CONTROL-ORIENTED DYNAMIC MODELING AND CALIBRATION OF A CAMPUS THEATER USING MODELICA

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Abstract

In order to design and assess the dynamic performance of building automation systems, accurate control-oriented models are needed. Previous modeling languages do not accurately capture transients and state information to the fidelity that is needed for rigorous control-theoretic analysis. With the recent progress in building energy modeling in Modelica, these transients, and the dynamics of the system in general, can are captured more accurately. In this paper we will discuss necessary methodologies that are needed to construct and calibrate an energy model for the purpose of control system design and tuning. We will discuss topics pertaining to this process including selection of appropriate steady state and dynamic data for model tuning. A case study will be included which investigates the dynamic performance of a building containing a movie theater and acoustic sound stage. Frequency domain control analysis will be presented using the calibrated model.

Introduction

Building energy modeling is often performed for trade studies during the design process and to establish compliance for various accreditations. As these energy models become more accurate and easier to use, their use in the design of the operation (e.g. control) of a building is increasing. Operational design of a building can be as coarse as identifying optimal scheduling strategies, or which sensors are best for different control loops (e.g. the topology of the control loop). More detailed model-based studies include controller synthesis and controller parameter tuning and optimization. In the later case, a different modeling paradigm is often needed that addresses specific concerns in the analysis of feedback control systems that include analysis of the dynamics on shorter time scales than what is historically studied in whole building energy simulation (e.g. EnergyPlus, DOE2, or TRNSYS).

Control-oriented modeling involves deriving simple physics based models that accurately capture system level dynamics and nonlinearity (Chapter 2 of (Åström and Murray 2008)). Another aspect of control-oriented modeling is that the model size (e.g. number of differential variables) should be manageable for rapid simulation and for tractable frequency-based analysis. Control-oriented modeling for a system of systems like a large building should not consider all of the detailed physics that may occur as it is more important in this case to have an analytical physics-based understanding of the dynamics than to have an extremely complicated model that perfectly captures all physics. One example of a modeling library that captures these features is the Modelica Building System Library (Wetter 2009), which is what is used in this paper.

Control analysis of a building management system can occur prior to construction by using a physics-based model that contains parameter information from manufacturer data and other information about the design. As is often the case, a model constructed like this may not match reality immediately due to the modeling assumptions and lack of other information. Because of this, once data is available, it is useful to calibrate the model using sensor data to get a better representation of reality.

In terms of calibration, most previous studies study the output of year long energy calculations to capture relatively static effects (e.g. (Reddy, Maor, and Panjapornpon 2007)). In (Haberl and Bou-Saada 1998) the definition of goodness of fit based on different statistical metrics (e.g. hourly mean bias error, root mean squared error, coefficient of variation of the root mean squared error) was addressed, and many of these topics have been formalized into formal guidelines (see (ASHRAE 2002) and (Liu et al. 2003)). In addition to this, fundamental mathematical considerations of the model calibration process for building models was presented in (Sun and Reddy 2006). In this work the issue of identifiability of parameters in terms of unique parameter sets that will result in model data matching sensor data was addressed. In summary, only parameters that are not interdependent can be identified uniquely. Sensitivity analysis can be performed to identify these dependencies and has been recently used in various studies ((Eisenhower et al. 2011), (Coakley et al. 2011) , (Raftery, Keane, and Costa 2009), (Heo, Choudhary, and Augenbroe 2012), and (O'Neill et al. 2011)).

The primary function of the calibration studies in the above literature is to estimate long term performance of a building (monthly and yearly). Recent work has been performed to calibrate models on a much shorter time scale for control analysis. In (McKinley and Alleyne 2008), the parameters of a reduced order model and load data was identified using optimization approaches. An in-depth control-oriented analysis was performed for a resistor-capacitor type of building model in (Bengea et al. 2011) where model predictive control routines were included with the model identification process.

In this paper, we discuss an approach that performs both static and dynamic calibration of a physics-based control-oriented model. The model we use is more complex than a simple resistor-capacitor type of model as it includes a dynamic thermodynamic equation of state. We also include uncertainty analysis in the study as a tool to investigate uncertainty in the calibration process and robustness of the controlled building.

The remainder of the paper introduces the building and the data available from it. Following this, a description of the preprocessing performed on the data is described. The calibration approach is then discussed, which is followed by uncertainty analysis of control-related metrics of the model.

Description of the Building

In this work, we study a theater building on the campus of the University of California Santa Barbara as it is an interesting case study for control analysis as its occupancy is typically very predictable with respect to time, and somewhat predictable with respect to number of occupants (additionally, occupancy density is often larger than typical commercial buildings). Their design is significantly insulated acoustically and the main viewing area usually has no glazing. Both of these aspects thermally isolate the theater from the ambient environment. Additionally, lighting is often dimmed during a performance resulting in a low internal equipment load during showings. All of these aspects make the analysis of the dynamic response of a theater very manageable. However, a theater also experiences significant transient disturbance at the beginning of a show, and often the Heating, Ventilating, and Air Conditioning (HVAC) system is not tuned properly to react to this disturbance and oscillations in thermal comfort occur through occupied times.

The theater is primarily a single screen theater seating 300 people which is used during the day as a lecture hall, and for public showings at night and on weekends. In addition to the screening area of the building, there are a few offices around the perimeter as well as an acoustically isolated sound stage behind the theater. The building is approximately 12.8 kft^2 (1200 m^2) with a 4 kft^2 (370 m^2) screening area, and a 1.3 kft^2 (118 m^2) isolated sound stage. The model presented in this paper considers two thermal zones (the theater and the sound stage), each with their own Variable Air Volume (VAV) box (a flow damper and reheat coil are in each box). A rough layout of the building is presented in Figure 1.

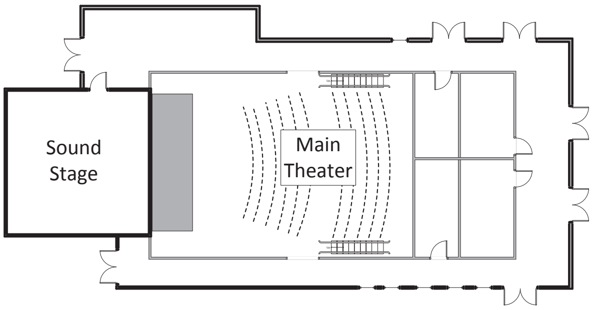

Figure 1: Architectural Layout of the Theater Building.

The entire building is served by two Air Handling Units (AHU) for cooling, heating, and air quality conditioning. The first AHU is a solitary unit (9000 CFM) that conditions the lobby and some office space on the perimeter of the building. A second unit is a multi-VAV unit (12500 CFM) that conditions both the main theater area and the sound stage. The building was constructed in 2009 and hence its envelope and equipment are relatively new and energy efficient. In this study, we only analyze the zones connected to the second AHU (the main theater and sound stage). A schematic of the HVAC equipment is presented in Figure 2.

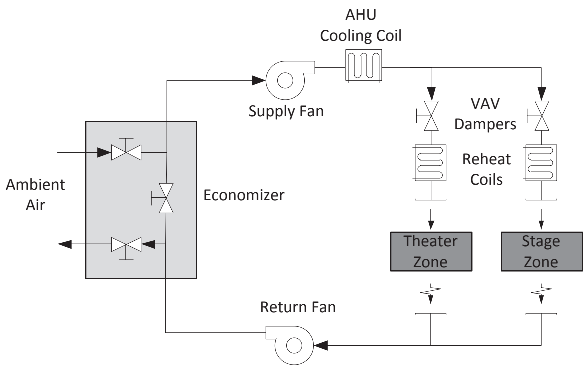

Figure 2: Schematic of the heating and cooling equipment in the Theater.

There are currently two issues with the performance of the building that motivate a model-based analysis. Within the first year of operation, the control system had been commissioned and fine tuned, but until recently, the main theater area did not maintain comfort levels when large groups of attendees occupied the area. The temperatures in this zone would go through delayed transients prior to settling to a comfortable condition, which was typically only reached near the end of an event. This was mitigated by adding a cooling boost functionality that is manually triggered by theater staff (open loop feedforward control). It is likely that the original control system would be able to maintain a comfortable environment if it were tuned optimally. In addition, model-based occupancy detection would also likely accelerate the response of the control system and alleviate the need for manual intervention at each event. These concerns are one reason that this control-oriented model is being developed and calibrated.

A second motivation for performing a model-based analysis is that the discharge temperature from the reheat coil in the sound stage undergoes persistent peak to peak oscillation of about 25 F (14 C). This may be due to sub-optimal coefficient selection for the local controllers of that zone, while it may be possible that it is aggravated by thermal interaction with main the theater zone. It is possible that both of these issues can be solved by a heuristic, or 'build and bust' approach. The motivation for creating this model is to initiate an approach that is scalable to other buildings on campus (the UCSB campus has 70 buildings, some of which have very similar issues as this theater). Future publications will address control-based solutions to the above issues using the model developed in this paper.

Modeling

To summarize the model requirements, the goal of the modeling in this work is to create a calibrated physics-based model of the theater and sound stage that accurately captures transients important to the control system while being manageable in size. To accomplish this task, we utilize the Modelica Buildings Library developed at the Lawrence Berkeley National Laboratory. One of the main intended purposes of the library is to provide a virtual building for control synthesis and analysis, which is useful for addressing control related problems stated above.

The Buildings Library is created in a tiered approach, with the fundamental thermal physics established at the base level and component models that are specific to building energy systems that utilize or extend these properties. Medium models exist at the base, which include anything from single-phase substances (e.g. dry air), to reactive mixtures and multi-phase and component substances (e.g. moist air with CO_2, or boiling water). On top of these mixture medium properties, fundamental heat and mass transfer relations are added with varying complexity that are use-selectable (in terms of scale, dynamics, and nonlinearity). The model library is currently under development which is addressing scalability, robustness, and general useability. The focus of this paper is not to introduce the Buildings Library as a scalable solution for building energy modeling, but rather to illustrate a usage example that has the benefit of making a particular building more comfortable and energy efficient.

In this study, a constant density moist air medium was chosen with an additional mass balance on CO_2. A single stirred reaction volume was chosen for each zone (the theater and sound stage), which was connected to a thermal mass through a thermal resistance element. Two volumes were also chosen to capture dynamics in the HVAC plenum with an additional transport delay. Constant and occupant-driven heat sources are added to the main mixing volumes and a heat source was added to the supply stream to the zones to capture the effect of VAV reheat. The fluid flow relations are relatively common and discussed in the calibration session to follow. Because we are analyzing only the core of the building, no attempt was made to include thermal interaction with the ambient environment (because the perimeter is conditioned by its own HVAC unit), which includes any influences due to infiltration or leakage.

Each volume has three state variables (Temperature, mass fraction, and CO_2), and with three volumes in both the sound stage and main theater, there are 18 state variables that describe the fluids of the building. The thermal capacitance in each zone also contains a state (2 states total), and in addition to this, a first order lag is added to the actuator commands of both the reheat command (modeled as a heat source) and damper command for each of the two zones. In total, the model contains 24 state variables and takes less than a second to simulate 5 days of operation using a 2.8GHz laptop computer.

Model Calibration

Once assembled, the model contains on the order of 25 parameters that need to be tuned in the calibration procedure. Some of these parameter values were chosen by modeling the same building using EnergyPlus and extracting quantities like volumes and thermal mass from the more detailed model. A range for the other parameter values was approximated from intuition (e.g. actuator lags). In the sections to follow we discuss a method to fine tune these parameters to values that are needed to accurately capture the dynamics. It should be noted that some of the final parameter values may not match measured values at the building due to the approximations inherent in the model. That is, in some cases we are calibrating to identify *effective* parameter values for this reduced order model.

At the time of writing, only 8 months of sensor data was available for analysis. For model calibration, various temperatures, flows, CO_2, and actuator command signals were used from the building management system. The temperatures include supply air temperature, as well as discharge and zone temperatures for each zone. Command signals were available for the fan, dampers, and reheat coils. A CO_2 measurement was available for supply and return air which gives an indication of occupancy.

The uncertain parameters in the model contribute in either a static or dynamic way. Because of this, the sensor data was isolated into both steady-state and dynamic subsets of the original data. Each of these subsets was then equally divided into calibration and verification data.

Isolation of Steady State Data

An algorithm was derived to isolate steady state data from the 8 months of original data. A finite difference time derivative was calculated from a weighted combination of data points (sensors and commands) of interest. These time derivatives were combined into a single scalar number for each data point throughout the year by taking the norm

$$\kappa(i) = \sum_j \left\| \frac{w_j(y_j(i) - y_j(i-1))}{t(i) - t(i-1)} \right\|_2, \tag{1}$$

where i is the time instant of data, and j is the sensor number for variable y, and w_j is a normalizing factor (to normalize the data between 0 and 1) for each sensor. The variable $\kappa(i)$ is an indicator of how steady the data is, when this variable is small, the data is steady. Using a finite difference to calculate a derivative introduces noise into the signal and a filtering method may result in improved performance, while in this study, we did not observe any issue with this approach.

As will be discussed in calibration section, the static data was primarily used for identification of the flow network and elements of the model that are expected to have fast time constants. Therefore, to isolate steady-state data, only the flowrates and damper signals were chosen for Equation 1. Once a time series of the derivative norm ($\kappa(i)$) has been calculated, sequences are isolated where $\kappa(i)$ is persistently small for a period of time. After some tuning, we chose a threshold for the norm to be $\sqrt{0.1}$ at a persistence length of about 4 minutes. In doing this, 1965 unique steady state points were identified in the time period April 1 through November 28, 2011. After automatically collecting this data, some outliers were removed, resulting in 1904 valid steady state data points for calibration and verification.

Flow network identification

The model that was assembled to represent the building contains numerous nonlinearities and dynamics which at times exhibit bi-stability (multiple equilibria) and other nonlinear response. One of the more sensitive aspects of the model is the balance of the flow network. If starting with very uncertain parameter values for the flow network, it is very easy to generate a simulated response with flows going in directions that are unexpected or proportionally very different than what is desired. Because of this, we performed much of the initial parameter selection for the flow network using algebraic flow relations in Matlab using the same relationships that are in the full Modelica model.

The flow network in this model is comprised of two main elements; the supply fan, and the pressure drops between the supply plenum and return plenum. In between these two plena are two parallel branches (one for the theater, one for the sound stage). For each branch, the pressure drop is comprised of a series combination of a variable pressure drop due to the VAV damper and a pressure drop from each zone. We combine both of these contributions into one pressure drop for each branch in the analysis below.

Identification of Nonlinear Dampers Characteristics

The first step in the calibration process for the flow network is to identify any possible nonlinearity due to dampers in the VAV boxes. The pressure-flow relation is linearly dependent on the discharge coefficient which arises from different flow openings, while this discharge coefficient may have a nonlinear functional relation to its command signal. To identify this functional relation, we use the fact that the flow that comes from the AHU is split proportionally between the theater and stage branches with an equivalent pressure drop for each (this assumes equivalent leakage for each branch). The simplified constitutive relation for mass flow through each branch is

$$\dot{m} = C(u)A\sqrt{2\rho\Delta p}, \tag{2}$$

where $\dot{m}$ is mass flow, $C(u)$ is the flow coefficient depending on the damper variable u, A is the cross sectional area, ρ is density, and Δp is the pressure drop across the zone.

In the Buildings Library, the flow coefficients are entered as a nominal mass flow ($\hat{\dot{m}}$) and pressure drop ($\Delta\hat{p}$) which absorb the information about the density (ρ) and area (A). That is,

$$\dot{m} = C(u)\left(\frac{\hat{\dot{m}}}{\sqrt{\Delta\hat{p}}}\right)\sqrt{\Delta p}, \tag{3}$$

which results in the following two equations for the pressure drops across the branches

$$\Delta p_{Th} = \left(\frac{\Delta\hat{p}_{Th}}{\hat{\dot{m}}_{Th}^2 C^2(u_{Th})}\right)\dot{m}_{Th}^2 \tag{4}$$

$$\Delta p_{St} = \left(\frac{\Delta\hat{p}_{St}}{\hat{\dot{m}}_{St}^2 C^2(u_{St})}\right)\dot{m}_{St}^2. \tag{5}$$

With mass flow being conserved, the pressure drop across each branch is equivalent, which results in

$$\frac{\Delta\hat{p}_{Th}\dot{m}_{Th}^2}{\hat{\dot{m}}_{Th}^2 C^2(u_{Th})} = \frac{\Delta\hat{p}_{St}\dot{m}_{St}^2}{\hat{\dot{m}}_{St}^2 C^2(u_{St})}. \tag{6}$$

For convenience, we equate the scaling variables $\hat{m}$ and $\Delta\hat{p}$ and capture any of the differences of each branch in the two functions $C(u)$, where u is the command signal sent to the damper. Since the flows $\dot{m}$ are available in data, we have an equation regarding how the damper flow coefficients in the model need to be related in order to achieve conservation of mass, for instance

$$C(u_{St}) = \sqrt{\frac{\dot{m}_{St}}{\dot{m}_{Th}}} C(u_{Th}). \quad (7)$$

With this relation, residual analysis is performed for the steady state flow data, considering the actual u available in the data and the needed damper variable u (in Equation 7). Using this approach, it was found that an affine relation

$$C(u_{Th}) = 0.3u_{Th} + 25 \quad (8)$$
$$C(u_{St}) = 0.49u_{St} + 20.42 \quad (9)$$

was the simplest relation that would provide an equivalent pressure drop given the damper command and measured mass flow.

After choosing the final functional form, the coefficients were chosen using regression. The data used for this regression fit, as well as data verifying the fit (not used to calculate the coefficients) is illustrated Figure 3. In this

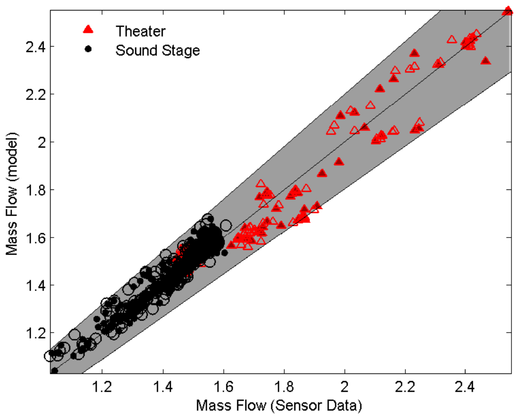

Figure 3: Calibration of the steady state flow network, the solid markers are calibration data and the empty markers are verification data. The grey area identifies the bounds of 10% error.

figure, it is evident that that after tuning the coefficients using the calibration data, the model still matches the verification data well (both of these data sets are within 10% error).

Fan modeling

The Buildings library contains multiple choices for HVAC flow machines (fans) where pressure head is calculated based on a performance curve as a function of normalized volumetric flow through the fan. Efficiencies of the fan are also calculated based on user supplied curves. Using manufacturers data for the fan, we chose a linear relation (`linearFlow` in the library) for the fan flow equation (more complicated fan characteristics were tested with no noticeable improvement in the ability to fit data)

$$\Delta p_{SF} = c_1(rN^2) + c_2(rN)V, \quad (10)$$

where Δp is the pressure head from the fan, rN is a normalized motor speed, V is the volume flow through the fan, and c_i are two unknown coefficients. The parameter c_1 is related to the flat part of the fan curve and therefore was immediately chosen as 1736 Pascals (using manufacturer information). To obtain the second unknown coefficient c_2, a numerical search was performed to find c_2 such that the pressure rise from the fan in Equation 10 is equal to the mean pressure drop of the two zones in Equations 4 and 5.

Initially a search was attempted to find one value for c_2 that would result in an adequate fit for all of the 802 calibration data points, but there was significant error in the fit. To resurrect this issue, a different value of c_2 was fit for each data point. The resulting series of coefficients were trended against variables relevant to the flow characteristics of the fan and it was found that a very strong planar characteristic was evident between this fitted coefficient and the pressure head of the fan

$$c_2 = a_1 rN + a_2 \Delta p_{SF} + a_3. \quad (11)$$

This results in a fan equation of the form

$$\Delta p_{SF} = c_1(rN^2) + (a_1 rN + a_2 \Delta p_{SF} + a_3)(rN)V \quad (12)$$
$$= \frac{c_1(rN)^2 + a_1(rN^2)V + a_3(rN)(V)}{1 + a_2(rN)V} \quad (13)$$

where in this case, $a_1 = -7815.7$, $a_2 = 0.79$, and $a_3 = 3556.1$. At the time of the writing, the physical significance of this is not clear. Although our intent is to keep the model physics-based, we feel that adding this amount of empiricism does not adversely effect the modeling effort and provides a way to obtain a good fit of the flow network as seen in Figure 4.

Dynamic Calibration

After calibrating the parameters that influence static quantities in the model (the flow network), dynamic data is used to calibrate the remaining unknown constants. These

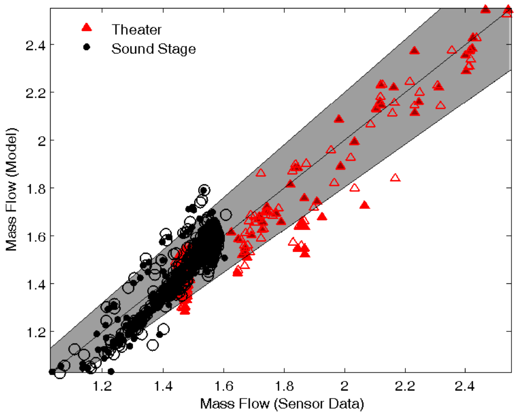

Figure 4: Calibration of the steady state flow network including the fan. The solid markers are calibration data and the empty markers are verification data. The grey area identifies the bounds of 10% error.

constants include scaling factors for both the capacitance and volume of both zones, a time delay for flow transport, a nominal and occupant heat load to the zone and heat transfer coefficient between the zone volume and all heat sources as well as a conduction coefficient between the zone capacitance (thermal mass) and the zone air balance (9 total uncertain parameters for each zone). Initial values for these parameters were taken from design documents, intuition, and information from the EnergyPlus model. These parameter values were refined using data and uncertainty analysis was then performed to gain information on a range of control-oriented predictions from the model.

To perform this calibration, sequences of dynamic sensor data from the building was extracted and compared to response of the model. An optimization algorithm was wrapped around this comparison to minimize the difference between the model solution and dynamic data. The subsets of dynamic data were chosen by manually investigating the time traces of data. There is currently no information about the exit conditions of the supply air cooling coil, so dynamic data was chosen only when this coil was turned off (in the climate of this study, cooling is not necessary throughout the whole year). With this in mind, data was sought that had persistent excitation from both disturbances and the control system so that the dynamics of the model can be accurately identified. In the end, a series of 10 sets of dynamic data (each set contains on the order of 10-50 hours of data) was selected.

To automatically tune the parameters of the model, a global optimization algorithm (pattern search) was used to minimize the cost

$$f(p) = k_1 \|y_m - y_s\|_2 + k_2 \left\| \frac{dy_m}{dt} - \frac{dy_s}{dt} \right\|_2, \qquad (14)$$

where y is the zone temperature (m for model, s for sensor), and k_1, and k_2 are user-selectable parameters used to scale two components of the cost function. At the current time, airflow in this model is not connected through the economizer (the model is just open-loop with respect to flow) and therefore the two zones do not interact. Because of this, the optimization can be performed on each zone separately, which makes the approach for systems like this very scalable to larger buildings. Five optimization experiments were performed using different initial conditions, cost function weights, and convergence tolerances for each of the 10 data sets. Time traces of the model response (simulated using Dymola 2012 FD01) next to the sensor response for some of these cases is presented in Figure 5. It should be noted that there was no dynamic data available wherein the sound stage did not exhibit temperature (and control actuator) oscillations.

Control Analysis

When the optimization for dynamic calibration was complete, there was slight variation in the optimized parameters for each data set which is likely due to the coarseness of the model and because data is taken from different times throughout the year when the building is operated in different ways. This is expected, as to accurately fit a model in this way would require and infinite amount of sensor data. In light of this, we performed uncertainty analysis on the parameter sets that resulted from the calibration.

To perform uncertainty analysis, the parameters for all optimization cases (18 parameters, 50 cases) were gathered and the boundary of this set was identified (max and min of each parameter). A new set was generated that extending this boundary by 30% of the calibrated set and 300 samples were taken within this range using a deterministic sampling approach. Three hundred model realizations were then generated and each of these models was simulated to steady state (using nominal actuator and disturbance variables) and linearized at this final value. From this linearization, the frequency response was generated between the actuator commands (reheat valves) and zone temperatures for both the theater and stage zones (illustrated in Figure 6).

To better understand control-oriented information about the model (and hence building), the stability margins of the uncertain model sets was calculated. In Figure 7, the distribution of gain margins is presented, illustrating that the reheat controller in the sound stage is more likely to go unstable (smaller gain margin means that the system is closer to instability). In addition to this, the phase mar-

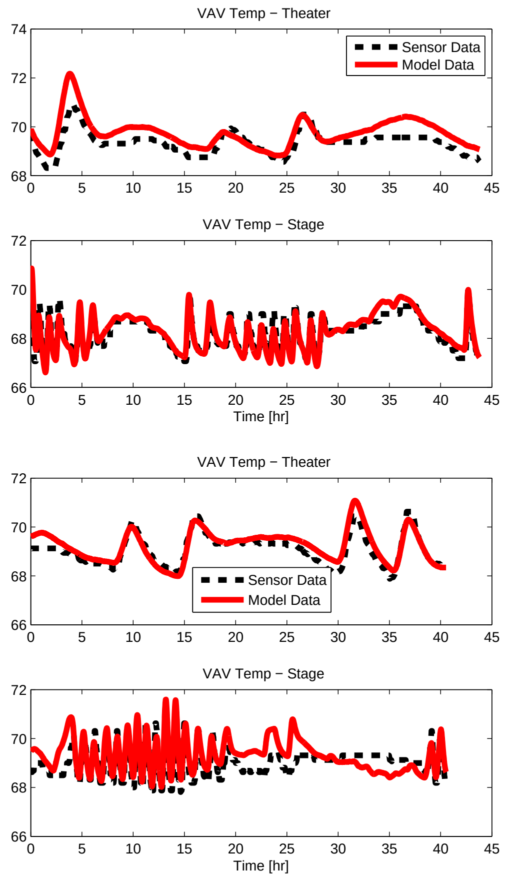

Figure 5: Dynamic Response of the Zone Temperatures in the Theater and Sound Stage for the Calibrated Model Compared to Sensor Data (two different cases).

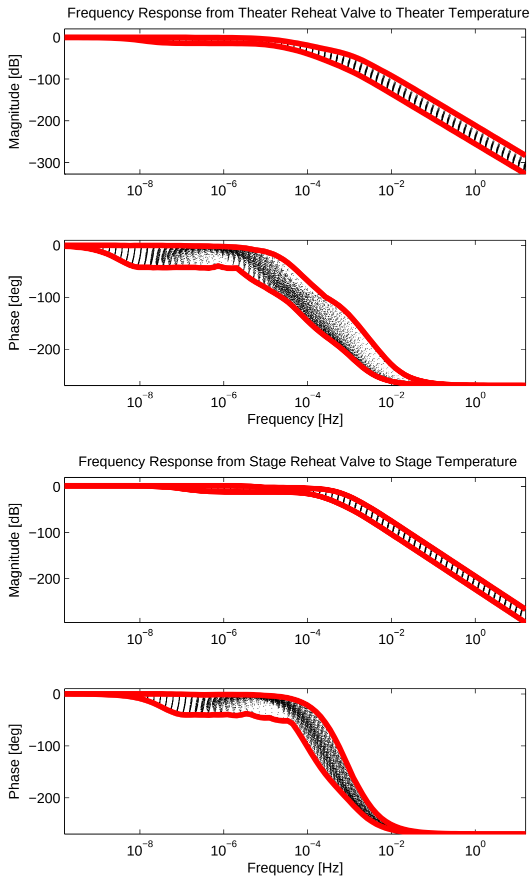

Figure 6: Bode response for the reheat function of both the theater and sound stage. Three hundred realizations of different parameter combinations captures the uncertainty in the identified model. The solid lines illustrate the boundary of the uncertain set of the frequency response.

gin for the theater controller is always infinite, while for the stage, there are finite values of this margin. It should be noted that these calculations are for the plant only (not the loop gain) and the introduction of phase from a controller (e.g. time delay or compensator phase) and gain, will further drive the margins towards instability. These stability metrics suggest why the stage is experiencing unstable oscillations.

Summary

In this paper we developed a control-oriented dynamic model of a theater and sound stage and discussed a method to tune this model to data in order to perform model-based analysis. The first part of the method included isolating steady state data and calibrating the flow network of the model. The second part of the approach included calibrating the parameters of the model that pertain to the dynamic portions of the model. Since even the parameter set that best fits model time domain data still has significant uncertainty, uncertainty analysis was performed to gain control-oriented information from the model. This information illustrated a reason why there exists instability in one of the controllers in the building and will be used to tune this controller for better performance.

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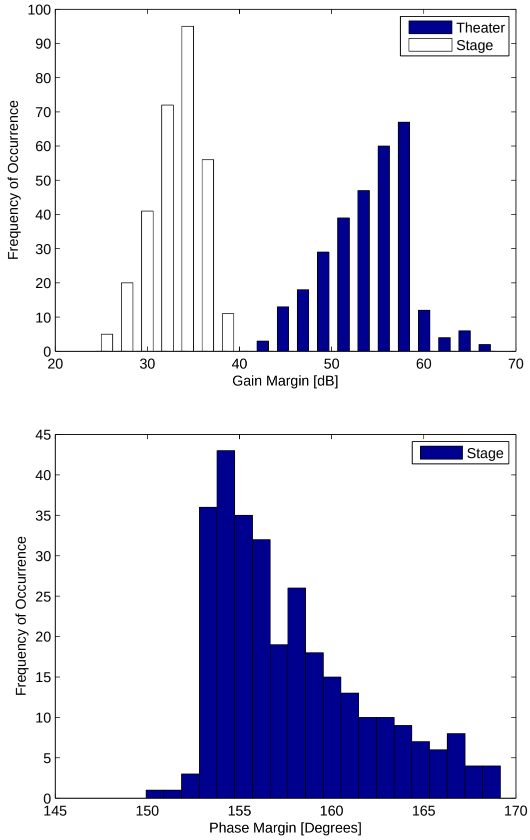

Figure 7: Gain and phase margins for the reheat control. Three hundred realizations of different parameter combinations captures the uncertainty in the identified model. The phase margin for the theater is infinite within the bounds of uncertainty in parameters.

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