00). The (green) polygons show the applicable thermal comfort zone according to the adaptive thermal comfort theory (Szokolay 2004). The psychometric charts display a similar trend. R3, as the best-equipped room, was 38% less outside the thermal comfort zone compared to R1. Likewise, R2 was about 24% less outside the thermal zone than R1.

In addition to such numeric comparisons, we also requested user feedbacks via questionnaires. In general, users in R2 and R3 generally had a better view of the thermal environment than in the reference room. Nighttime ventilation regime, added shading devices, and the – principally given – possibility to control the devices with the system's GUI was explicitly rated positive. The noise generated by the motorized actuators while opening or closing windows and blinds was commented on negatively. Moreover, users expressed the need for a more fine-tuned glare control.

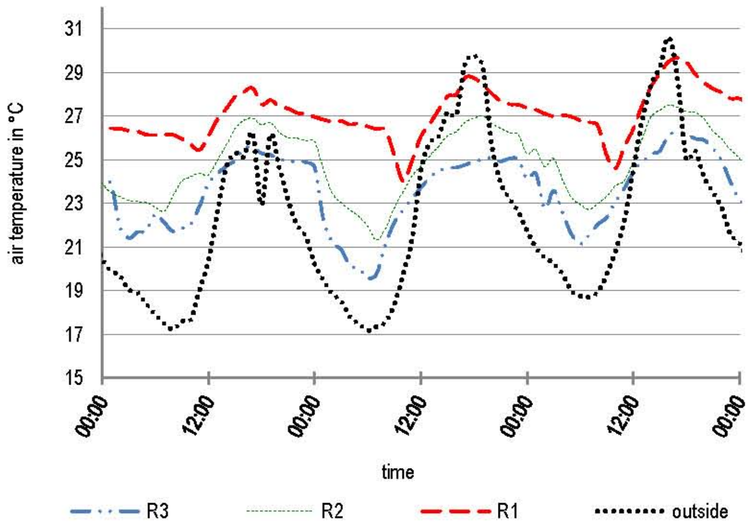

Figure 14. Typical air temperature trends in July 2010

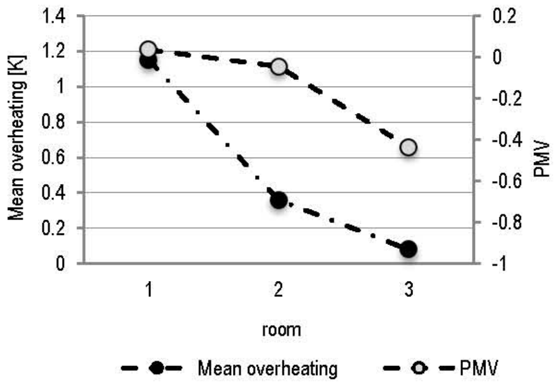

Figure 15. Mean overheating of indoor air and mean PMV values (VUT, August 2010)

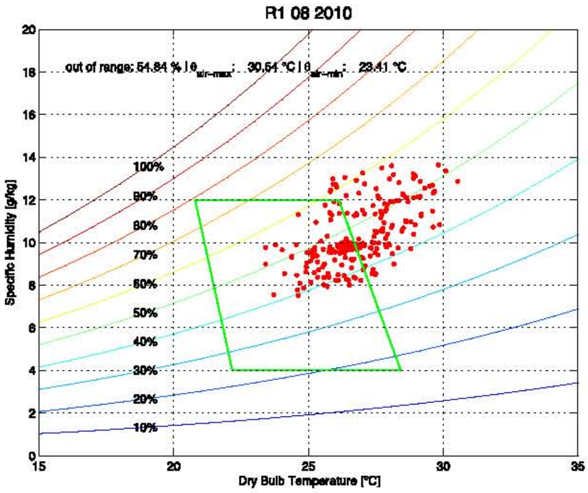

Figure 16. Measured temperature and humidity in R1 (VUT) during working hours, August 2010

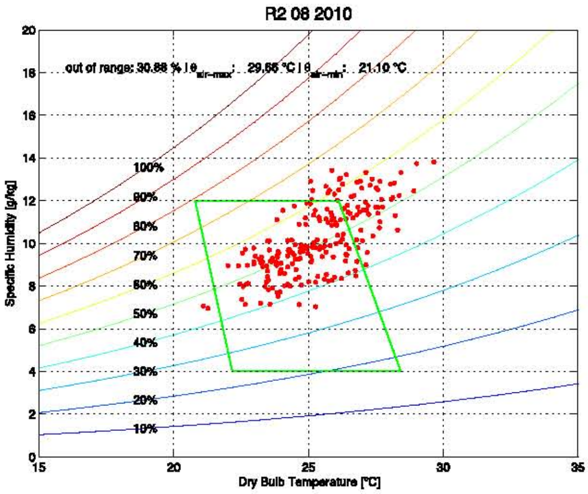

Figure 17. Measured temperature and humidity in R2 (VUT) during working hours, August 2010

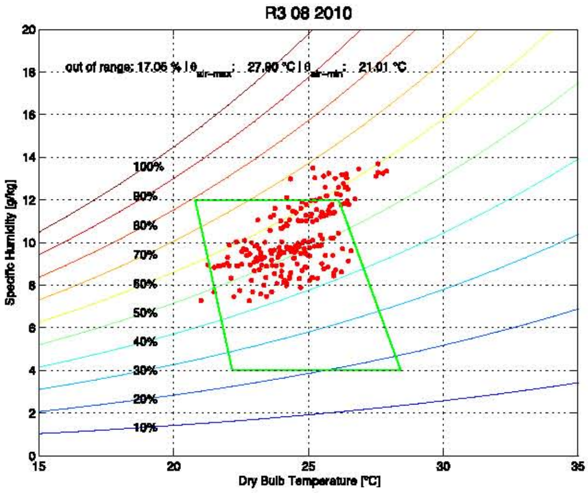

Figure 18. Measured temperature and humidity in R3 (VUT) during working hours, August 2010

4.2. FIBAG

Monthly mean PMV and overheating values for test spaces in FIBAG are shown in Figure 19. As compared to the reference room 2, room 1, which was operated via the simulation-based control method, provided better thermal conditions. Mean PMV amounts almost to zero (compared to 1 in room 2), whereas mean overheating is merely 0.5 K (compared to 2 K in the reference room).

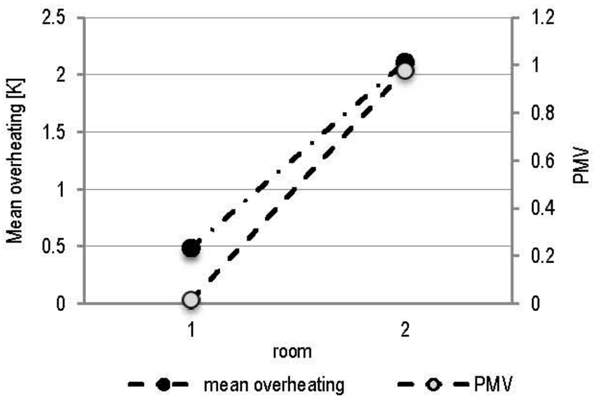

Figure 19. Mean overheating of indoor air temperature and mean PMV values (FIBAG, August 2010)

Psychometric charts (August 2010) display a similar trend (see Figures 20 and 21). As compared to the reference room 2, thermal conditions in room 1 were 35% longer in the thermal comfort zone (working hours).

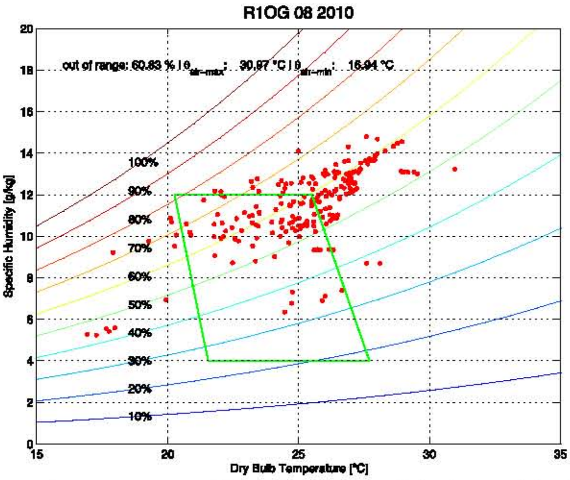

Figure 20. Measured temperature and humidity in room 1 during working hours (FIBAG, August 2010)

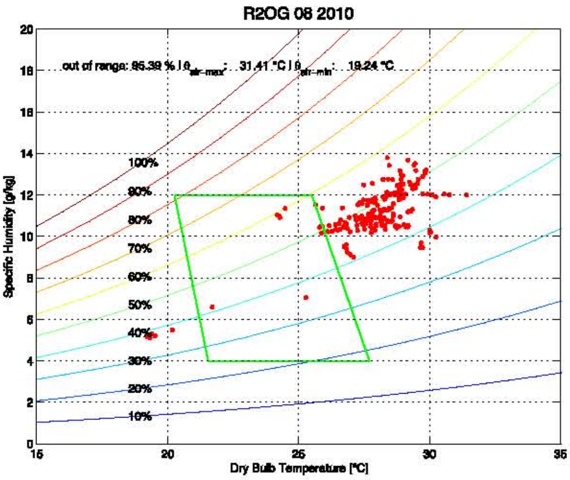

Figure 21. Measured temperature and humidity in room 2 during working hours (FIBAG, August 2010)

4.3. Weather prediction quality

The Quality of the integrated online weather forecasts was analyzed in terms of differences to the stored local monitored weather data. Generally speaking, forecast for air temperatures showed quite acceptable deviations in an overall one-degree range with some outliers around 2 to 4 degrees (Figure 22).

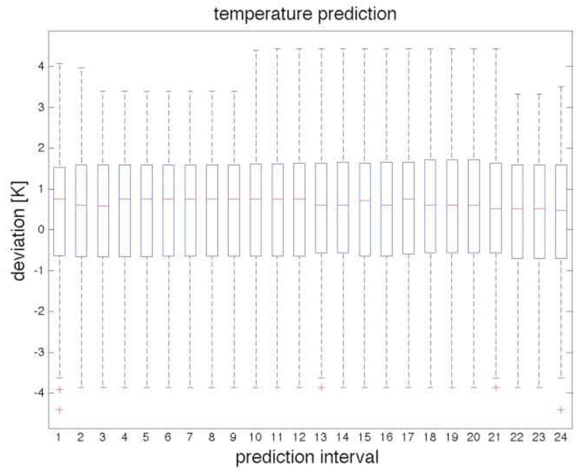

Figure 22. Temperature forecast deviation of 2010 data for 1 to 24 hour prediction

5. CONCLUSION

The research results illustrate the potential of the proposed predictive simulation-assisted approach to offer low-cost and energy-efficient indoor environmental control. Compared to the reference rooms, the rooms with the predictive control systems clearly demonstrated preferable indoor climate conditions. A number of measures would allow to further improve the performance of the system:

- The minimization of internal loads: The installed power of the electric devices (computers, artificial lights, etc.) should be minimized. Devices should be switched off (or hibernate) when not in use.
- The importance of informing the users: Users should be instructed regarding the proper operation of building systems. Moreover, the users should be given proper feedback about the implications of their actions and behavior.
- The accuracy of input parameters for the predictions: The quality of the weather forecast is critical. Especially the prediction of solar radiation needs improvement.

Nonetheless, the results and the experiences with the implementation show that the proposed approach can be generally realized in existing structures with a reasonable degree of investment.

ACKNOWLEDGEMENT

The author gratefully acknowledges Dr. Matthias Schuß and his instrumental role in the implementation of the research project presented in this keynote paper. This research was supported in part by a fund from FFG "Naturally Cool" (Project-Nr: 817575). Additional support was provided via the K-Project "Multifunctional Plug

& Play Façade" (Project-Nr: 815075) and the "Hans Höllwart Forschungszentrum für integrales Bauwesen AG".

REFERENCE

Chang, S., Mahdavi, A. 2002. A hybrid system for daylight responsive lighting control. Journal of the Illuminating Engineering Society, Volume 31, Number 1, Winter 2002, pp. 147 - 157.

Garça, G.C., Linden, P.F., McConahey, E., Haves, P. 2003. Design and testing of a control strategy for a large, naturally ventilated office building. Proceedings of the 8th International IBPSA Conference, Building Simulation 2003 , pp. 399 - 406, Augenbroe, G., Hensen, J. (eds.), Volume 1, Eindhoven, Netherlands.

García, C. E., David M. Prett, D. M., Manfred Morari, M. 1989. Model predictive control: Theory and practice—A survey. Automatica, Volume 25, Issue 3, May 1989, Pages 335-348, Elsevier Science Ltd.

Krausse, B., Cook, M.J., Lomas, K.J. 2007. Environmental performance of a naturally ventilated city centre library. Energy and Buildings 39, Issue 7, pp. 792 - 801, Todorovic B., Meier A.K. (eds.), Elsevier.

Lomas, K. J. 2006. Architectural design of an advanced naturally ventilated building form. Energy and BuildingsVolume 39, Issue 2, pp. 166 - 181, Elsevier.

Mahdavi, A. 1997. Toward a Simulation-assisted Dynamic Building Control Strategy. Proceedings of the Fifth International IBPSA (International Building Performance Simulation Association) Conference, Vol. I, pp. 291 - 294.

Mahdavi, A. 2001. Simulation-based control of building systems operation. Building and Environment, Volume 36, Issue 6, ISSN: 0360-1323. pp. 789-796.

Mahdavi, A. 2008. Predictive simulation-based lighting and shading systems control in buildings. Building Simulation, an International Journal, Springer, Volume 1, Number 1, ISSN 1996-3599, pp. 25 - 35.

Mahdavi, A., Chang, S., Pal, V. 2000. Exploring Model-Based Reasoning in Lighting Systems Control. Journal of the Illuminating Engineering Society, Volume 29. Number 1. Winter 2000. pp. 34 - 40.

Mahdavi, A., Orehounig, K., Pröglhöf, C. 2009. A simulation-supported control scheme for natural ventilation in buildings. Proceedings of the 11th IBPSA Conference, Building Simulation 2009, pp. 783 - 788, Glasgow, Scotland.

Mahdavi, A., Pröglhöf, C. 2004. Natural ventilation in buildings – Toward an integrated control approach. Proceedings of the 35th Congress on Heating, Refrigerating and Air-Conditioning, pp. 93 – 102, Belgrade, Serbia.

Mahdavi, A., Pröglhöf, C. 2005. A model-based method for the integration of natural ventilation in indoor climate systems operation. Proceedings of the 9th International IBPSA Conference, Building Simulation 2005, pp. 685 – 692, Montreal, Canada.

Mahdavi, A., Pröglhöf, C. 2006. A model-based approach to natural ventilation. Building and Environment, Volume 43(4), pp. 620 – 627, Elsevier.

Matlab, 2010. MATLAB Release 2010a, The MathWorks, Inc., http://www.mathworks.com.

Mo, Z., Mahdavi, A. 2003. An agent-based simulation-assisted approach to bi-lateral building systems control. Proceedings of the Eight International IBPSA Conference (Eindhoven, Netherlands), Vol. 2. pp. 887-894, Augenbroe, G., Hensen, J. (eds). ISBN 90 386 1566 3.

Radiance, 2010. Radiance Synthetic imaging system Version 4, *University of California*, http://radsite.lbl.gov/radiance/.

Salmeron, J.M., Sanchez, J., Ford, B., van Steenberghe, T., Alvarez, S. 2009. Passive and hybrid downdraught cooling in buildings and software for design. Rehva Journal. Volume 46, Issue 6, pp. 34 – 39, ISSN 1307-3729.

Schuss, M., Pröglhöf, C., Orehounig, K., Dervishi, S., Müller, M., Wascher, H., Mahdavi, A. 2010. Predictive model-based control of ventilation, lighting, and shading systems in a building. BauSIM 2010, Martens B., Mahdavi A. (eds.), Vienna, Austria.

Szokolay, S.V., 2004. Introduction to architectural science: the basis of sustainable design. *Elsevier Science, Oxford*, pp. 16 – 22, ISBN 0 7506 58495.

van Schijndel, A.W.M. 2007. Integrated heat air and moisture modeling and simulation. PhD thesis, Eindhoven University of Technology, available at: http://alexandria.tue.nl/extra2/200612401.pdf or http://sts.bwk.tue.nl/hamlab [accessed June 2010].