Panel Discussion

What’s New in Building Energy Model Calibration?

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Covered topics

- Calibrate building model with sensor data (Zheng O’Neill)
- Bayesian calibration (Yeonsook Heo)
- Automated calibration
  - Optimization-based (Mark Adams)
  - Pattern-based (Kaiyu Sun)
Calibration with sensor data
Integrate monitoring and simulation models of building energy use to identify sources of waste and savings potential.

BCVTB: Building Control Virtual Test Bed
Building Model Calibration

Create Energy Model → Identify uncertain parameters, perform sampling → Perform numerous simulations, pre-process output → Calculate full order meta-model

Perform UA/SA → Calculate reduced-order meta-model → Perform Calibration/Optimization → Verify Calibration

- 2063 parameters were varied ± 25% of nominal value
  - Varied concurrently using a quasi-random sampling approach
  - 6500 model realizations
  - Derivative based sensitivities

- Two outputs (measured data): monthly electricity and plug electricity
- Perform optimization on \( \sqrt{\sum (\text{model} - \text{data})^2} \)

<table>
<thead>
<tr>
<th>Error</th>
<th>Plug Electricity</th>
<th>Total Electricity</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE</td>
<td>0.02%</td>
<td>-2.31%</td>
</tr>
<tr>
<td>CV(RMSE)</td>
<td>0.47%</td>
<td>2.80%</td>
</tr>
</tbody>
</table>
Building Model Calibration Issue

- Measured data is significantly far from the baseline model such that changing the parameters by +/- 25% does not move the output into the range of the measured data.

- To alleviate this concern, optimization was performed with constraints on the output variables. Optimal parameters were defined such that the output did not leave an ellipse (in black color) that encompasses the data.

The meta-model and actual E+ simulation with optimal values has some difference, the meta-model is least accurate at its edges.
Bayesian Calibration
New Calibration Methodology

Bayesian Calibration (Kennedy and O’Hagan, 2001)
Bayesian approach updates prior beliefs on true values of uncertain parameters $\theta$ in a computer model given observations.
What is the Value of Bayesian Calibration?

Standard Calibration vs Bayesian Calibration (BC)

Bayesian process can enhance the reliability of the baseline model
How Does Bayesian Calibration Perform Under High Uncertainty?

CVRMSE values of model predictions

<table>
<thead>
<tr>
<th>Level</th>
<th>Uncalibrated Model</th>
<th>Calibrated Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 3</td>
<td>0.29</td>
<td>0.04</td>
</tr>
<tr>
<td>Level 2</td>
<td>0.32</td>
<td>0.12</td>
</tr>
<tr>
<td>Level 1</td>
<td>0.38</td>
<td>0.13</td>
</tr>
</tbody>
</table>
Is It Necessary to Calibrate All Uncertain Parameters?

Both cases calibrate the top four uncertain parameters:

- **Case B**: the remaining uncertain parameters are set at base values (mode of uncertainty distribution)

- **Case I**: the remaining uncertain parameters are fixed at true values (95-quantile of uncertainty distribution)
Optimization-based Automated Calibration
Case Study #1

- Model manually “de-tuned”
- 24 faults
- 63 input changes, +/- 40%
- Goal: Can Autotune recover data it did not use for calibration?
Case Study #1 Results

- Recovery 63 inputs (with +/- 40% ranges)
  - 32 of 63 (50%) within 10% of their original value
  - 22 (35%) between 10% and 30%
  - 9 (14%) above 30%

- Variables important for energy were better
  - COP of Chiller:Electric:EIR was off by 0.27%

Daily electric energy use is shown as a function of outdoor air temperature to demonstrate the accuracy of simulation before (left) and after (right) Autotune calibration. Autotune calibration reduced CV(RMSE) = 31.04% and MBE = 27.46% to CV(RMSE) = 1.7% and MBE = 0.4% (final_003_512).
Case Study #2

- Typical calibration workflow
- Residential Home
- 166 variable changes (35 types), +/- 30%

Goal: Can Autotune do as well as a human expert calibrator?
Case Study #2 Results

<table>
<thead>
<tr>
<th></th>
<th>CV(RMSE)</th>
<th>NMBE</th>
<th>Man-effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>G14 Req.</td>
<td>30%</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>PhD</td>
<td>10.4%</td>
<td>0.18%</td>
<td>45 hours</td>
</tr>
<tr>
<td>Autotune</td>
<td>11.82%</td>
<td>-1.27%</td>
<td>35 minutes</td>
</tr>
</tbody>
</table>

Results for a 2720 ft² residential building
For more information


Pattern-based Automated Calibration
Pattern-based automated approach

- Basic idea => Tune the model according to the patterns of the measured and simulated data, using experience in modeling and engineering.

**Universal Bias**

Simulated results consistently lower than electricity use.

Simulated results consistently higher than NG use.

**Seasonal Bias**

Interception points

miss-matched peak

miss-matched tails
### Calibration process

**Input**
- Monthly electricity bill
- Monthly gas bill
- Original model
- Reheat type (elec/gas)
- Weather data

**Output**
- Calibrated model

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameters to tune</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Internal loads</strong></td>
<td>- Occupant density</td>
</tr>
<tr>
<td></td>
<td>- Lighting power density</td>
</tr>
<tr>
<td></td>
<td>- Electric equipment power density</td>
</tr>
<tr>
<td></td>
<td>- Outdoor air flow rate</td>
</tr>
<tr>
<td></td>
<td>- Infiltration rate</td>
</tr>
<tr>
<td><strong>HVAC system</strong></td>
<td>- Cooling equipment efficiency</td>
</tr>
<tr>
<td></td>
<td>- Heating equipment efficiency</td>
</tr>
<tr>
<td></td>
<td>- Fan efficiency</td>
</tr>
<tr>
<td></td>
<td>- Cooling set point (schedule)</td>
</tr>
<tr>
<td></td>
<td>- Heating set point (schedule)</td>
</tr>
<tr>
<td></td>
<td>- Economizer status</td>
</tr>
<tr>
<td><strong>Construction</strong></td>
<td>- Window U-value</td>
</tr>
<tr>
<td></td>
<td>- Window SHGC</td>
</tr>
<tr>
<td><strong>Schedules</strong></td>
<td>- HVAC operation schedule</td>
</tr>
<tr>
<td></td>
<td>- Lighting schedule</td>
</tr>
<tr>
<td></td>
<td>- Electric equipment schedule</td>
</tr>
</tbody>
</table>
Case Study

- Single-story office building
- 10,000 ft$^2$
- San Francisco
- Built in 1977
### Calibration Actions

<table>
<thead>
<tr>
<th>Tuning</th>
<th>Calibration actions</th>
<th>Before tuning</th>
<th>After tuning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>prior to calibration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 1</td>
<td>Decrease lighting power density (W/m²)</td>
<td>21.4</td>
<td>14.9</td>
</tr>
<tr>
<td>Step 2</td>
<td>Increase occupant density (person/m²)</td>
<td>0.11</td>
<td>0.14</td>
</tr>
<tr>
<td>Step 3</td>
<td>Increase average outdoor air flow per person (m³/s·person)</td>
<td>0.007</td>
<td>0.008</td>
</tr>
<tr>
<td>Step 4</td>
<td>Increase cooling COP</td>
<td>3.1</td>
<td>3.7</td>
</tr>
</tbody>
</table>

### Performance Metrics

<table>
<thead>
<tr>
<th></th>
<th>NMBE Electricity (%)</th>
<th>NMBE Gas (%)</th>
<th>CVRMSE Electricity (%)</th>
<th>CVRMSE Gas (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>20.8</td>
<td>-41.2</td>
<td>23.4</td>
<td>50.7</td>
</tr>
<tr>
<td>Step 1</td>
<td>6.8</td>
<td>-32.7</td>
<td>10.6</td>
<td>38.9</td>
</tr>
<tr>
<td>Step 2</td>
<td>7.6</td>
<td>-9.9</td>
<td>11.3</td>
<td>13.8</td>
</tr>
<tr>
<td>Step 3</td>
<td>7.1</td>
<td>-0.2</td>
<td>10.9</td>
<td>14.1</td>
</tr>
<tr>
<td>Step 4</td>
<td>4.7</td>
<td>-0.2</td>
<td>8.5</td>
<td>14.1</td>
</tr>
</tbody>
</table>

### Graphs

- **Electricity**
  - Baseline: Before Calibration
  - Step 1: Decrease lighting power density
  - Step 2: Increase occupant density
  - Step 3: Increase average outdoor air flow per person
  - Step 4: Increase cooling COP

- **Natural Gas**
  - Baseline: Before Calibration
  - Step 1: Decrease lighting power density
  - Step 2: Increase occupant density
  - Step 3: Increase average outdoor air flow per person
  - Step 4: Increase cooling COP
Open Discussion
Questions for panel discussion

• Key impact factors on the calibration accuracy?
• Updates on district/community-level calibration? What are the keys?
• Application of different calibration methods on large-scale data set?
• The application of widely-used sensors (e.g. temperature) data to model calibration?
• Matching monthly or hourly utility bills to Guideline 14 is great, but how do we know the calibrated model matches the real building?
• Is ASHRAE Guideline 14 good enough?
• What metrics define the “best” calibration methodology?
Questions and Discussion

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