TOWARD A SIMULATION-ASSISTED DYNAMIC BUILDING CONTROL STRATEGY

Ardeshir Mahdavi
Department of Architecture, Carnegie Mellon University, Pittsburgh, PA, USA
and
School of Architecture, National University of Singapore

ABSTRACT

This paper explores a simulation-assisted building control strategy. Specifically, the use of generate-and-test as well as bi-directional inference methods is proposed to derive preferable control schemes and required attributes for control variables based on parametric and iterative simulation runs. The feasibility of the approach is demonstrated *via* illustrative computational examples from the thermal control domain.

1. INTRODUCTION

Traditionally, building control systems have operated on the basis of a homeostatic short-term feed back mechanism. For example, thermostatic control of HVAC components involves typical operations (on/off, change in volume and/or temperature of heating/cooling media, etc.) that are essentially guided by temperature sensing in space. More recently, building control systems have become increasing sophisticated. One of the approaches has been to utilize various methods and tools (including neural nets) to accurately capture buildings thermal dynamic characteristics so as to provide a more reliable basis for the control of its behavior (Curtis 1996, Curtis et al. 1993, Mistry and Nair 1993, Osman et al. 1996). In this scenario, control options can be improved ("optimized"), as their past impact on the buildings' dynamic behavior is reflected in the collected information by the sensing system. This paper argues that the above intention, namely to capture building's long term dynamic behavior toward enhanced control strategies, can be effectively supported using advanced computational performance simulation routines.

2. THE IDEA

In the past, performance simulation tools have been mainly used for purposes of building design analysis and evaluation. Less attention has been paid, however, to their potential in view of active control strategies for building service systems (particularly HVAC and lighting devices). In order to realize this idea, a conventional building automation system must be supplemented with a multi-aspect virtual model of the building that runs parallel to building's actual operation. While the real building reacts "only" to the actual climatic conditions, occupancy interventions, and building control operations, the simulation-based virtual model allows for additional operations:

- The virtual model can move backward in time so as to analyze the building's past behavior and/or to calibrate the program toward improved predictive potency.
- The virtual model can move forward in time so as to predict the building's response (e.g. its hygrothermal behavior) to alternative control scenarios.

Given the availability of fairly reliable short-term (e.g. three days period) weather prognosis data *via* internet, the predictive capability of the simulation program may be expected to be significantly enhanced, thus providing a useful basis for the evaluation of multiple control options. Obviously, data pertaining to other factors such as the fluctuation of occupancy as well as lighting and equipment use may be provided to the virtual model to further increase its predictive potential. Above and beyond enhancing the effectiveness of dynamic control systems, the suggested approach may yield additional benefits. These include:

- calibration of simulation tools for long-term design and modification feed back,
- prediction of the effects of changes to building hardware and its control systems,
- beta-testing of building control system hardware on simulated data from the virtual building,
- pre-training of neural network and machine learning systems prior to their field utilization using simulation data on building behavior,
- re-training of neural network and machine learning systems to account for the effects of abrupt modifications to building characteristics (e.g. renovation) using simulation data,
- reduction of the number of sensing units necessary for capturing building's real time operational status.

3. TWO APPROACHES

A critical task toward realization of a simulation-assisted building control system lies in the development of a strategy to create a well-defined set of control options as the basis for comparative and/or parametric simulation runs. While there may be numerous methods to derive at such control options, we focus in this paper on two principal approaches (cp. figure 1):

The Generate-and-Test Method (GAT)

This method involves the rule-based generation of a finite number of discrete control options. Such control options may involve, for example, various on/off timing schemes for intermittent heating/cooling. These schemes are then evaluated and ranked (possibly in view of multiple criteria involving energy, cost, emissions, comfort, etc.) based on the results of multiple simulation runs.

The Bi-directional Inference Method (BDI)

This method (Mahdavi 1993) involves the explicit definition of control and performance variables. An example of a control variable would be the deviation of heating/cooling set-point temperature from the space target temperature. Examples of a performance variable are the annual building energy need, the average cumulative deviation of the maintained space temperature from the set-point temperature, or the average cumulative PPD (predicted percentage of dissatisfied) in a space. Starting from an initial operational state, the bi-directional inference facilitates the derivation of required changes in the control variable(s) based on desired changes in the performance variable(s). This derivation can be accomplished *via* the investigative projection technique (Mahdavi and Berberidou 1995, 1994).

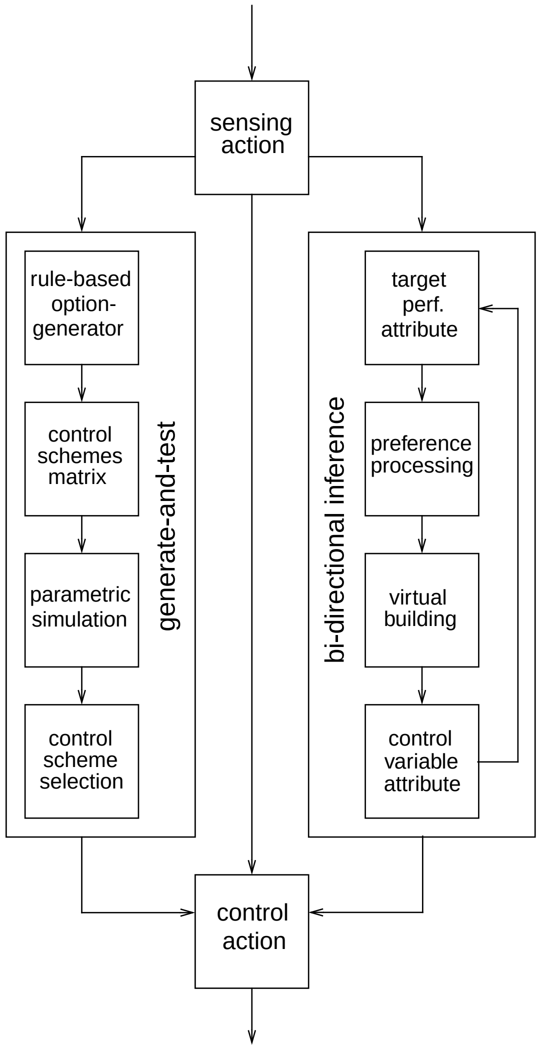

Figure 1. Schematic illustration of the use BDI and GAT for simulation-assisted building control

4. A DEMONSTRATIVE EXAMPLE

What follows is a simple computational example to demonstrate the feasibility of the proposed approach. Assume a single-story single-zone quadratic building (6 m by 6 m in plan and 3 m high) located in Pittsburgh, PA, USA. The construction consists of stud-walls with 10 cm fiberglass insulation and 30% single glazing on south and north, light-weight flat roof with 20 cm insulation, and concrete floor slab atop 10 cm insulation. We have fixed this design variables for the specific purposes of the present demonstrative example, since the idea is to emulate an existing structure. If desired, such design variables could also be subject to parametric studies of the kind discussed below. (For example, deployment of shading devices would have a dynamic effect on the energy transmission through the glazing and could be thus modeled as a control variable.)

The problem statement is now to derive a control strategy based on the results of a well-planned set (or sequence) of simulations. We suggested that this "planning" may be accomplished *via* generate-and-test (GAT) and bi-directional inference (BDI) approaches. However, we have to first establish a set of pertinent control and performance variables. For the purposes of clarity, we limit ourselves in this case to only one control variable and two performance variables. We select as control variable the numeric deviation of the heating/cooling set-point temperatures from the target space temperature (Δt_{sp}), i.e. we specify the extension of the temperature dead-band with our control variable. As our first performance variable we consider the annual total (heating and cooling) energy need of the building q_a. (Obviously, we could define many other similar or related variables such as seasonal energy use levels or separate heating, cooling, and electrical loads.) Our second performance variable, the temperature deviation factor (TDF) captures the deviation of the predicted maintained space temperature from the target space temperature. It is defined as the average cumulative temperature deviation according to the following formula:

$$TDF = \sum_{i=1}^{n} \frac{w \cdot \left(\frac{|t_d - t_i|}{t_d}\right)}{n} \cdot 100 \qquad [\%] \qquad eq.1$$

In the above equation t_d is the target space temperature, t_i is the space temperature at time step *i*, *n* is the total number of time steps, and *w* is a weighting variable to penalize larger deviations of the maintained temperature from the target space temperature. For the purposes of the present study a simple linear relationship is applied:

$$w = |t_d - t_i| \cdot 5^{-1} \qquad eq.2$$

The simulation engine used for the following case studies is the dynamic (heat-balance-based) thermal module in SEMPER (Mahdavi 1996a, 1996b, Mahdavi and Mathew 1995).

<u>Use of GAT</u>
As mentioned before, this method involves first the generation of a finite number of discrete control options. For the present example five such schemes have been generated for the relevant control variable, i.e. Δt_{sp}. Table 1 represents these schemes labeled A to E.

Control Scheme	**Target Space Temp. [°C]**	**Heating Set-point [°C]**	**Cooling Set-point [°C]**	***Δt_{sp}* *[K]***
A	22	21.5	22.5	0.5
B	22	21.0	23.0	1.0
C	22	20.0	24.0	2.0
D	22	19.0	25.0	3.0
E	22	18.0	26.0	4.0

Table 1: Generated Control Schemes

Once these schemes are established, exploratory simulations can be performed immediately. The simulation results provide then a matrix which can be used to organize, rank, and evaluate various control strategies in view of their implications for the relevant performance criteria. For our specific example, such a matrix is given in table 2. This table numerically documents the intuitively expected goal conflict between minimization of energy use on one side and minimization of the deviations of the maintained space temperatures from the target values on the other side. In the present case the resolution of this conflict requires only the definition of the maximum tolerable attribute for TDF. In more complex cases involving larger matrices, well-known methods from the operation research domain can be applied.

Control Scheme	***Δt_{sp}* *[K]***	**q_a [kWh.m^{-2}.a^{-1}]**	***TDF [%]***
A	0.5	320	0.0
B	1	290	0.1
C	2	240	1.0
D	3	210	3.0
E	4	185	6.1

Table 2: Simulation Results

<u>Use of BDI</u>
The use of a bi-directional inference mechanism for active convergence support in performance-based computer-aided design has been previously documented (Mahdavi 1993, Mahdavi and Berberidou 1995, 1994). In particular, a preference-based method and an investigative projection technique have been developed to cope with the ambiguity problem inherent to the performance-to-design mapping operation. However, we must now demonstrate that BDI can be also applied toward facilitating simulation-assisted building control processes. Using again the previous building example, and starting from an initial operational state, we would have to map desired changes in a performance variable such as q_a or TDF into a control variable such as Δt_{sp}. Since in the present example all design variables are locked (i.e. factors such as building's thermal mass, glazing area, etc. cannot be changed), only q_a, TDF, and Δt_{sp} can be manipulated *via* BDI. Let us demonstrate this with two illustrative scenarios (cp. the BDI-driven trajectory as illustrated in figure 2):

- The building is in an initial operational state in which is Δt_{sp} is 1 K, the predicted energy consumption is 290 kWh.m^{-2}.a^{-1}, and TDF is 0.1%. The control aim is to minimize TDF without exceeding a q_a value of 255 kWh.m^{-2}.a^{-1}. The gradual decrease of the q_a value is translated *via* BDI in an increase of Δt_{sp} accompanied by increase in TDF. For a predicted energy consumption rate of 255 kWh.m^{-2}.a^{-1}, the control variable Δt_{sp} must be set at 1.7 K to minimize TDF.
- The building is in an initial operational state in which is Δt_{sp} is 3.5 K, the predicted energy consumption is about 200 kWh.m^{-2}.a^{-1}, and TDF is 4.5%. The control aim is to minimize the energy consumption rate without exceeding a TDF of

2.5%. In this case, the gradual decrease of TDF is translated *via* BDI in a decrease of Δt_{sp} accompanied by an increase in q_a. The control aim is realized around a predicted energy consumption of 220 $kWh.m^{-2}.a^{-1}$, and the control variable Δt_{sp} must be set at 2.7 K.

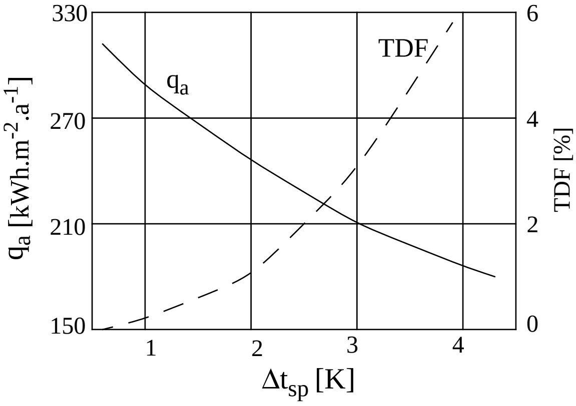

Figure 2. BDI-driven trajectory of performance indicators q_a, TDF and control variable Δt_{sp}

5. CONCLUDING REMARKS

To facilitate the understanding of the proposed simulation-assisted building control strategy, we dealt only with examples involving a rather simple building and a relative small set of control scenarios. However, there is no theoretical or methodological reason why much more complex cases cannot be handled using a GAT-based or a BDI-driven control strategy. For example, in the case of BDI, multiple transient control scenarios, dynamic design features, and complex performance criteria may be considered, as long as the corresponding variables and the nature and range of their attributes are non-ambiguously defined. Obviously, in cases where more than one independent control variable may respond to changes in a performance indicator, some form of a weighting or preference methodology must be applied.

Needless to say, beyond their potential for the real-time identification of preferable building control strategies for operational buildings, the above discussed GAT- and BDI-supported methods can also facilitate the effective consideration of control issues already in the building design phase.

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