EXPERIMENTAL STUDY ON CONTROL-ORIENTED SIMULATION MODELS FOR BUILDING CONTROL AND ENERGY MANAGEMENT

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ABSTRACT

Heuristic rule-based control (RBC) is widely used in the building industry for building automation systems (BASs). Recently, researchers demonstrated that model-based control has the potential to improve the building energy efficiency. Model Predictive Control (MPC) is one of the promising approaches that caught much attention of the research community. The system dynamics model play an important role in model-based control, but constructing the model can be challenging, especially under realistic engineering conditions.

In this paper, we experiment a hybrid approach to construct building thermal dynamics model for integrated, advanced control, under the guide of control theory. The approach for developing this control-oriented model is different from that for a first principle simulation model, such as a Trnsys model. Our model development method is tightly coupled with the controller development, and is intended to reduce development efforts. We designed an MPC controller using a technique called feedback linearization. We tested the design of our model and controller using a Trnsys simulation model for Intelligent Workspace (IW) at Carnegie Mellon University (CMU).

INTRODUCTION

Heuristic rule-based control (RBC) is widely used in the building industry for building automation systems (BASs). For standard industry practices, field engineers need to walk through the target building, define “if-then-else” style rules based on experience, implement the rules in control sequence, then conduct field tests. PID controller is also often the used. Both RBC and PID are non-model-based approaches.

Recently, researchers demonstrated that Model Predictive Control (MPC), a model-based control scheme, has the potential to improve the building energy efficiency in simulations (Y. Ma et al 2011, OptiControl, Oldewurtel et al 2010). For example, genetic algorithm and dynamic programming have been applied to a non-linear MPC controller. (B. Dong 2010). MPC is an Optimal Control method that has been widely accepted in chemical and process control industries (S Qin et al 2003). However, MPC has not been widely accepted by building automation industry for control and energy management.

On one hand, model-based control has great potentials to outperform non-model-based approaches. With more knowledge of the plant, we have more chances to develop better control strategies. On the other hand, model-based control is more costly in terms of the development efforts. Given the complexity of typical office buildings, a simple “paper and pencil” approach is certainly not an option. In addition, a controller based on a coarse model with significant error might be even worse than non-model-based control. The engineering practices call for a low labor cost, systematic approach, and which computer assistant.

The methods to develop models for MPC controllers are domain-specific. In the past several decades, many MPC modeling and controller design approaches have been explored to meet the requirements of different applications (S Qin et al 2003). Some building simulation tools, such as Trnsys or EnergyPlus, are not designed from the control theory perspective. We can use them in the MPC controller. However, we also want to explore an alternative option, i.e., develop control-oriented models.

In the MPC society (S. Qin et al 2003), first principle models are the analytical model created following physics; data-driven models are fitted using experimental (or simulation) data; hybrid models that adopt both methods are also widely used in the process control industry. Follow this terminology, Trnsys and EnergyPlus models are mainly first principle models. For certain controllers, hybrid models can be accurate enough, yet not too difficult to develop.

1 In control theory terminology, a “plant” is the object under control.
In this paper, we attempt to experiment the idea, by creating a control-oriented model for CMU IW north. We perceive the control-oriented model a class of simulation models specialized for control purposes. Control-oriented models has tight coupling with the controller design process and adopt control system (dynamics) models, such as state space or transfer functions. Notice that there are large overlaps between control-oriented and first principle simulation models. They can be used for both simulation and control purpose, but their emphasis is different. Control-oriented models call for unique features, such as, supporting with state space/transfer function models, coupling with controller design, allows frequency domain analysis, etc.

In certain sense, the way to construct control-oriented model is more important than the features of the model. We are motivated to save the effort for the modeling process. Improving the performance of MPC controller is secondary. First principle simulation models can be difficult to develop. We need guidance from control theory to develop a model with “just enough” details.

This paper is organized as follows: We firstly describe the unique HVAC systems of CMU IW building. The focus is the water thermal system. Then we review control theory in brief. Next, we present our MPC design, followed by our simulations. After discussion, we summary the concluding remarks.

**INTELLIGENT WORKSPACE**

CMU IW building is a research laboratory equipped with innovative thermal, ventilation, and lighting systems (Y. Yu et al 2011). Due to the limit length, we only address the major part of the thermal system. Unlike typical office buildings, IW is equipped with water thermal systems, including Cool Waves, Cool Ceilings, and Water Mullions. Chilled or hot water is provided by the campus. Cool Waves are chilled beam ventilators installed under ceiling with no primary air supply. An oscillating fan in each Cool Wave generates pulsating streams of cool air for occupants. Cool Ceilings are radiant panel units only for cooling purposes. Water Mullions are water pipes attached to window frames to both heating and cooling purposes. As shown in Figure 1, there are 13 zones (areas) in IW north, which is less than the number of actuators, i.e., Cool Waves, Cool Ceilings, and Water Mullions.

At summer time, external air may be too humid, so that a dehumidification equipment is necessary in order to prevent condensation on the radiant surfaces. A dedicated outdoor air system, SEMCO, is installed to provide dry air with appropriate temperature. Conventional dehumidification is not energy efficient, because outdoor air is cooled to dew point and reheated to offset the excessive sensible cooling. Significant energy is lost due to the simultaneous heating and cooling. SEMCO is featured with a total heat recovery wheel and a solid desiccant wheel. The desiccant wheel absorbs moisture of the air stream and is regenerated with a gas burner.

![Figure 1: IW north floor map. (CW: cool wave; RC: radiant panel/cool ceiling; WM: water mullion)](image)

**BRIEF REVIEW OF CONTROL THEORY**

A standard control system block diagram is shown in Figure 2, where “reference” is the desired output; “error” is reference minus output; “input” is the signal from controller to plant, such as the IW building; “plant” is the object being controlled; “output” are the sensor measurements from the plant, such as temperature or humidity.

In control theory, control systems always have feedback loops. The term “system model” or “model,” in this context, is the mathematical descriptions of the plant. Typical models are in the forms of state space or transfer function. Equation (1) is a standard form of discrete state space model for a linear time invariant (LTI) system, where \( k \) is the discrete time, i.e., the iteration number; \( x, u, y \) are the state variable, input and output, respectively.

\[
\begin{align*}
  x_{[k+1]} &= Ax_k + Bu_k \\
  y_k &= Cx_k + Du_k 
\end{align*}
\]

Equation (2) is one example of a transfer function.

\[
F(s) = \frac{Y(s)}{X(s)}
\]

Each state space model can be converted into a set of transfer functions, i.e., transfer matrix, and vice versa. This intrinsic connection allows us to study a control system from both time domain and frequency domain. While time domain is also addressed in simulation, frequency domain analysis is important for controller designs.
Frequency domain analysis is the cornerstone for robust control and stability analysis in classical control theory. Frequency domain methods, such as Bode plots, are widely used to test stability of physical control systems.

**Requirements on Modeling Due to the Design of MPC**

MPC is a matured method that has been used in process control industry for decades (S. Qin et al. 2003). Figure 3 is the system block diagram of a generic MPC system. In the context of building control, “plant” can be the building model; \( \mathbf{v} \) is measured disturbance, such as weather conditions; \( \mathbf{r} \) is set points to the controller; \( \mathbf{d} \) is the unmeasured disturbance. The purpose of the MPC controller is to minimize a cost function in the form of Equation (3),

\[
\min_{\mathbf{u}(k)} \sum_{j=0}^{n} \left[ y(j) - y_r(j) \right]^2 + \sum_{j=0}^{n} \left[ u(j) - u_r(j) \right]^2
\]

Subject to:

\[
\mathbf{u}(j) \in \left[ u_{\text{min}}, u_{\text{max}} \right]
\]

\[
y(j) \in \left[ y_{\text{min}}, y_{\text{max}} \right]
\]

where \( n \) is the length of prediction horizon; \( \mathbf{W}_1 \) and \( \mathbf{W}_2 \) are weighting factors that designate the importance of tracking performances vs. energy consumptions; footnotes \( \cdot \) or \( \cdot \) are the \( i \)-th or \( j \)-th variable; the notes \( u \) or \( y \) are the lower and upper limits. Thanks to the flexibility of the MPC framework, sophisticated constraints, such as upper and lower limits on \( u \), and \( y \), can be easily considered.

Notice that the name “predictive control” comes from the predictive horizon \( n \), which is the period to minimize energy consumption without comprising comfort level. The predictive control should not be confused with weather prediction. An MPC controller may or may not use weather forecast data.

Instead of strictly following the standard MPC architecture in Figure 3, our controller has a MPC core with a set of inverse functions. The architecture is shown in Figure 4. This design is featured with a feedback linearization technique, which is often seen in robotic control systems (R. M. Murray et al. 1994).

The essential idea of feedback linearization is to simplify a nonlinear system to a linear system using inverse function in the control law. For example, suppose a nonlinear dynamic system in Equation (4), where the notations are defined the same as in Equation (1), then it is possible to find a linearized input \( \mathbf{u}^* \), such that Equation (5) holds.

\[
x_{k+1} = h(u_{k+1}; x_k)
\]

\[
y(k) = C\mathbf{x}
\]

\[
x_{k+1} = \mathbf{A}x_k + \mathbf{B}u(k)
\]

\[
y(k) = C\mathbf{x}(k)
\]

\[
\mathbf{u}(k) = f^{-1}(\mathbf{u}(k))
\]

Let us illustrate the concept using a trivial example. Assuming a system with nonlinear dynamics

\[
x_{k+1} = x_k + \sin(x_k) + u_k
\]

We can define

\[
\mathbf{u}^*(k) = \sin(x_k) + u_k = f(x_k)
\]

where \( f \) is the actuator model. So, we have

\[
x_{k+1} = x_k + \mathbf{u}^*(k)
\]

\[
\mathbf{u}_{\text{ref}} = -\sin(x_k) + \mathbf{u}^*(k) = f^{-1}(\mathbf{u}^*(k))
\]

Therefore, as shown in Equation (6), our controller can firstly solve \( \mathbf{u}^*(k) \) just as a linear system, then find the associated \( \mathbf{u}_{\text{ref}} \), finally send \( \mathbf{u}_{\text{ref}} \) to plant. Notice that, in this example, for illustration purposes, it is easy to derive \( f^{-1} \) from \( f \). But, for generic nonlinear function \( f \), the analytical solution of \( f^{-1} \) may not exist. For example, the Water Mullions do not have an analytical inverse function. In this paper, we find numerical solutions based on

![Figure 2: Control system block diagram.](image)

![Figure 3: Diagram of a generic MPC system.](image)

![Figure 4: Proposed MPC with feedback linearization.](image)
CONTROL-ORIENTED MODEL

Our control-oriented model is a hybrid model with the following features:

1. First principle modeling methods are used to model actuators.
2. Room dynamic model is built based on data-driven modeling methods.

There are several reasons to adopt this hybrid approach. First, this modeling method supports the proposed MPC controller, as mentioned. Second, for model reuse purposes, the first principle models (mathematical models) of Water Mullions, Cool Waves, and Cool Ceilings already developed in implemented in Trnsys (G Gong et al. 2007). Third, the room dynamics in Trnsys model is complicate and it is not available in state space model. So, we use simulation data to identify the parameters in Equation (4). We create room dynamics model with a data driven approach. Define $T_{i,k}$ the zone temperature vector at the $k$-th time step; $T_{i|k}$ the temperature of zone $i$ at the $k$-th time step; the linearized input $u_{i,k}^T = [Q_{wm|k}^T Q_{cw|k}^T Q_{cc|k}^T]^T$, where $Q_{wm|k}, Q_{cw|k}, Q_{cc|k}$ are the column vectors for unit time heat from Water Mullions, Cool Waves, Cool Ceilings. The system input $u_{i,k} = [u_{wm|k}^T u_{cw|k}^T u_{cc|k}^T]^T$.

where Water Mullion and Cool Ceiling’s inputs, $u_{wm|k}^T, u_{cc|k}^T$ are the valve openings from 0% to 100%; $u_{cw|k}^T$ is the binary input to turn on or off Cool Waves. Let $Q_L$ be the unit time thermal load of each zone and $T_{OA|k}$ the outdoor temperature.

Then, we have a simple room dynamics in Equation (6), where $k$ and $l$ are unknown constants. For unconnected zones, zone $i$ and zone $j$, the associated $k_{i,j}$ is 0. We converted Equation (6) into standard state space model in Equation (7), where $v$ is a measurable disturbance to MPC. It is easy to see

$$v_{i,k} = IT_{O\ell|k} + Q_{L|k}$$

$$T_{k+1} = T_k + \sum_{i=1}^{n} k_{i,1}(T_{i|k} - T_{1|k}) + \sum_{i=1}^{n} k_{i,2}(T_{i|k} - T_{2|k}) + \ldots$$

$$T_{k+1} = T_k + \sum_{i=1}^{n} k_{i,1}(T_{i|k} - T_{1|k}) + \sum_{i=1}^{n} k_{i,2}(T_{i|k} - T_{2|k}) + \ldots + Q_L + Bu_{i|k}$$
We use the Water Mullion heating mode model to present the creating of inverse function. Pseudo code for Water Mullion model is shown in Table 1.

Table 1: Water Mullion Heating Mode

| T_S: Water temperature. |
| MKGH: Water flow rate in kg/hr. M is the same flow rate in gpm. |
| N=4: Number of pipes for each set of Water Mullions. |
| T_A: Ambient temperature. |
| T_REW0=0.7845(T_S*1.8+32)+15.369; |
| C1=(T_S*1.8+32-80)/40*0.0268+0.1351; |
| C2=T_REW0-C1*72; |
| C3=0.3199*(M/0.23)^3-1.0182*(M/0.23)^2+1.1185*(M/0.23)+0.5798; |
| T_REW1=C1*(T_A*1.8+32)+C2; |
| T_REW=(C3*T_REW1-32)/1.8; |
| Q=(MKGH*4.186*(T_S-T_REW))*N; |

The analytical inverse function does not exist, as we see that there is no analytical mapping from C3 to M. So, we acquire numeric solution using Matlab nonlinear optimization function: fsolve.

2 We create a Matlab function named WaterMullionHeat, which implement the actuator model in Table 1. The inverse function is shown in Table 2, where use Q (heat), water and air temperature as input, and the output is the Mullion valve opening.

Table 2: Water Mullion Inverse Function

We experimented the hybrid modeling approach using Trnsys and Matlab and present our preliminary results in this section. After simulation-based testing, we will implement the MPC controller at CMU IW and conduct hardware-based testing.

For illustration purposes, we only present zones 7, 8, and 9 in heating seasons. The inputs signals are the opening of the Water Mullion valves in the zones. The linearized inputs are unit time heat from those Water Mullions. The openings of the valves are calculated using inverse function as shown in Table 2.

The first step is to impose excitation signals to the Trnsys model and record the system response. As shown in Figure 5, we open valves one after another one and transfer heat to the environments. For simplicity, the two sets of Water Mullions in zone 7 have the same opening level. Thus the heat from zone 7 is larger than other zones.

![Figure 5: Excitation signals.](image)

Next, we employ grey box identification function, idgrey, from Matlab system identification toolbox to construct a grey box model, which is sent to the pem function to derive a state space model. We obtain a continuous LTI model from pem. With the c2d, tf functions, we convert it to discrete LTI model or transfer function.

In Figure 6, we compare the measured data (from Trnsys) and the estimation based on the identified model. Figure 7 is the step response from Water Mullion 7 to zone 8 air temperature. If the heat from Water Mullion 7 is 1kJ/hr, this heat will contribute to 1.4 degree Celsius temperature raise in zone 8 in about 2500 seconds. Figure 8 is a Bode plot, where the input is Water Mullion 9 and the output is zone 8 temperature. Bode plots capture important frequency properties that can guide controller designs. For example, Figure 8 indicates that signals in order of 0.1 Hz and above are strongly attenuated in magnitude. Therefore, there is no need to have a sensor data sampling rate much higher than this frequency, according to the Shannon theory. Same for the actuators.

2 There are other methods to find the inverse function, but we will not present the details due to the limit space. An analytical inverse function is possible if we simplify the original model. But this simplification introduces extra error. We can also use curve/surface fitting methods to acquire the inverse functions.

\[
T_{k+1} = AT_k + Bu_k + v_k
\]  

(8)
CONCLUDING REMARKS

In this paper, we present a MPC controller featured with a control-oriented model for integrated, advanced control to save building energy consumptions. We adopted a feedback linearization technique to segment building dynamics model into linear and non-linear parts. In order to ensure performance and reduce workload for both controller design and modeling, we cancel the non-linear effects using inverse functions. Finally, we transform the original complicated non-linear MPC problem to a much simpler linear MPC problem.

We experiment a control-oriented model to support the MPC design. Both control-oriented model and first principle simulation model can be applied to simulation and controller design. However, the proposed control-oriented model is developed from the control theory perspective, and tightly coupled with the MPC controller design process. The control-oriented model has some unique features, such as, supporting with state space/transfer function models, tightly coupling with controller, allows frequency domain analysis, etc. While building the model, we utilize both first principle and data-driven modeling techniques. In this sense, the control-oriented model is a hybrid model.

In future, we will test our controller on the real hardware. To prepare for the hardware experiment, we will augment the control-oriented model by considering more input, output and state variables, such as relative humidity, solar radiation etc. Robustness will be of vital importance for hardware realization. With the linearized control-oriented model, we are ready to apply robust control methodology and ensure reliable implementations.
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