**Temperature Prediction and Optimization Model for Night Flushing**

Carlos Duarte & Jared Landsman

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Abstract

We have developed a hybrid (First Principles/Data Driven) model to predict the instantaneous air and mass temperatures of a classroom in the La Escuelita Education Center, located in Oakland, CA. The building’s primary mode of cooling is night flushing: the use of forced ventilation at night with the combination of thermal mass walls and floors, allowing radiant cooling to take place during the day when the building is occupied. We have obtained trends of the airflow, mass temperature, room temperature, and outdoor air temperature from the school’s building management system (BMS) for the months of June to November (the cooling season). With the BMS data set and our prediction model, we have developed a control strategy for the ventilation system to minimize energy and maintain comfortable temperatures.

Introduction

Buildings in the U.S. consume about 40% of the primary energy, where a large percentage goes into HVAC and lighting systems of the building [1]. A strategy that has the potential to reduce energy consumption and peak demand is through thermal storage capacity. There are two versions of building thermal capacity, active and passive. Active building thermal capacity refers to thermal energy storage systems that mechanically create and store chilled water or ice for later use. On the other hand, a passive building thermal storage capacity refers to the use of the building’s envelope, internal construction, and furniture to help cool the building throughout the day [2]. Simulation exercises have shown to have an energy reduction potential of 0-35% and a demand peak reduction of 15-15% through the use of this strategy [3]. For this project, we will investigate a semi-passive building thermal storage capacity in which ventilation rates are increased throughout the cooler temperatures of the night to precool the building during summer days. This strategy is commonly known as “night flushing” and has the greatest savings potential when the mass of the building is large and night time ambient temperatures are low [2], [4].

This strategy, along with other passive strategies, are becoming more common as Net Zero Energy Buildings (NZEBs) become more prevalent. That being said, not many data sets from buildings that use night flushing currently exist. This provides a unique opportunity to investigate and optimize its performance in the La Escuelita Education Center Building. This education building is 21,470 ft2 in size with 10 classrooms that use night flushing. The current controls of the building’s night flushing strategy are not optimized resulting in a required morning warmup of the building, preventing the temperatures of thermal mass surfaces from getting too low and making occupants feel thermally uncomfortable. Thus, eliminating the morning warmup of the building will reduce the building’s energy consumption and yield greater energy savings.

There will be some challenges in optimizing this building’s strategy because there are not many systems like this in the field in which we can reference. Design engineers of the building had to set the control strategy with many assumptions. A positive is that there are laboratory studies and simulation studies that have addressed these issues. For example, Kintner-Meyer and Emery (1994), Braun (2003), and Lui and Henze (2005) established cost functions based on the costs of electricity and demand charges to optimize night flushing strategies and active building thermal capacity strategies [2], [4], [5]. A similar approach will be taken when optimizing the number of night flushing hours for this project. In addition, we do not know which parameters are important to build a first principles model. That is, we do not know if ventilation flow rates or occupancy will be important to build a model. Another challenge in creating a first principles model will be how to take into account the thermal mass of the classroom surfaces. Furthermore, the design team has logged various data that can help with the model, but we are unsure of how to incorporate it. Figure 1 shows an initial schematic of the parameters that we are planning to incorporate. Table 1 describes the nomenclature along with the respective units.

Methodology

*System Modeling*

**Modeling Objective**

Determine the relationship between supply temperature and ventilation rate with indoor air temperature and mass temperature for a classroom using mechanical night flushing. Determine how this relationship can be used to predict instantaneous air temperature and mass temperature.

*Table 1: Description of parameters & variables in dynamical equations*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| ***Symbol*** | ***Description*** | ***Units*** |  | ***Subscript*** | ***Description*** |
| T | Temperature | [°F] |  | z | Zone |
| R | Thermal Resistance | [°F-hr/BTU] |  | a | Ambient |
| C | Thermal Capacitance | [BTU/°F] |  | w | Wall |
| V | Ventilation Rate | [ft3/hr] |  | f | Floor |
| s | Ventilation State | [0/1] |  | v | Supply |
| ρ | Density | [lb/ft3] |  |  |  |
| c | Specific Heat | [BTU/lb-°F] |  |  |  |
| P | Ventilation Power | [BTU] |  |  |  |

Explain reason for having two different models.

**Model Version 1**

Controllable Inputs:

Uncontrollable Inputs:

Outputs:

Parameters:

The following are the dynamical equations, state definition, and input definitions chosen for model 1.

(1)

(2)

(3)

(4)

(5)

Because equation 1 is non-linear in the inputs & states (4th term), we had to linearize around equilibrium. We chose blah as equilibrium points because… To linearize the system, we used equation 6, which produces new dynamical equations, 7, 8 and 9.

(6)

(7)

(8)

(9)

When we set up the dynamical equations into state space form, we see that almost all of the terms of equation 7 that do not contain a state or an input disappear, with the exception of one term. Because = 0, this final term also disappears. Matrix A and B are seen below in equations 10 and 11.

(10)

(11)

**Model Version 2**

Controllable Inputs:

Uncontrollable Inputs:

Outputs:

Parameters:

The following are the dynamical equations, state definition, and input definitions chosen for model 2. Model two is linear and does require any further linearization. Define s(t).

(12)

(13)

(14)

(15)

(16)

Matrix A and B are seen below in equations 10 and 11.

(17)

(18)

*Parameter Identification*

The following are the dynamical equations expressed in theta-phi form.

(19)

(20)

(21)

(22)

(23)

(24)

* Persistence of Excitation
* Method 1
  + Choose initial theta & eta
  + Gradient Update Law
  + Compare simulation to training data
  + Adjust initial theta & eta and repeat
* Method 2 (ask Carlos)

*Parameter Validation*

**Validation using Test Data**

**Validation using Real Parameters**

*Table 2: Description of room and material properties*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| ***Symbol*** | ***Description*** | ***Units*** |  | ***Subscript*** | ***Description*** |
| ρ | Density | [lb/ft3] |  | conc | Concrete |
| c | Specific Heat | [BTU/lb-°F] |  | cem | Cement |
| t | Thickness | [in] |  | ceil | Ceiling |
| L | Length | [ft] |  | air | Air |
| W | Width | [ft] |  | room | Room |
| H | Height | [ft] |  | film, in | Inside air film |
| Rei | Thermal Resistance per Inch | [°F-ft2-hr/(BTU-in)] |  | film, out | Outside air film |
| Re | Thermal Resistance | [°F-ft2-hr/BTU] |  | ins | Insulation |

*Table 3: Values of room and material properties*

|  |  |
| --- | --- |
| ***Variable*** | ***Value*** |
| Lroom | 38 |
| Wroom | 49.5 |
| Hroom | 10 |
| tconc | 4 |
| tcem | 2 |
| tceil | .5 |
| ρconc | 145 |
| ρcem | 95 |
| ρair | 0.0749 |
| cconc | 0.23 |
| ccem | 0.37 |
| cair | 0.2403 |
| Reiconc | 0.07 |
| Reicem | 0.26 |
| Reiceil | 0.45 |
| Reins | 20 |
| Refilm,in | 0.68 |
| Refilm,out | 0.17 |

(?)

(?)

(?)

(?)

(?)

(?)

(?)

Explanation of calculation of P

(?)

*Optimization*

The current setpoints in the actual building are causing the night flushing to overcool the room. For this reason, the temperature of the room must fall within the comfort range during occupied hours, the system is doing a morning warmup before any occupants enter the building. This preheating is unnecessarily consuming energy that can be avoided through optimization. Figure 1 shows a sketch of the current control of the system in red. We are beginning to outline our objective function and constraints based on this overcooling problem. You will see a new variable below for operative temperature (TOP), which is a function of zone temperature, wall temperature, and floor temperature. You will also see that each of the constraints is broken down by occupied and unoccupied times.

Our objective is to reduce (or even eliminate) preheating, therefore we want the operative temperature to be very close to the minimum bound of the comfort range () when occupancy begins. This translates to minimizing the number of unoccupied hours during which the operative temperature falls below the minimum bound. The challenge will be in predicting the start time of night flushing because the rate at which thermal mass is cooled depends on current ambient air conditions which are changing throughout the night.

Objective: Minimize # of unoccupied hours at which .

Constraints:

Results

References

[1] U.S. Energy Information Administration, “Commercial Building Energy Consumption Survey (CBECS),” 2012. [Online]. Available: http://www.eia.gov/tools/faqs/faq.cfm?id=86&t=1. [Accessed: 26-Feb-2015].

[2] S. Liu and G. P. Henze, “Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory: Part 1. Theoretical foundation,” *Energy Build.*, vol. 38, no. 2, pp. 142–147, Feb. 2006.

[3] J. Braun, “Reducing Energy Costs and Peak Electrical Demand Through Optimal Control of Building Thermal Storage,” *ASHRAE Trans.*, vol. 96, no. 2, pp. 876–887, 1990.

[4] J. E. Braun, “Load Control Using Building Thermal Mass,” *J. Sol. Energy Eng.*, vol. 125, no. 3, pp. 292–301, Aug. 2003.

[5] M. Kintner-Meyer and A. F. Emery, “Optimal control of an HVAC system using cold storage and building thermal capacitance,” *Energy Build.*, vol. 23, no. 1, pp. 19–31, Oct. 1995.

[6 ] G. P. Henze, C. Felsmann, and G. Knabe, “Evaluation of optimal control for active and passive building thermal storage,” *International Journal of Thermal Sciences*, vol. 43, no. 2, pp. 173–183, Feb. 2004.

[7] G. P. Henze, J. Pfafferott, S. Herkel, and C. Felsmann, “Impact of adaptive comfort criteria and heat waves on optimal building thermal mass control,” *Energy and Buildings*, vol. 39, no. 2, pp. 221–235, Feb. 2007.

[8] K. Lee and J. E. Braun, “Model-based demand-limiting control of building thermal mass,” *Building and Environment*, vol. 43, no. 10, pp. 1633–1646, Oct. 2008.