“Identification of Building Model Parameters and Loads Using On-Site Data Logs”

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Presentation Topics

• Motivation

• Project Objective and Strategy

• Building Model Structure

• Validation of Model Calibration Procedures

• Conclusions

• Future Work
Motivation: Limit Growth in Carbon Emissions Due to Building Energy Consumption

Limiting carbon emissions growth will require progress on several fronts…

Stabilization Wedge Concept:
Motivation: Limit Growth in Carbon Emissions Due to Building Energy Consumption

Limiting carbon emissions growth will require progress on several fronts…

…with commercial and residential buildings being a key sector.

Stabilization Wedge Concept:
Ref: Pacala and Socolow, Science, Aug 2004

Ref: US DOE Annual Energy Outlook

**Inputs**

**Sensors:**
- Temp
- Humidity
- Air Flow Rate
- Electricity Usage

**Forecasts:**
- Occupancy
- Equipment Usage
- Weather
- Utility Price Schedule

**EMCS**

**Building System Model**

**Off-Line Optimization**

**Data Analysis**

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  - Air Flow Rate
  - Electricity Usage

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  - Utility Price Schedule

**Outputs**

- **Set-Point Schedules:**
  - Thermostat
  - Humidistat
  - OA Ventilation Rate

- **Diagnostics:**
  - Estimated Occupancy
  - Estimated Solar Load
  - Estimated Infiltration

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**Focus area of this study**
Obstacles to Model Development for Control Purposes

• Lack of detailed information:
  – Construction drawings not available
  – As built vs as spec’ed construction
  – Unknown / uncertain usage and occupancy

• Limited resources for model creation and calibration:
  – For small buildings, implementation cost may overwhelm expected cost savings
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• Proposed Solution:
  – Use simplified, low order models
  – Minimize the number of parameters
  – “Self-calibrate” using on-site datalogs
Why Self-Calibrating Models?

- **Opportunity:** Market below 100,000 sq ft presents a tremendous growth opportunity for EMCS.

- **Challenge:** Providing return on investment for owner.

- **Contribution:** Self-calibrating models promise lower implementation costs.

Project Objective and Strategy

• Achieve “proof of concept” of self calibrating, low order building models.

• Measures of Success (Competency):
  – **Accurate**: Mean error between estimated and known parameters
  – **Repeatable**: COV of parameter estimates
  – **Efficient**: Ratio of processing time to logging time
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**Strategy**: Use *model generated* data, so that known and estimated parameters can be compared.
A Simple Building Model

Building Thermal Network

\[ \frac{dT_o}{dt} = \frac{1}{R_o C_o} (T_{AMB} - T_o) + \frac{1}{R_{WALL} C_o} (T_i - T_o) + \frac{\dot{Q}_{SOL-O}}{C_o} \]

\[ \frac{dT_i}{dt} = \frac{1}{R_{WALL} C_i} (T_o - T_i) + \frac{1}{R_i C_i} (T_{ZONE} - T_i) + \frac{\dot{Q}_{SOL-I}}{C_i} \]

\[ \dot{Q}_{STRUC} = \frac{T_i - T_{ZONE}}{R_i} + \frac{T_{AMB} - T_{ZONE}}{R_{WIND}} \]

Unknown Parameters: \( R_o, R_{WALL}, R_i, R_{WIND}, C_o, C_i, m_{INF}, m_{ZONE} \)
The Test Case: A Small Office Building

- Location:
  - Urbana-Champaign, IL
- Application:
  - General Office
- Occupancy:
  - 8 AM-10 PM, Mon-Fri
  - 85 people maximum
- Floor Space:
  - 17,000 sq ft
- HVAC System:
  - VAV with terminal reheat
- Time Period Studied:
  - July 15-22
Data Logging Assumptions

Every 2 minutes, log:

- Temperature and Humidity
  - Ambient
  - Supply Air
  - Zone

- Supply Air Mass Flow Rate

- Solar Flux *

* = Inside and outside solar load computed from measured flux and building simulation.
Procedures for Self Calibrating Models

• Off-Line Parameter Estimation

• Load Estimation
  – Off-Line
  – On-Line
Off-Line Parameter Estimation Method

• The Objective:
  – Find the eight unknown parameters \((R_O, R_{WALL}, R_I, R_{WIND}, C_O, C_I, m_{INF}, m_{ZONE})\) for known loads.

• The Method:
  – Run the model for an assumed parameter set.
  – Calculate an error function.
  – Use an optimization algorithm to vary the parameter set so that the error function is minimized.
Off-Line Parameter Estimation Method

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• The Method:
  – Run the model for an assumed parameter set.
  – Calculate an error function.
  – Use an optimization algorithm to vary the parameter set so that the error function is minimized.

• Key Choices:
  – What is an appropriate error function?
  – What is an efficient optimization algorithm?
Off-Line Parameter Estimation Method: Temperature-based Error Function

- Error Function:

\[ e_T = \frac{\int_{t_1}^{t_f} (T_{ZONK\ MEAS} - T_{ZONK\ PRED})^2 dt}{\int_{t_1}^{t_f} (T_{AMBI\ MEAS} - T_{ZONK\ MEAS})^2 dt} \]

- Optimization Algorithm: SQP

- Repeatability: Poor!

Results for Ten Trials With Random Starting Point
Off-Line Parameter Estimation Method: Composite Temp and Humidity-based Error Function

Error Function:

\[ e_T = \frac{\int_{t_i}^{t_f} (T_{ZONE, MEAS} - T_{ZONE, PRED})^2 \, dt}{\sqrt{\int_{t_i}^{t_f} (T_{AMB, MEAS} - T_{ZONE, MEAS})^2 \, dt}} \]

\[ e_{m_{INF}} = \frac{\hat{m}_{INF, PRED} - \hat{m}_{INF, MEAS}}{\hat{m}_{INF, MEAS}} \]

\[ \hat{m}_{INF} = \frac{\int_{t_i}^{t_f} m_{SUP} (W_{ZONE} - W_{SUP}) \, dt - \int_{t_i}^{t_f} m_{W-LATENT} \, dt}{\int_{t_i}^{t_f} (W_{AMB} - W_{ZONE}) \, dt} \]

\[ e = \sqrt{\left( e_T \right)^2 + \left( e_{m_{INF}} \right)^2} \]

- Optimization Algorithm: SQP
- Accuracy & Repeatability: Excellent!
- Run Time: <1% of logging time

Proof of concept achieved

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean Error</th>
<th>Coefficient of Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>R_I</td>
<td>-0.123%</td>
<td>0.003%</td>
</tr>
<tr>
<td>R_O</td>
<td>-0.228%</td>
<td>0.011%</td>
</tr>
<tr>
<td>R_WALL</td>
<td>-0.078%</td>
<td>0.017%</td>
</tr>
<tr>
<td>R_WIND</td>
<td>0.013%</td>
<td>0.002%</td>
</tr>
<tr>
<td>C_I</td>
<td>0.085%</td>
<td>0.005%</td>
</tr>
<tr>
<td>C_O</td>
<td>0.009%</td>
<td>0.023%</td>
</tr>
<tr>
<td>m_INF</td>
<td>-0.007%</td>
<td>0.019%</td>
</tr>
<tr>
<td>m_ZONE</td>
<td>0.149%</td>
<td>0.013%</td>
</tr>
</tbody>
</table>

Results for Ten Trials With Random Starting Point
Off-Line Load Estimation Method

• The Objective:
  – Find an unknown load (e.g. inside solar load) for known parameters.

• The Method:
  – Run the model for an assumed load trace.
  – Calculate an error function.
  – Use an optimization algorithm to vary the trace so that the error function is minimized.

• Key Choices: (same as before)
  – What is an appropriate error function?
  – What is an efficient optimization algorithm?
Off-Line Load Estimation Method:
Composite Temp and Humidity-based Error Function

- Error Function:
  \[ e_T = \frac{\int_{t_1}^{t_f} (T_{ZONE, MEAS} - T_{ZONE, PRED})^2 dt}{\sqrt{\int_{t_1}^{t_f} (T_{AMB, MEAS} - T_{ZONE, MEAS})^2 dt}} \]
  \[ e_{INF} = \left| \frac{\hat{m}_{INF, PRED} - \hat{m}_{INF, MEAS}}{\hat{m}_{INF, MEAS}} \right| \]
  \[ \hat{m}_{INF} = \frac{\int_{t_1}^{t_f} (W_{ZONE} - W_{SUP}) dt - \int_{t_1}^{t_f} m_{W-LATEN} dt}{\int_{t_1}^{t_f} (W_{AMB} - W_{ZONE}) dt} \]
  \[ e = \sqrt{(e_T)^2 + (e_{INF})^2} \]

- Optimization Algorithm: SQP
- Accuracy & Repeatability: Excellent!
- Run Time: <5% of logging time
- **Proof of concept achieved**
Off-Line Load Estimation Alternate Approach #1: The Greedy Algorithm

- Use a so-called “greedy algorithm.”
- Consider the problem one hour at a time.
- Solve the 15 parameters in chronological order over each one-hour time segments
- This results in 15 one-dimensional optimizations
- Simulation time is shortened by an order of magnitude.
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Load Estimation Alternative Approach #2: The Direct Inversion Method

Differentiate the measured zone humidity ratio WRT time

\[ \frac{dW_{ZONE}}{dt} \]

Solve for the latent load from conservation of water mass

\[ \dot{m}_{W-LATENT} = m_{ZONE} \frac{dW_{ZONE}}{dt} - \dot{m}_{SUP}(W_{SUP} - W_{ZONE}) - \dot{m}_{INF}(W_{AMB} - W_{ZONE}) \]

Calculate zone internal energy from measured temperature and humidity ratio

\[ u_{ZONE} = u(T_{ZONE}, W_{ZONE}) \]

Differentiate the zone internal energy WRT time

\[ \frac{du_{ZONE}}{dt} \]

Solve for the heat transfer rate between the structure and the zone from the energy equation.

\[ Q_{STRUC} = m_{ZONE} \frac{du_{ZONE}}{dt} - \dot{m}_{SUP}(h_{SUP} - h_{ZONE}) - \dot{m}_{INF}(h_{AMB} - h_{ZONE}) - \dot{m}_{W-LATENT} h_{W-LATENT} - Q_{SENS} \]
Load Estimation Alternative Approach #2: The Direct Inversion Method (Cont’d)

- Solve for the inside surface temperature
  \[ T_i = T_{ZONE} + R_i \left[ \dot{Q}_{STRUC} - \frac{(T_{AMB} - T_{ZONE})}{R_{WIND}} \right] \]

- Differentiate the inside surface temperature WRT time
  \[ \frac{dT_i}{dt} \]

- From an assumed initial condition, integrate the governing equation for outside surface temperature
  \[ \frac{dT_o}{dt} = \frac{1}{R_o C_o} (T_{AMB} - T_o) + \frac{1}{R_{WALL} C_o} (T_i - T_o) + \frac{\dot{Q}_{SOL-O}}{C_o} \]

- Solve for the inside solar load
  \[ \dot{Q}_{SOL-I} = C_i \frac{dT_i}{dt} - \frac{(T_o - T_i)}{R_{WALL}} - \frac{(T_{ZONE} - T_i)}{R_i} \]
Accuracy and Robustness: The Direct Inversion Method

Estimated vs True Load

- Load Variation Due to +/- 10% Changes in Model Parameters

Except for occasional noise, results are very accurate

Results are robust to model parameter variations
Advantages of the Direct Inversion Method

- Accurate
- Repeatable: No stochastic variation
- Efficient: Run time < 0.03% of logging time
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- Accurate
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- Suitable for on-line use
  - Involves only differentiators, integrators, and algebraic expressions

- Predicts latent load as a by-product:
  - In some cases, can then relate this to occupancy
Conclusions

• Proof of concept of low order, self-calibrating building models has been achieved.

• These models could be embedded in energy management systems for control and diagnostic purposes.

• A composite temperature and humidity error function was required to avoid parameter confounding.

• A novel direct inversion method was proposed and validated for on-line sensible and latent load estimation.
Future Work

• Application to higher order building models
  – Multiple zones
  – Separate dynamics for roofs, walls, and interior partitions

• Development of solar collection efficiency curves from EnergyPlus building simulation output

• Application to real buildings

• Set-point optimization using the models derived by these methods
Thank You
For Your Attention
And Participation!
Appendix

• Appendix material follows this slide