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A MODEL-BASED METHOD FOR THE INTEGRATION OF NATURAL VENTILATION IN INDOOR CLIMATE SYSTEMS OPERATION

Ardeshir Mahdavi and Claus Pröglhöf
Department of Building Physics and Building Ecology
Vienna University of Technology
Vienna, Austria

ABSTRACT

This paper presents an in-situ calibrated model-based approach to treat natural ventilation as an integral element of the operation of the buildings' thermal systems. Specifically, the potential of statistically-based and numeric air flow models is explored as part of a hybrid building controls scheme. Toward this end, two case studies are described. In one case, the underlying predictive model is based on the statistical treatment of data obtained from a set of in-situ measurements in a typical office space. In the second case, a multi-zone air-flow model is used to predict the fresh air volume flows into the building interior. The resulting air flow models can be integrated within a model-based control approach toward the operation of the buildings' ventilation systems.

MOTIVATION AND BACKGROUND

Access to outdoor environment and fresh air is increasingly deemed to be essential for the health, comfort, and satisfaction of the occupants of buildings. However, the prevailing paradigm in indoor environment control (particularly in office buildings) often excludes natural ventilation, partly because its dynamic (and not easily predictable) nature could interfere with the smooth operation of mechanical conditioning systems in pressurized buildings. Given the current indoor environmental control expectations in modern buildings, and given the outdoor climate constraints in various regions of the world, it is not likely that all buildings could be operated with passive technologies only. This necessitates the integration of natural ventilation into the design and operation of indoor environmental control systems. In response to this need, this paper presents an in-situ calibrated model-based approach to treat natural ventilation as an integral element of the operation of the buildings' thermal systems. Specifically, the potential of statistically-based and numeric air flow models is explored as part of a hybrid building controls scheme. Toward this end, two case studies are described. In one case, the underlying predictive model is based on the statistical treatment of data obtained from a set of in-situ measurements in a typical office space. In the

second case, a multi-zone air-flow model is used to predict the fresh air volume flows into a test space as a function of building geometry, status (opening position) of operable windows, and outdoor conditions.

The resulting air flow models can be integrated within a control system toward the model-based operation of the buildings' ventilation systems (Mahdavi et al. 1999). In such a system, control actions are triggered due to changes in the state of *a)* boundary conditions (outdoor temperature, wind velocity, relative humidity); *b)* indoor climate (temperature, relative humidity, CO_2 concentration); and *c)* occupancy (presence) and occupancy settings (e.g. preferred temperature levels). The control process is as follows. Upon the occurrence of one or more of the above changes, the control application considers a set of alternative combinations of the states of control devices (e.g. position of operable window elements). Subsequently, this set of alternatives is subjected to predictive assessment of the implications of these alternative control actions, resulting in corresponding performance indicators such as indoor air temperature, relative humidity, air change rate, and air velocity. These results are then compared and ranked according the objective function (preferences) set by the users. The alternative control option with the most desirable performance in terms of this objective function is selected and communicated to the user or to the control system.

MODEL-BASED CONTROL

Conventional indoor climate control systems are "reactive" in the sense that they operate by activation and modulation of networked thermal energy sources and sinks in spaces based on thermostatic feed back. For such a control system to function smoothly, there must be a certain match between the variation of the thermostatic feed back and the modulation of the source/sink action. Operation of devices for natural ventilation (mostly operable windows) introduces challenges for conventional thermal control systems in – typically pressurized – buildings. The operation of windows by occupants may result in rapid and large changes in the temperature, humidity, and

pressure of the indoor air. For example, in buildings with radiant cooling systems, indoor surface condensation may result from uncontrolled window ventilation under hot and humid outdoor conditions. It is thus not surprising that most designers and operators of conventional HVAC (heating, ventilation and air-conditioning) have been rather uncomfortable with natural ventilation strategies in general and operable windows in particular.

A possible approach to address this problem is to provide both the buildings' occupants and the control system with information on the implications of operating natural ventilation devices for the indoor environment. Specifically, the control system must possess an internal model of these implications, allowing it to anticipate and accommodate control actions pertaining to natural ventilation. In order to realize a model-based building systems control strategy (Mahdavi 2001), a conventional building control system must be supplemented with a virtual model of the building that runs parallel to the building's actual operation. While the real building can "only" react to the actual contextual conditions (e.g., local weather conditions), occupancy interventions, and building control operations, the virtual model can move forward in time so as to predict the building's response to alternative control scenarios. Thus, alternative control schemes may be evaluated based on their predicted outcome (in terms of pertinent performance indicators pertaining to indoor climate, occupancy comfort, operation cost, environmental impact) and ranked according to applicable objective functions. This results in establishing a "control state space". Subsequently, multiple predictive applications of the model are used to map this control state space to a corresponding building performance space. The objective functions of the control task act as a navigation guide in this performance space. Once a preferable point in the space is identified, it can be mapped back to a corresponding point in the control state space (Mahdavi 2004).

Thus, the proposed model-based control system scenario for the integration of natural ventilation in the operation of the building's indoor environmental control system involves the following steps:

i) The control zone state at time t_i is compared with the desirable state. Control zone state indicators (reported by corresponding sensors) can include, for example, indoor air temperature, relative humidity, and CO_2 concentration. In case of a significant difference between the existing and desirable states, a control action is necessary. Moreover, explicit user requests could establish the necessity of a control action.

ii) The region within the overall multi-dimensional control device state space is identified that should

be explored. The dimensions of this space represent the various systems and devices. In case of natural ventilation, this space consists of as many dimensions as available natural ventilation devices (typically windows). The position of each device (e.g. the degree of the opening of a window) is represented as discrete value on the corresponding dimension. Thus, the sub-set of window positions to be explored is identified.

iii) The set of alternative control device states are submitted to the behavioral model to predict the values of control zone state indicators at time t_{i+1}. To accomplish this, the controller must possess predictive models to forecast energy and mass flows in the building. Necessary information input for the model regarding weather conditions at time t_{n+1} are derived based on the trend analysis of the previously monitored data. Main model predictions pertain to the air change rates (and the resulting changes in indoor temperature, indoor air flow speed, relative humidity, and the CO_2 concentration).

iv) The model's prediction results are evaluated based on the control objectives.

v) A control device state (e.g. window position) is identified that, according to the model's predictions, corresponds to the most preferable control zone state at time t_{n+1}.

vi) The user is informed as to the preferable control device state. Alternatively, in the case of automated control systems, the relevant actuator is instructed by the control application to update the state of the control device.

PREDICTION MODELS

Introductory remark

We argued that, for natural ventilation to become a standard element of the thermal environmental control system in buildings, the control application must possess knowledge of the workings and impact of the relevant control devices (e.g., operable windows). Moreover, it must integrate this knowledge in the control methodology it uses. There may be different ways of understanding, describing, and utilizing the indoor environmental implications of the control devices for natural ventilation. In the following, we present two related case studies. One explores the potential of simple empirically-driven models. The second considers a numerical simulation application as the predictor of relevant performance indicators (such as air change rate and mean indoor air flow speed).

An empirical model

Based on systematic measurements in existing buildings, predictive – statistically based – models

can be constructed that use the information on the prevailing outdoor weather conditions (air velocity, temperature, humidity) to estimate the values of ventilation performance indicators such as air change rate or mean air flow speed in a room. Given that pertinent external and internal features can be very different from building to building, it is not feasible to formulate such statistically-driven models in a way that would be valid for all buildings. We thus examined the possibility of constructing such a model based on a limited set of in-situ measurements in a specific space. Toward this end, we selected a typical office in a building of the Vienna University of Technology (TU-Vienna). The office is naturally ventilated using three casement windows with multiple operable parts (Figure 1). We considered a number of window opening configurations (see Table 1 for the illustration of these positions as well as the associated geometric leakage areas). Air change rate was measured for seven window configurations and mean indoor air flow speed was measured for eleven window configurations (see Table 1) under different outdoor conditions.
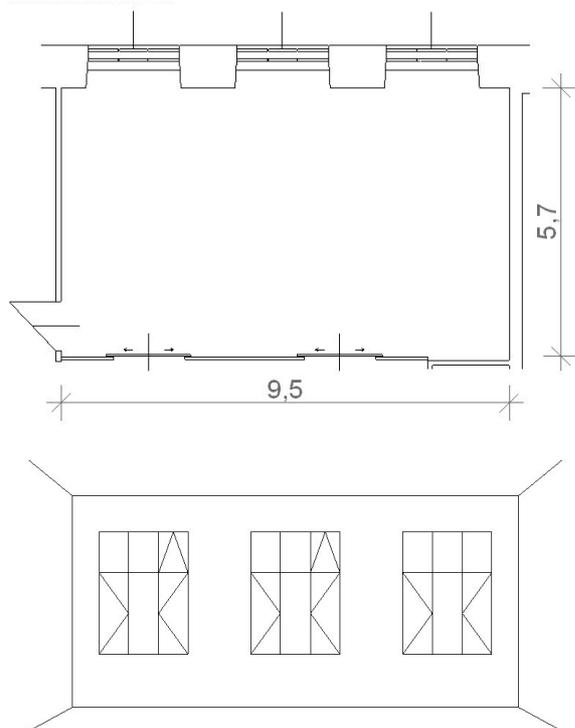
Figure 1 Plan (above) and inside elevation (below) of the test space (TU-Vienna)

To arrive at a simple predictive function, we hypothesized that air change rate (ACH) and mean indoor air flow speed ($v_{i,m}$) are affected by the window opening position (expressed in terms of geometric leakage area A_{GL}, i.e. the area of the open cross section of the window opening for a given window opening position), out door air speed (v_e), and temperature difference between outdoor and indoor air temperature (Δt). This implies the following general functions:

$$ACH = f_1\left(A_{GL} \cdot v_e \cdot \sqrt{\Delta t}\right) \qquad \text{Eq. 1}$$

$$v_{i,m} = f_2\left(A_{GL} \cdot v_e \cdot \sqrt{\Delta t}\right) \qquad \text{Eq. 2}$$

The above simple functions were found in authors' previous investigations to be effective in reproducing measurement results. However, they differ from common functions found in literature (see, for example, ASHRAE 2001).

Table 1 Selected window opening configurations with associated geometric leakage areas (shaded areas signify open wings)

WINDOW OPENING POSITION	A_{GL} [m²]
	0,08
	0,29
	0,29
	0,51
	3,01
	5,17
	5,60
	3,88
	3,66
	3,45
	3,45

The results of a sample of 20 air change rate measurements and a sample of 96 mean indoor speed measurements were plotted against the product of the hypothesized influencing factors ($A_{GL}.v_e.\Delta t^{0.5}$). The results are shown in figures 2 and 3 along with the corresponding regression functions.
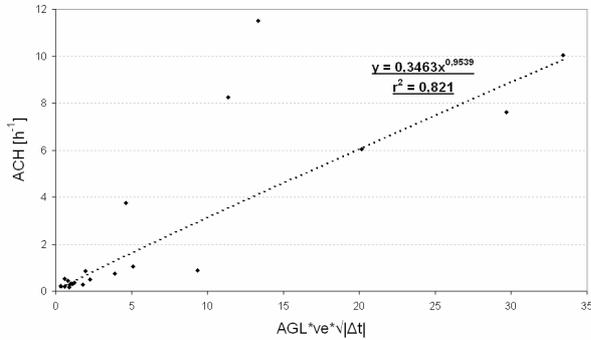

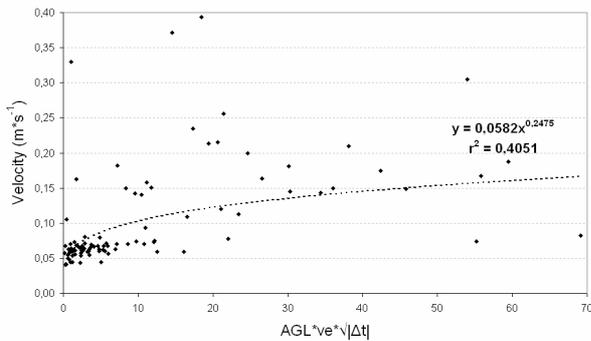Figure 2 Measured air change rate Against $A_{GL}.v_e.\Delta t^{0.5}$

Figure 3 Measured mean indoor air flow speed against $A_{GL}.v_e.\Delta t^{0.5}$

To examine if these functions can be used to predict air change rate and indoor air flow speed in the aforementioned office space, two additional set of control measurements (20 air change and 95 mean indoor speed measurements) were considered. Figures 4 and 5 illustrate the relationship between these control measurements and the corresponding predictions based the previously derived regression functions.
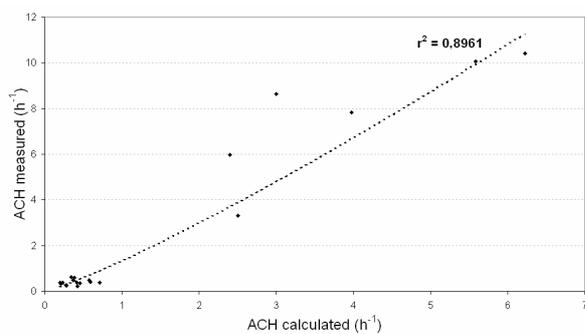
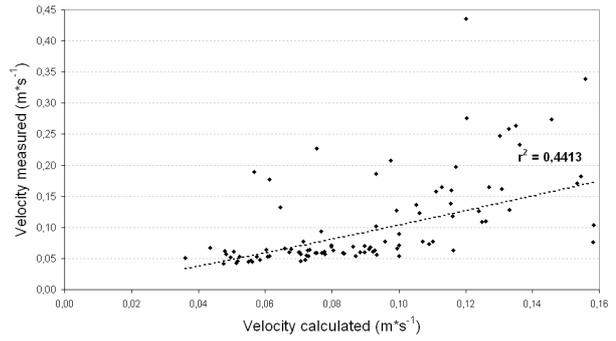Figure 4 Predicted air change measurements versus control measurements

Figure 5 Predicted mean indoor air flow speed measurements versus control measurements

Figure 6 shows the frequency of the relative deviations of the air change rate measurements from calculations. Analogously, Figure 7 shows the frequency of the deviation of the mean indoor air flow speed measurements from calculations. Given a measured parameter x_m and the corresponding calculated parameter x_c, the relative deviation is defined as follows:

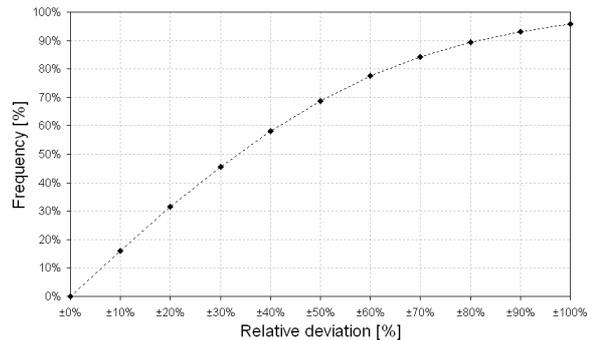$$RD = (x_c - x_m) \cdot x_m^{-1} \cdot 100 \qquad [\%] \qquad \text{Eq. 3}$$

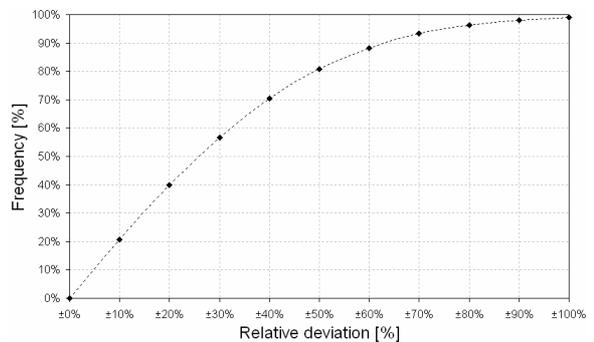Figure 6 Deviation frequencies of air change measurements from calculations

Figure 7 Deviation frequencies of mean indoor air flow speed measurements from calculations

Numeric simulation

As an alternative to empirical functions derived based on spot measurements in a specific building, we can envision the use of a numeric simulation tool. To explore this possibility, we used the numeric multi-zone air flow simulation program BACH (Wong and Mahdavi 2000) since we had access to the source code of this program. As such, similar applications such as CONTAM (Dols and Walton 2000) or COMIS (Feustel and Smith 1997) could be applied for this purpose as well.

To evaluate the predictions based on BACH and the potential for its calibration, empirical data was necessary. We selected an office bay in a building on Carnegie Mellon university (CMU) campus in Pittsburgh, USA (see Figure 8). This bay has a total of four windows, two external doors, and a passive ventilation cap.
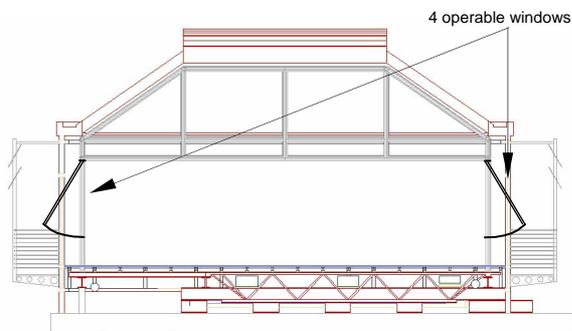

Figure 8 Test space (office bay), CMU

Measurements were performed in this office for different window, door, and cap opening configurations under varying outdoor conditions resulting in a sample of 18 air change rates.

Using these window configurations and building geometry data as well as information on prevailing outdoor conditions (wind velocity and direction) at the time of the measurements, we simulated the air change rates in this office using BACH.

Figure 9 illustrates the relationship between measurements and simulations. We then explored the possibility, if the simulation tool can be further calibrated using measurement data. Toward this end, we used the regression function as per Figure 9:

Let ACH_s be the air change rate as computed using BACH. A modified (corrected) ACH_c is derived then as per the following equation:

$$ACH_c = 2,358 \cdot ACH_s^{0,567} \qquad \text{Eq. 4}$$

To examine the effectiveness of this calibration approach, an additional set of control measurements was performed in the aforementioned office space resulting in 19 air change rates.

Figure 10 illustrates the relationship between these control measurements and the corresponding (non-calibrated) simulations.

For comparison purposes, Figure 11 shows the relationship between the control measurements and the corrected simulation results as per equation 4.

Figure 12 shows the frequency of the relative deviations (see Eq. 3) of the air change rate measurements from both non-calibrated and calibrated (using a small set of in-situ measurements) simulations.
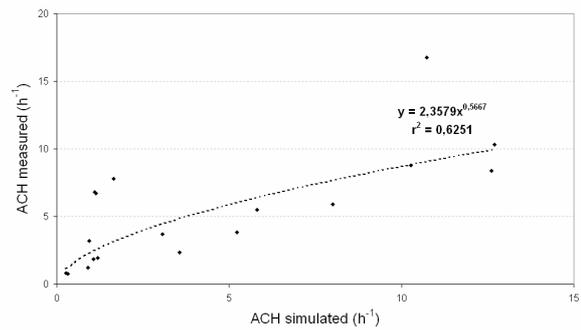

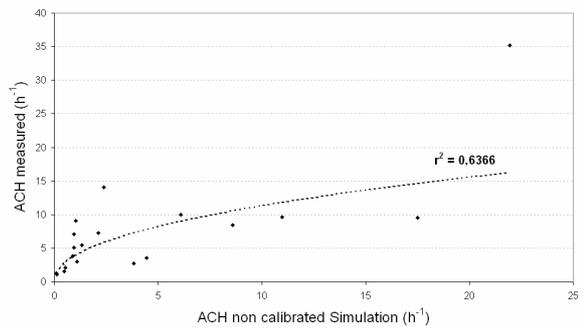*Figure 9 Measured versus simulated air change rates for a test space (cp. Figure 8)*

Figure 10 Air change measurements (control set) versus non-calibrated simulations
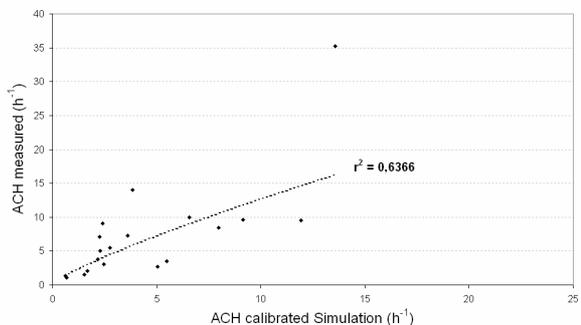

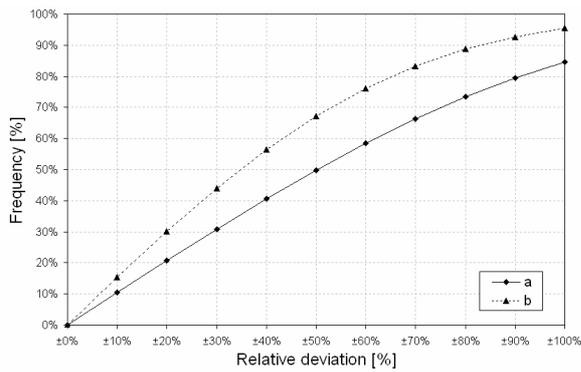*Figure 11 Air change measurements (control set) versus corrected simulations*

Figure 12 Frequency of relative deviations of the measured air change rates from both non-calibrated (a) and calibrated (b) simulations

Discussion

Our results imply that, using simple empirically-based equations (based on a small set of in-situ measurements), it is possible (at a probability level of 80%), to predict air change rates in a room within a deviation range of ± 65% indoor and air flow speed within a deviation range of ± 50%. When we used a numeric simulation program (calibrated with a small set of in-situ measurements), we could predict air change rates in an office space within a deviation range of ± 65% (at a probability level of 80%).

Modest as these results may appear, they must be gauged in the proper context. Airflow simulation is typically affected by multiple sources of error (weather conditions, building geometry, crack, and leakage data). Validation studies of multi-zone models even under controlled laboratory conditions reveal considerable simulation errors. For example, the relative differences between simulated and measured airflow rates under controlled conditions in a test facility was found to be between the range of 25% and 50% (Haghighat and Li 2004).

Conducting a larger set of in-situ measurements is likely to increase the predictive performance of both empirically-based equations and numeric simulation. We believe a deviation range (for model predictions) under ± 40% would satisfy the practical requirements of a control system for natural ventilation.

A DEMONSTRATIVE CONTROL SCHEME

Given a predictive model that maps the state of control devices (e.g. window opening position) onto corresponding values of relevant performance indicators (e.g. air change rate, indoor air flow speed), model-based control schemes may be developed. To demonstrate this point, consider the illustrative control sequence shown in Figure 13. Given a certain device position at time step t_i, the system regularly examines if a control action is

needed, for example due to a mismatch between the actual and the desired room temperature. In that case all (or an appropriate sub-set) of possible device positions are considered. These options are then communicated (along with the building model) to a performance prediction tool (i.e. an empirically-based function or a numeric simulation application). The computed results (for example predicted room temperatures) are then evaluated in terms of their proximity to the desired value, leading to the identification of the most desirable control option for time step t_{i+1}.
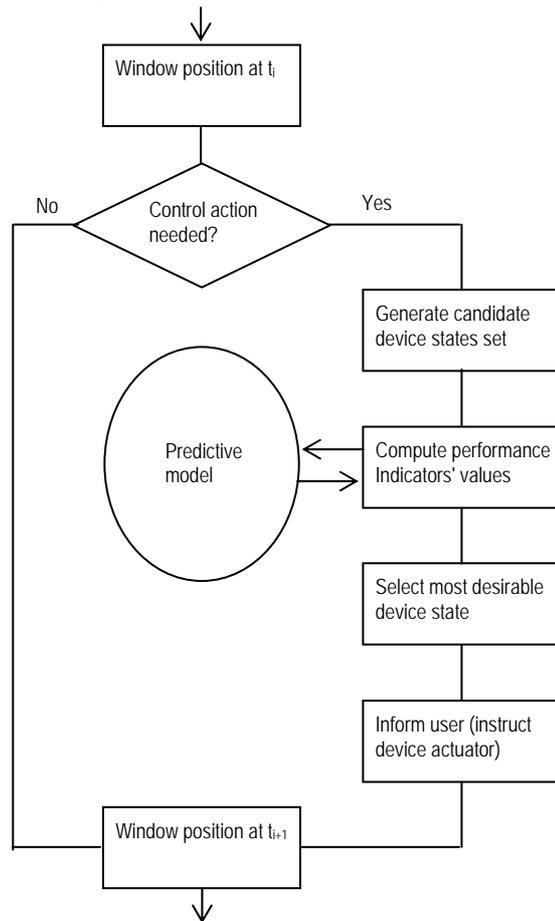

Figure 13
An illustrative model-based ventilation control scheme

To further illustrate the potential of model-based ventilation strategies, consider the previously mentioned CMU office bay. We used the aforementioned application BACH along with an energy simulation tool to simulate the air change rate and indoor air temperature in this space for two scenarios (without active heating and cooling). To provide a benchmark, we first simulated these parameters under the assumptions that windows, external doors, and the ventilation cap were closed throughout the day. For the second scenario, we emulated a model-based ventilation control scenario. Toward this end, a number of device opening options

were considered and simulated for each time step. Upon comparison of the simulation results for these options, the one with the minimum deviation of actual room temperature from the desired room temperature was selected. Figures 14 and 15 illustrate the results for two typical days (May, October). Figures depict the courses of outdoor temperature (t_e), simulated indoor temperature under all devices closed scenario (t_c), simulated air change rate (ACH_m) and indoor temperature ($t_{i,m}$) under the model-based control scenario, and the desired indoor temperature ($t_{i,d}$).
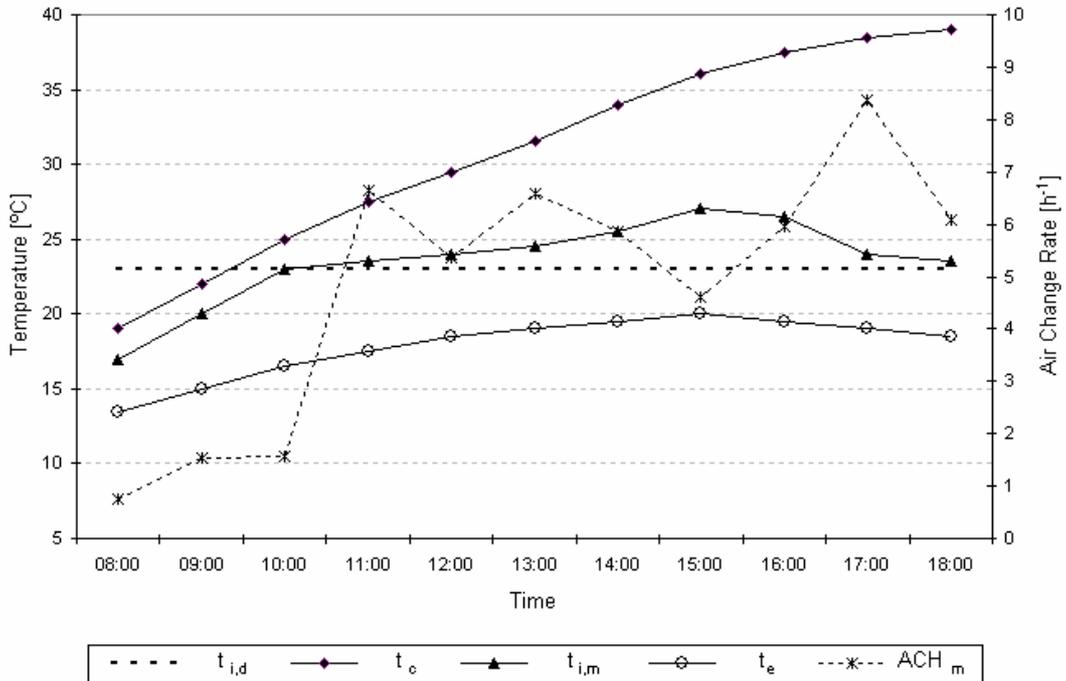

Figure 14

Simulated indoor air temperatures (for a typical day in May) in CMU office bay for a model-based ventilation strategy ($t_{i,m}$) as compared with closed apertures scenario (t_c)
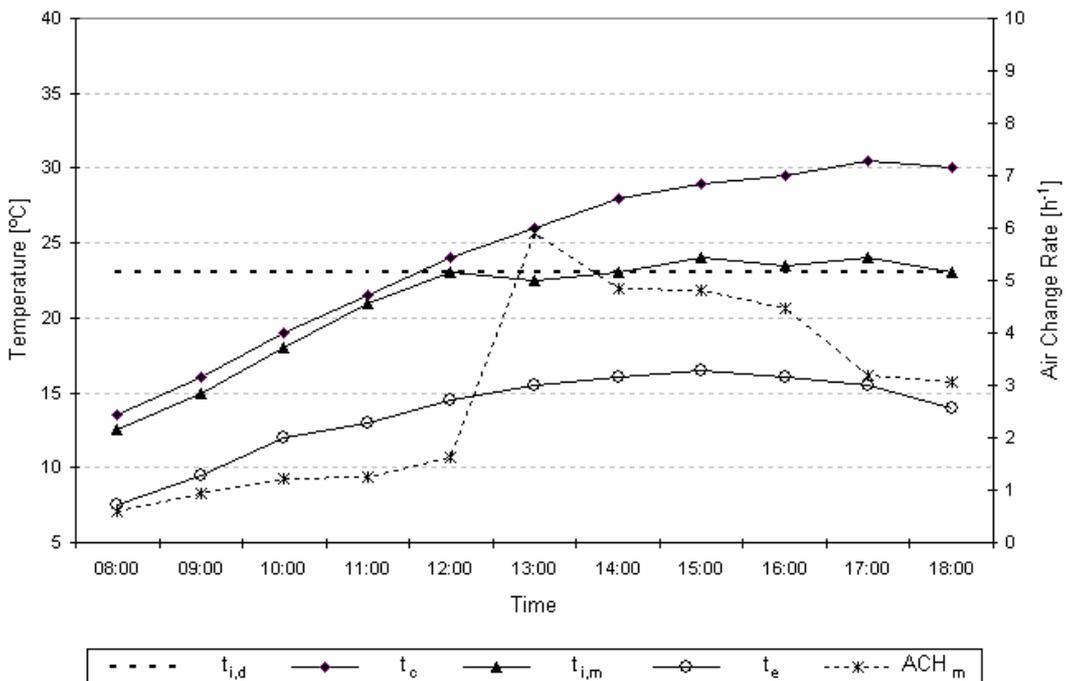

Figure 15

Simulated indoor air temperatures (for a typical day in October) in CMU office bay for a model-based ventilation strategy ($T_{i,m}$) as compared with closed apertures scenario (t_c)

As it can be seen from these Figures, a model-based control strategy has the potential to maximize the extent of time periods in which a preferred indoor air temperature regime may be maintained without reliance on active heating and cooling measures and devices. Moreover, the model-based prediction of the implications of various control settings (e.g. window opening positions) for the indoor environmental conditions provides the basis for the integration of natural ventilation strategies in the overall operation of a building's thermal control system.

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