FIRST-PRINCIPLES STRUCTURED IDENTIFICATION FOR PREDICTIVE HVAC CONTROL

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Abstract— This paper presents a first-principles structured identification approach for thermal environments equipped with Heating, Ventilation and Air Conditioning (HVAC) systems. Linear data-driven identification and first-principles modeling are combined to produce an accurate and computationally efficient model. The objective is to find out which model is best suited for energy-saving and comfort control strategies. A proportional integral (PI) controller running a conference room at the University of Kaiserslautern, using PMV (Predicted Mean Vote) comfort index, is quite satisfactory as regulator, but it is not anticipatory, wasting energy and lasts long to reach the comfort zone when room utilization changes. A model-based predictive controller is anticipatory and can cope with actuator saturations. The first-principles structured model allows the separation of the different heat flow contributions simplifying the parameter identification. The theoretical foundations and experimental results are presented considered heating, cooling, outside temperature, neighboring rooms and solar radiation.

Keywords— Building Automation, process identification, first principles modeling, model-based predictive control.

1 Introduction

The climatisation of rooms in buildings can be quite a complex control problem if high degrees of comfort and energy saving are required. There are many factors influencing an environment: humidity, outdoor temperature, solar radiation, neighbouring rooms, people presence, furniture in the room, heat sources (as computers), windows, heaters, coolers etc. All these factors have a complex interaction with the comfort and the energy demand.

From the automation point of view, the objective of modeling a building is not to precisely calculate the temperature in every point of a room, but to have information that can lead to a successful controller design. This means that the distributed, continuous, and eventually non-linear process should, with sufficient precision, be described by a lumped LTI parameters model. If the room is architecturally well designed and the actuators well placed, comfort and energy-saving can be obtained.

A predictive HVAC controller can potentially obtain the best compromise between comfort and energy saving. The scheduled room occupation can be prepared with the just needed in-advance acclimatization, a quite unique characteristic of predictive controllers.

Model-based Predictive Control (MPC), as the name suggests, needs a model of the process to generate the control sequence that minimizes the predicted error. One great advantage of this technique is that saturations are accounted automatically. That means that driving the process at its limits can potentially give the best energy-saving results (Maximum Principle of Pontryagin).

In this work, we join physical first-principles comprehension and data-driven identification to get a practical model aiming at predictive HVAC control.

2 Model-Based HVAC Identification

Most controllers used in buildings are very simple. The on-off controller with hystheresis is perhaps the most widely used building controller due to its simplicity. The also very popular PI controller is often designed empirically. In both cases no process model is used. To really enhance the control with respect to energy-saving and comfort, some kind of model-based approach is needed. With this objective, different approaches have been proposed.

Virk et al., 1995, presents a practical methodology to identify buildings as linear MIMO ARMAX models. Heating, cooling and humidification are used as inputs. Climatic variables and occupants are considered disturbances. The output variables are the temperature and the relative humidity of an office zone. For the test room considered, with 5min sampling, a 3rd order model was obtained. The authors point out the need for excitation rich input signals over long periods of time. They carried out 3 days of data acquisition.

The latter approach is known as black-box identification because no information about the inner process is used to guide the identification. Only the input-output dynamic behavior is. The underlying assumption is that the excitation signals are almost white noise (indeed approximated by PRBS) so that no frequency band is benefited by the identification routine. When dealing with climate signals as outside temperature, solar radiation and wind, it is virtually impossible to guarantee a good excitation.

In (Souza, 1997), a Takagi-Sugeno fuzzy system is employed to model and control the non-linear HVAC process. A combination of predictive and inverse control is implemented. The fuzzy model is used to predict the future moves of the process and also to inversely compensate the non-linear system dynamics. The heating valve is used as the control input. The supply temperature (measured after the coil) and the mixed-air temperature (measured just before the fan) are the only variables considered. The Takagi-Sugeno fuzzy model used is a kind of interpolation of dynamic linear systems that makes feasible the analytical inversion of the assumed non-linear HVAC system. While the linear MIMO 3rd model used by (Virk, 1995) uses 8 input signals and one disturbance to predict the temperature and the humidity, the non-linear fuzzy model proposed by (Souza, 1997) is a SISO system.

Sitompul, 2004, uses neural networks with online parameter adjustment to identify the nonlinear dynamics of the conference room 12-478 at the University of Kaiserslautern. The room temperature dynamics is modeled as a function of the outside temperature and the solar radiation. Two delayed samples of the room temperature, the outside temperature and the solar radiation are used to estimate the actual room temperature.

When each element in the room and the surrounding environment is physically modeled using thermodynamics energy conservation laws, we can expect a qualitatively good approximation of the reality. This kind of modeling is employed in commercial buildings simulation tools like TRNSYS and TAS. Felgner et al., 2003, developed an open building and HVAC library in the object-oriented language Modelica. The air volume in the room, the furniture are considered as lumped capacitors. The walls are modeled by networks of heat capacitors and thermal resistors. The outdoor temperature as well as solar radiation can be included using measured data.

Similarly, Spasokukotskiy et al., 2003, proposes to use a simplified lumped-parameters thermo-dynamic model of the building to access the PMV comfort index (see section 4). The weather is assumed to be a disturbance.

Argüello-Serrano and Vélez-Reyes, 1999, present a work on the non-linear control of HVAC with thermal load estimation. Starting with energy conservation principles relating temperatures, humidity and volumetric air flow, they give a nonlinear differential equation system of the conditioned room. The controller with disturbance rejection is projected using the Lyapunov stability theory. Only simulation results are presented.

The most important practical difficulty of such first-principles modeling is the great quantity of parameters defining the thermal behavior of the building materials and their interaction with the room air and the outer climate. This kind of modeling is, therefore, quite cumbersome for a practical application in predictive control.

In the next sections, we will present a modeling approach joining data-driven identification and first-principle structure.

3 The Testing Environment

The conference room in building 12 of the University of Kaiserslautern (~102 m^3) was used as our test environment, see figures 1 and 2. The room is equipped with a Building Automation System (BAS), where meetings can be scheduled. An EIB network accesses the sensors and actuators, Table 1.

Table 1. Thermal modeling - relevant sensors and actuators.

To	Room temperature - inner east wall
Ts	Building outside south temperature
Gs	Solar radiation on south wall
h	Heating: 3 radiators
c	Cooling: Air-conditioner

Figure 1 South view of the conference room.

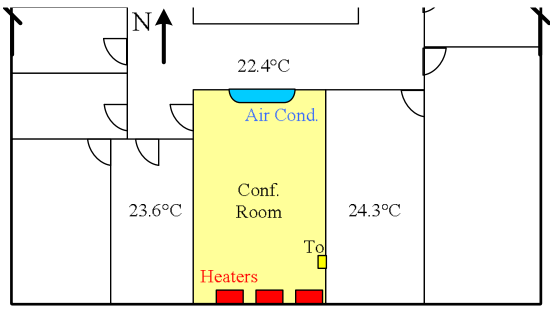

Figure 2. Localization of the conference room in building 12. Typical vicinity temperatures are shown (9:30 March 23, 2006).

The room is equipped with three heaters and one air-conditioning cooler. Since the heaters and the cooler can only be turned on or off, a pulse width modulation (PWM) is applied.

The location of the conference room in building 12 is shown in Figure 2. It is relevant to note that an open roof shaft connects all rooms of the same floor. This connection and the walls will be further referred to as the room's vicinity.

4 PMV PI-Control of the Test Room

The Predicted Mean Vote (PMV) index was proposed by Fanger (Fanger, 1974) as a thermal comfort measure. Actually more than 30 different norms for themal comfort are available. PMV is academically one of the most accepted norms (ISO 7730), due to its phyical-based reasoning. The building automation praxis, hovewer, still uses almost exclusively temperature-based controllers.

A proportional-integral control of the PMV-index for the conference room was implemented. An http interface allows scheduling of meetings, specifying the expected number of persons and the activity level of each activity. When the system clock coincides with a scheduled meeting the corresponding PMV controller is started. Figure 3 shows the result of the PMV control when scheduling a standing meeting (88W/m^2-activity) every 2 hours with two hours vacancy in between. After midnight a sitting 81W/m^2-activity was assumed.

During a meeting the control objective was established to maintain: $-0.01 \le PMV \le +0.01$. This avoids the chattering between heating and cooling when $PMV = 0$ is targeted by the PI controller. When the no occupation is scheduled, $-2 \le PMV \le +2$ was used, so that the room temperature would not drift arbitrarily. Without this bound we would have no energy cost during unoccupied periods, but it would last too long to make the room operative again.

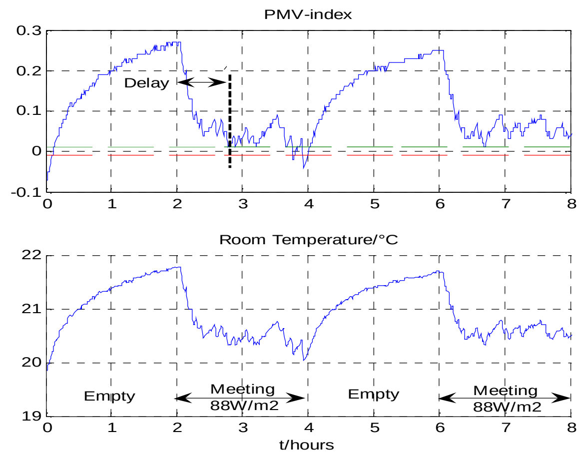

Figure 3 PI-control of PMV index, March 28-29, 2006.

In figure 3 we can clearly see that the PI-PMV controller can lead the system to the ±0.01 target band, however it takes almost 40 min until that objective is reached. The experiment was carried out in the night hours so to avoid the solar radiation and the spurious presence of people in the room during a normal working day.

The employed PI-Controller with anti-windup was designed empirically. No dynamical model was used, only the successive approximation of *Kp* and *Ki* until satisfactory response was obtained.

To obtain better comfort and energy-saving results a predictive controller seems to be a natural choice. The process is slow and acting in advance could considerably improve a meeting's comfort.

5 Identification of the Test Room

Different techniques can be used to produce a dynamical model that can be used to predict the room's thermal behavior. Figure **4** shows a typical data acquisition set of the conference room.

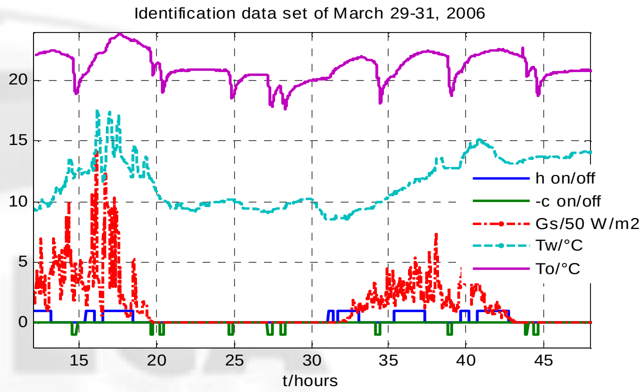

Figure 4. A typical identification data set.

Heating and Cooling were generated by a pseudo-random binary signal. The solar radiation influence on the external and internal temperature is quite obvious. We choose the following variables to thermally characterize the conference room:

Cooling (c) – One 3kW air conditioner delivers 4°C cold air flux. (Settings: max. ventilation, min. temperature). On-Off.

Heating (h) – Three parallel radiators supplied with 50°C hot water. On-Off.

Outside Temperature (Tw) – Windows of the room exposed to the south side of the building.

Vicinity (Tv) – Medium temperature of the inner building vicinity of the conference room.

Solar Radiation (Gs) – Solar radiance measured at the top of the building, converted to direction of the room's outside wall.

To obtain a suitable prediction model, two approaches will be examined: a) The modeling based on linear multi-input identification of experimental data (black box) and b) The first-principles structured identification.

a) Linear MISO approach

The linear MISO approach will adjust state-space matrices (**A**, **B, C, D, E**) to best fit the training data using the Least Mean Squared Error sense.

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{Ax} + \mathbf{Bu} + \mathbf{Ee} \\ y &= \mathbf{Cx} + \mathbf{Du} \end{aligned} \qquad (1)$$

x – State vector,
u – Input vector plus measurable disturbance signal,
e – Immeasurable disturbance signal,
y – Output signal (room temperature).

If we use a 6th order model with **u**=[h c Tw] we have relatively good approximation results, but the step responses of such a system, figure 5, show that the common sense physical intuition is violated. In steady state, heating can reach maximally 22°C. Continuously cooling would reach -250°C. As the outside temperature gain is greater than one, in the steady state the room would get warmer than the heat source. Obviously, in the real life, all these factors act together onto the plant.

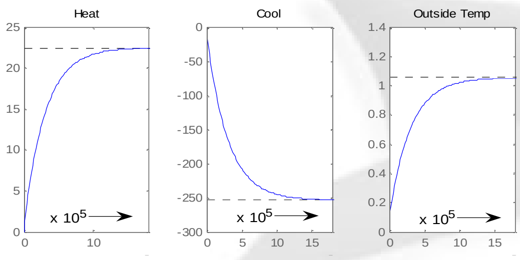

Figure 5. Step responses of a 3 inputs, 6th order linear MISO.

Using five inputs, **u** = [Th Tc Tw Tv Gs], where T_h and T_c are the effective temperature differences applied to the heating and cooling elements (see figure 10), we obtain the results in figures 6 and 7. Obviously, complex poles and non minimal-phase zeros are not compatible with a thermal process.

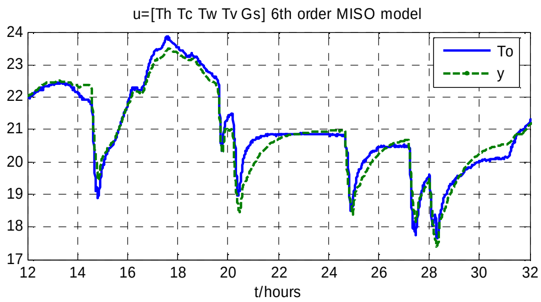

Figure 6. Response of the 4 inputs, 6th order linear MISO.

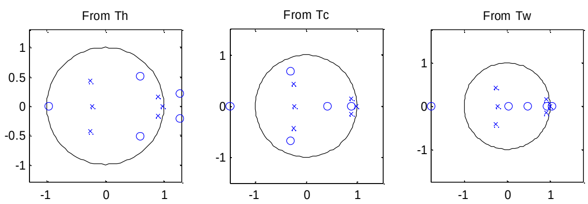

Figure 7. Three pole-zero maps of the 5 inputs MISO.

b) First-Principles Structured Identification

In this work, we propose a first-principles structured identification. The basic idea is to add the thermal energy flow in the conference room. Depending on the modeling effort employed, different physical phenomena can be included.

To model the heat transfer from the vicinity, the wall should be investigated. Fraisse, 2002, analyzed different wall models, e.g. 2R1C, 1R2C, 3R4C, 3R2C. In the simplest 2R1C conduction model, (Fraisse, 2002), we consider a wall internal thermal capacitance and two thermal conductivity elements (figure 8). The heat flow q between rooms depends on the difference T_o – T_{iv}. The temperature T_{iv} relates to a fictitious point in the middle of the wall.

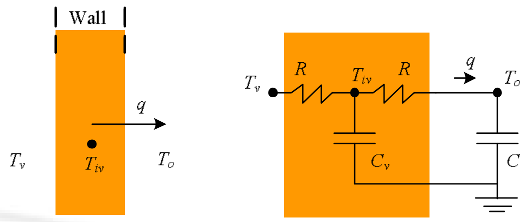

Figure 8. 2R1C analogy of the vicinity heat transfer.

Every neighboring room has, most often, a different temperature. The walls constitution can also differ. Ceiling and floor have very different thermal characteristics. In the present work we will assume that the dominant vicinity dynamics can be approximated by the simple 2R1C model, figure 9.

The weather contribution is similar, considering a fictitious temperature inside the windows glass. The sun radiance produces a heat transfer that could be delayed (first order assumed), but is not dependent on the room temperature. In the complete thermal model, figure 10, to simplify the notation, we considered for all heat generating elements $R_iC_i = a_i$, and $1/R_i=K_i$, for $i=h,c,v,w,r$. The parallel association $1/R_p = 1/R_v + 1/R_w$, is used when no heat or cooling is active. Otherwise, $1/R_p = 1/R_v + 1/R_w+1/R_h + 1/R_c$. The associated time constant is $R_pC = a$.

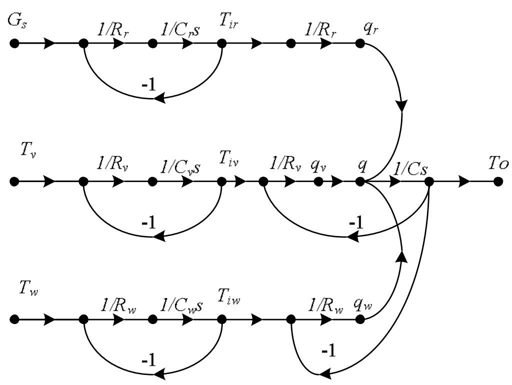

Figure 9. 2R1C-based disturbance model.

The air volume in the room is modeled as a concentrated thermal capacity C. $\hat{T}c$ is the predicted room temperature. In the first-principle model we sum the heat flows (q_c, q_h, q_w, q_r, and q_v) allowing a separate identification of each model component. A positive heat flow to C is accumulated and enhances the room temperature. A negative heat flow reduces the room temperature. See figure 10.

The cooler and the heater can be modeled as devices that have (55-T_o) or, respectively (4-T_o) as inputs. 55°C is the hot water entry temperature in the radiator and 4°C is the chilled air from the air conditioner. When "off" these devices internal temperatures (T_{ih} and T_{ic}) tend to reach T_o.

The value of C in our model is redundant, because it every time appears multiplied by a gain. We chose, C= 1, assuming its real value incorporated in each of the five model gains.

If heat (on/off) and cooling (on/off) are selected as inputs, we have a non-linear, operating point dependent system. To avoid this and to have a linear identification of heat and cooling, we considered (55°C − T_o) and (4°C − T_o) as inputs when "on". When "off" these inputs are T_o.

One interesting feature of the structured identification is that we can add the individual heat flow contributions. This allows the separated parameter identification of individual modules.

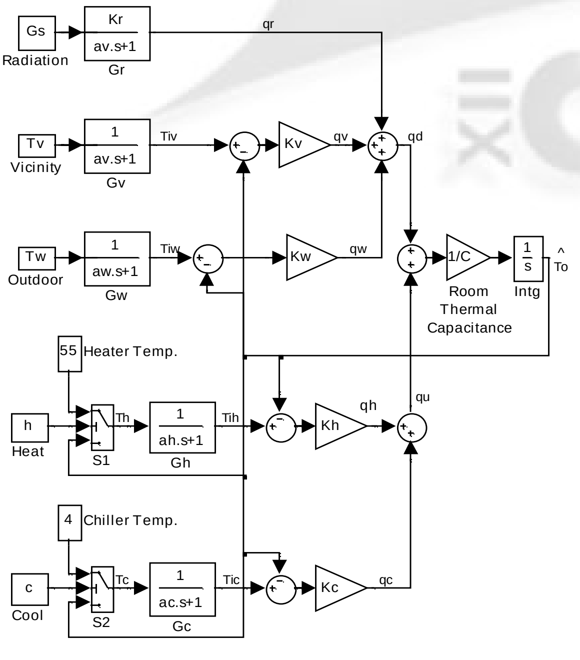

Figure 10 First-principles structured thermal model.

For example, if we have a disturbance model and wish heating and cooling parameters. The modeled disturbance heat flow is given by:

$$q_d = \frac{aK_r s.G_s(s)}{(as+1)(a_r s+1)} + \frac{aK_v s.T_v(s)}{(as+1)(a_v s+1)} + \frac{aK_w s.T_w(s)}{(as+1)(a_w s+1)}$$

The total heat flow is $q = d/dt(T_o)$, and the heating and cooling flow is $q_u = q - q_d$. We use $T_u = \int q_u dt$, the temperature variation caused by heating and cooling to identify the corresponding parameters. To avoid numerical errors the differentiation and integration should be carried out in the discrete domain. Initial condition should not be neglected in the procedure.

6 Results

If we use a first order approximation of the step responses obtained with the 5 input MISO model, we get the results in table 2. These parameters, however, are not compatible with our structured model. The simulation results are bad.

Table 2. Black-box identification, 5 inputs 6th order.

i =	r	v	w	h	c
a_i	2.500	2,220	3,060	2,780	2,360
K_i	2.8e-3	0.497	4.02e-2	1.93e-2	0.407

Using the first-principles structured approach the parameters associated with the sun radiation, weather, vicinity, heating and cooling have been obtained using the identification toolbox of MatLab. The parameters for the conference room in building 12, University of Kaiserslautern can be seen in Table 2. Using these parameters in the model we obtained the results shown in figures 11 and 12.

The first-principles structured model gives an RMSE error of 0.54°C with 0.67°C standard deviation for the validation data.

Table 3. First-principles structured model parameters.

i =	r	v	w	h	c
a_i	221.6	2,104	4,287	4,315	500
K_i	4e-6	1.2e-3	3.33e-4	1e-4	4e-4

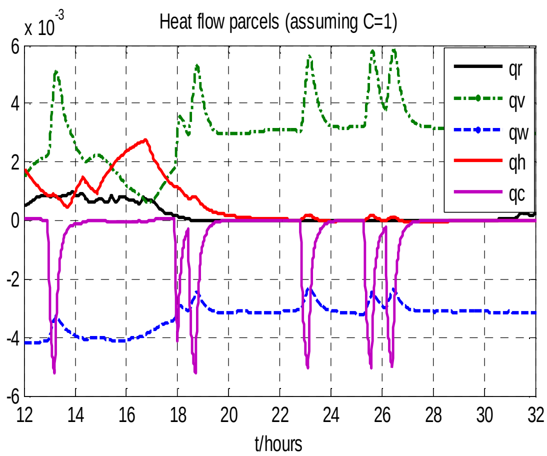

Figure 11. Heat flow obtained with the first-principles structured identification.

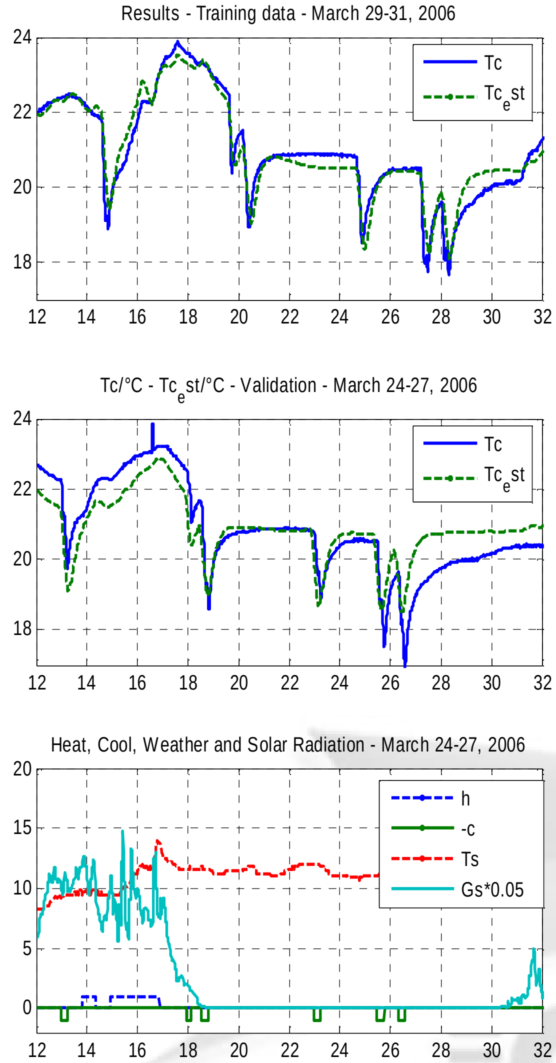

Figure 12. Results of the first-principles structured identification.

It is worthwhile to note that here we have an open-loop prediction of the thermal behavior over more than 20 hours while a predictive building controller seldom uses more than 2 hours as prediction horizon. The receding horizon approach even only uses the first calculated control signal and then update all signals.

7 Conclusion

Buildings as very complex dynamical systems can be more reasonably modeled using first-principles structures. If one aspect of the environment is changed, e.g., the use of blinds, we can easily adjust the corresponding K_w and a_w parameters. If we have another room with similar walls the K_v and a_v can be calculated. With the conventional black-box identification every time the whole model has to be identified. And worse, no physical meaning is associated to the internal states of the model.

More complex wall models, as the 3R2C, or separated vicinity could be used in the proposed methodology if higher accuracy is demanded.

The separation of the heat flow components allowed by the first-principles structured approach is thus a powerful modeling tool. The resulting analytical dynamic model is well suited for predictive HVAC control, which is, in principle, much better with respect to comfort and energy-saving than conventional controllers.

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