Modeling Challenges for High Performance Buildings

Bryan Eisenhower
IMA
June 2013
What are we up against?

How designers, users/occupants, managers influence high performance buildings
...anecdotes

the plural of ANECDOTE is not DATA
Two thermostats/actuators, same objective
Pitfalls in Building Operation

25F/15C Temperature swings < hour interval
Pitfalls in Building Design

Great building design, execution is lagging

Poor execution results in inefficient operation

Thermostat located outside main room volume, close to kitchen

Thermostat located above two toasters
Pitfalls in Building Operation

Occupant Control

Room # : 2264 | 2266 | 2272 | 2276 | 2278

Temperature data of second floor southwest offices from 7/1/2011 to 7/12/2011

Floor 2 mean temperature from 7/9/2011 to 7/12/2011
Five rooms: same part of building with similar equipment, one room is significantly cooler because of occupant behavior.
Occupant Feedback

Occupants as a part of the solution.....
Poor management

Separating time of day consumption for a daytime only building illustrates waste
Modeling
Lots of models available (~468@EERE) – different scales, focus, results, vintage
- Does not account for hand made models

Usage:
- Research / Academic / Forward looking
- Sizing
- Design
- Compliance
- ....more than one above / other

Challenges (Compliance models)
- Robustness traded for mathematical properties (e.g. Lipshitz, continuity)

Models in this talk
- Whole building compliant energy models
  - Compliant models are increasing in creation but rarely used!
  - Compliant models are becoming easier to use
- Physics-based (whether reduced or full compliant models)
What’s in a whole-building energy model (briefly)

- Parametric analysis
  - Uncertainty quantification
  - Meta-modelling
  - Sensitivity analysis
  - Optimization
  - Failure analysis
  - Assimilation

- Decomposition
  - Of Uncertainty propagation
  - Of structural dynamics
  - Frequency dependent
Whole-building energy models

- Constructions / Envelope
- Equipment / Lighting / Plant
- Climate / weather
- Occupants / loads
Parameters

- Constructions / Envelope
- Equipment / Lighting / Plant
- Climate / weather
- Occupants / loads

Materials
Shading
Orientation
Glass
...

Future predictability
Microclimates
Measurement error...

Equipment sizes, efficiency
Schedules...

Usage
Internal equipment...

Parameters
### Typical Parameters

#### Fixed in time

<table>
<thead>
<tr>
<th>Parameter Type</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heating source</td>
<td>Furnace, boiler, GSHP etc</td>
</tr>
<tr>
<td>Cooling source</td>
<td>Chiller, GSHP, etc</td>
</tr>
<tr>
<td>AHU</td>
<td>Coil parameters etc</td>
</tr>
<tr>
<td>Air Loop</td>
<td>Fans</td>
</tr>
<tr>
<td>Water Loop</td>
<td>Pumps</td>
</tr>
<tr>
<td>Terminal unit</td>
<td>VAV boxes, chilled beams, radiant heating</td>
</tr>
<tr>
<td>Zone external</td>
<td>Envelope, outdoor conditions</td>
</tr>
<tr>
<td>Zone internal</td>
<td>Occupant usage</td>
</tr>
<tr>
<td>Sizing parameters</td>
<td>Design parameters for zone, system, plant</td>
</tr>
</tbody>
</table>

#### Time-varying:

<table>
<thead>
<tr>
<th>Parameter Type</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>AHU</td>
<td>AHU SAT setpoint</td>
</tr>
<tr>
<td>Zone internal</td>
<td>Internal heat gains schedule</td>
</tr>
<tr>
<td>Zone setpoint</td>
<td>Zone temp setpoint</td>
</tr>
</tbody>
</table>
Large models can contain thousands of partially certain parameters

<table>
<thead>
<tr>
<th>Parameter Type</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material</td>
<td>205</td>
</tr>
<tr>
<td>Material: AirGap</td>
<td>34</td>
</tr>
<tr>
<td>Material: NoMass</td>
<td>65</td>
</tr>
<tr>
<td>People</td>
<td>1201</td>
</tr>
<tr>
<td>Lights</td>
<td>1741</td>
</tr>
<tr>
<td>Electric Equipment</td>
<td>1641</td>
</tr>
<tr>
<td>ZoneInfiltration: DesignFlowRate</td>
<td>216</td>
</tr>
<tr>
<td>ZoneVentilation: DesignFlowRate</td>
<td>559</td>
</tr>
<tr>
<td>ZoneMixing</td>
<td>477</td>
</tr>
<tr>
<td>ZoneHVAC: Baseboard: Convective: Water</td>
<td>153</td>
</tr>
<tr>
<td>ZoneInfiltration: DesignFlowRate</td>
<td>216</td>
</tr>
<tr>
<td>ZoneVentilation: DesignFlowRate</td>
<td>559</td>
</tr>
<tr>
<td>AirTerminal: SingleDuct: ConstantVolume: FourPipeInduction</td>
<td>1033</td>
</tr>
<tr>
<td>Coil: Heating: Water</td>
<td>1096</td>
</tr>
<tr>
<td>Coil: Cooling: Water</td>
<td>1196</td>
</tr>
<tr>
<td>Fan: VariableVolume</td>
<td>61</td>
</tr>
<tr>
<td>AirLoopHVAC</td>
<td>4</td>
</tr>
<tr>
<td>Schedule: Compact</td>
<td>2162</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>12,338</strong></td>
</tr>
</tbody>
</table>
Large Models
Even large models can be assimilated to data

....this process takes a long time

* Stanford Y2E2 Building
Sampled System Analysis

Sampled Inputs

Building Model

Perturbed Outputs
<table>
<thead>
<tr>
<th>Author(s)</th>
<th># Param.</th>
<th>Technique</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rahni [1997]</td>
<td>390-&gt;23</td>
<td>Pre-screening</td>
<td></td>
</tr>
<tr>
<td>Brohus [2009]</td>
<td>57-&gt;10</td>
<td>Pre-screening / ANOVA</td>
<td></td>
</tr>
<tr>
<td>Spitler [1989]</td>
<td>5</td>
<td>OAT / local</td>
<td>Residential housing</td>
</tr>
<tr>
<td>Struck [2009]</td>
<td>10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lomas [1992]</td>
<td>72</td>
<td>Local methods</td>
<td></td>
</tr>
<tr>
<td>Lam [2008]</td>
<td>10</td>
<td>OAT</td>
<td>10 different building types</td>
</tr>
<tr>
<td>Firth [2010]</td>
<td>27</td>
<td>Local</td>
<td>Household models</td>
</tr>
<tr>
<td>de Wit [2009]</td>
<td>89</td>
<td>Morris</td>
<td>Room air distribution model</td>
</tr>
<tr>
<td>Corrado [2009]</td>
<td>129-&gt;10</td>
<td>LHS / Morris</td>
<td></td>
</tr>
<tr>
<td>Heiselberg [2009]</td>
<td>21</td>
<td>Morris</td>
<td>Elementary effects of a building model</td>
</tr>
<tr>
<td>Mara [2008]</td>
<td>35</td>
<td>ANOVA</td>
<td>Identify important parameters for calibration also.</td>
</tr>
<tr>
<td>Capozzoli [2009]</td>
<td>6</td>
<td></td>
<td>Architectural parameters</td>
</tr>
</tbody>
</table>
### History

<table>
<thead>
<tr>
<th>Author(s)</th>
<th># Param.</th>
<th>Technique</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rahni [1997]</td>
<td>390-&gt;23</td>
<td>Pre-screening</td>
<td></td>
</tr>
<tr>
<td>Brohus [2009]</td>
<td>57-&gt;10</td>
<td>Pre-screening / ANOVA</td>
<td></td>
</tr>
<tr>
<td>Spitler [1989]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Struck [2009]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lomas [1992]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lam [2008]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firth [2010]</td>
<td>27</td>
<td>Local</td>
<td>Household models</td>
</tr>
<tr>
<td>de Wit [2009]</td>
<td>89</td>
<td>Morris</td>
<td>Room air distribution model</td>
</tr>
<tr>
<td>Corrado [2009]</td>
<td>129-&gt;10</td>
<td>Morris</td>
<td></td>
</tr>
<tr>
<td>Heiselberg</td>
<td></td>
<td></td>
<td>Elementary effects of a building model</td>
</tr>
<tr>
<td>Mara [2008]</td>
<td>35</td>
<td>ANOVA</td>
<td></td>
</tr>
<tr>
<td>Capozzoli [2009]</td>
<td>6</td>
<td>Architectural parameters</td>
<td></td>
</tr>
</tbody>
</table>

"… we’ve been doing this long enough to know which parameters are uncertain or of interest in these models"

"… based on our analysis, we believe that 100 parametric simulations is all that is needed to understand a building energy model"
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
  • Model Reduction
  • Optimization
  • Calibration
  • Failure Mode Effect Analysis
Parameter Selection & Variation

- All non-architectural parameters selected in the model
- Parameters varied 20-30% of their mean (sometimes %75)
- Parameters are varied simultaneously
- There are inequality constraints on some subsets (e.g. $a+b < 1$)

Distribution types are available in literature but not applied because of the large number of parameters.

20-30%

nominal
Sampling

Example: 1 – parameter at a time

0.3 Solar Transmittance 0.9

8 W/m² Lighting 20 W/m²

One parameter at a time takes too long and does not capture combinatorial effects
Sampling

Example: 1 – parameter at a time

One parameter at a time takes too long and does not capture combinatorial effects

Example: 2 – parameters at a time
- Traditional methods use random sampling
- This results in ‘clumps’ in the parameter space
Sampling

- Traditional methods use random sampling
- This results in ‘clumps’ in the parameter space

Use chaotic dynamics we can get much better sampling coverage

Lorenz Attractor
Deterministic Sampling

Resonance / Anti-resonance conditions

\[ |(\kappa, \bar{\omega})| < \frac{1}{c|\kappa|^v} \]

\((\kappa, \bar{\omega}) = \kappa_0 \omega_0 + \kappa_1 \omega_1 + \cdots + \kappa_M \omega_M\)

\(\kappa \in \mathbb{Z},\)

\(c, \nu \in \mathbb{R}^+\)

\(\omega_i = \text{Frequencies}\)
Deterministic Sampling

Resonance / Anti-resonance conditions

\[ |(\kappa, \tilde{\omega})| < \frac{1}{c|\kappa|^\nu} \]

\((\kappa, \tilde{\omega}) = \kappa_0 \omega_0 + \kappa_1 \omega_1 + \cdots + \kappa_M \omega_M \)
\(\kappa \in \mathbb{Z}, \quad c, \nu \in \mathbb{R}^+ \)
\(\omega_i = \text{Frequencies}\)

Ergodic:
- Time average and space average distributions are equal
- Originated in 1930’s (von Neumann)

\[ \hat{f}(x) = \lim_{n \to \infty} \frac{1}{n} \sum_{k=0}^{n-1} f(T^k x) \]
\[ \bar{f} = \frac{1}{\mu} \int f \; d\mu \]

\(T: \text{Measure preserving transformation on measure space}\)
\(x: \text{Initial point}\)
\(\hat{f}: \text{Time average}\)
\(\bar{f}: \text{Space average}\)
Convergence Properties

- Monte Carlo bound $\sim \frac{1}{\sqrt{N}}$
- Deterministic bound $\sim \frac{1}{N}$

Faster convergence means more parameters can be studied in the same amount of time!

Biggest difference between Monte Carlo & Deterministic is when $N$ is large

For whole-building analysis, $N$ must be large

[Eisenhower, JBPS 2012]
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Uncertainty Quantification

Uncertain Inputs

Building Model

Uncertain Outputs

Uncertain Inputs

Building Model

Uncertain Outputs
Typical Outputs

<table>
<thead>
<tr>
<th>Facility Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averaged Thermal Comfort</td>
</tr>
<tr>
<td>Gas Facility</td>
</tr>
<tr>
<td>Electricity Facility</td>
</tr>
</tbody>
</table>

**Sub-metered**
- Heating
- Cooling
- Pumps
- Fans
- Interior Lighting
- Interior Equipment

- **Data assessed in different ways:**
  - Peak demand
  - Seasonal demand
  - Monthly demand

- The ‘control’ mechanisms in the model drive distributions towards Gaussian although others exist as well

---

Nominal model
Uncertainty Quantification

Different Inputs:

Influence of Different Parameter Variation size

[E+ Drill Hall]

Input Uncertainty @ 10%

[Graphs showing variability in different parameters under 10% uncertainty]

Input Uncertainty @ 20%

[Bar charts showing variability in different parameters under 20% uncertainty]

[Eisenhower, JBPS 2012]
Uncertainty Quantification

Different Designs:

Nominal vs. High Efficiency Design

[E+ DOE Models]

[Data sourced from Eisenhower, Simbuild 2011]
Uncertainty Quantification

In Dynamics:

Detailed Whole-Building Model

Detailed Energy Software

Analytic Linear Meta-model

Uncertainty in closed loop performance

771 Physical parameters with uncertain bounds

$C_x \frac{dT}{dt} = \sum_{i=1}^{N_{zones}} \dot{Q}_{convi} + \sum_{i=1}^{N_{walls}} \dot{Q}_{mulli} + \sum_{i=1}^{N_{doors}} \dot{Q}_{di} + \dot{Q}_{vent} + \dot{Q}_{HVAC}$

$\dot{x} = A(x_0, p)x + B_u(x_0)u + B_w(x_0, p)w$

$y = Cx$

[Source: Eisenhower, CDC 2012]
Uncertainty in Singular Values

Considerable change throughout year

No Change for different times in year
Open topic: Much larger scales, 100K’s of buildings

Open topic: Propagation of dynamic ‘trajectories’ through system
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Meta-Modeling

- Can test many building configurations
- All modeled dynamics exist
- Usually black box
- Expensive evaluations
- Discontinuous functions

Original Model

- ~2000 parameters
- Comfort, Energy
Meta-Modeling

**Original Model**
- Can test many building configurations
- All modeled dynamics exist
- Usually black box
- Expensive evaluations
- Discontinuous functions

**Meta-Model (model of a model)**
- Same structure
- Configurations limited to data that is used for fit
- Known functional form
- Rapid evaluations
- Continuous functions

\[ f(x) \]

~2000 parameters

Comfort, Energy
Support Vector Regression used to create analytical model from whole building energy model data.

Analytical model representation (Gaussian Kernel):

\[
f(x) = \sum_{k=1}^{N} C_k \exp \left( -\gamma \left\{ (x_1 - x_{1,k}^0)^2 + (x_2 - x_{2,k}^0)^2 + (x_3 - x_{3,k}^0)^2 + \ldots \right\} \right)
\]

where \( x_{k}^0 \) is \( k \)th input parameter sample, \( \gamma \) and \( C_k \) are fit using an optimizer.

Unique minima to the optimization used to identify its coefficients (from convexity).
Meta-modeling results

**Comfort**

- Original Model
  - Meta-Model (same structure)

~2000 parameters

**Energy**

- Original Model

~2000 parameters

\[ f(x) \]
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Calculating Sensitivities

ANOVA-based approach:

Functional decomposition

\[ f(x) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{j>i}^{k} f_{ij}(x_i, x_j) + \cdots + f_{12\ldots k}(x_1, \ldots, x_k), \]

\[ S_i = \frac{D_i}{D} \quad S_{ij} = \frac{D_{ij}}{D} \]

Variance decomposition

\[ D = \sum_{i=1}^{k} D_i + \sum_{j>i}^{k} D_{ij} + \cdots + D_{12\ldots k}, \]

Total individual sensitivity

\[ S_{T_m} = S_m + \sum_{j>i}^{k} S_{ij} + \sum_{l>j>i}^{k} S_{ijl} + \cdots + S_{1\ldots m\ldots k}. \]
Calculating Sensitivities

ANOVA-based approach:

Functional decomposition

\[ f(x) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{j>i}^{k} f_{ij}(x_i, x_j) + \cdots + f_{12\ldots k}(x_1, \ldots, x_k), \]

\[ S_i = D_i / D \quad S_{ij} = D_{ij} / D \]

Derivative-based approach:

- L2-norm derivative sensitivity indices can be calculated as
  \[ N_{i}^{\text{tot}} = \frac{\alpha_i}{D} \frac{\sigma_i^2}{D} \int \left[ \frac{\partial f(x)}{\partial x_i} \right]^2 \rho(x) dx, \]

  where \( \sigma_i^2 = \frac{1}{2} \int (x_i - x'_i)^2 \rho(x_i) dx_i \rho(x'_i) dx'_i \)

  and \( \alpha_i \) is a constant for each distribution \( \rho(x_i) \)

- L1-norm derivative sensitivity indices can be calculated as
  \[ I_{i}^{\text{tot}} = \sqrt{\frac{\alpha_i}{D} \frac{\sigma_i^2}{D} \int \left| \frac{\partial f(x)}{\partial x_i} \right| \rho(x) dx} \]

- Average derivatives can be calculated as
  \[ M_{i}^{\text{tot}} = \sqrt{\frac{\alpha_i}{D} \frac{\sigma_i^2}{D} \int \frac{\partial f(x)}{\partial x_i} \rho(x) dx} \]

Variance is not always best to describe distribution

\[ D = \sum_{i=1}^{k} D_i + \sum_{j>i}^{k} D_{ij} + \cdots + D_{12\ldots k}, \]

Total individual sensitivity

\[ S_{Tm} = S_m + \sum_{j>i}^{k} S_{ij} + \sum_{l>j>i}^{k} S_{ijl} + \cdots + S_{1\ldots m\ldots k}. \]
Typically only a few parameters drive uncertainty in output.
Sensitivity Indices (examples)

After calculating uncertainty at different frequencies, sensitivity analysis is used to identify which parameters are influencing this uncertainty the most.

Sensitivities calculated as frequencies change
Sensitivity of Bandwidth

Bandwidth Sensitivity (Window Surface Temperature to Zone Temperature)

- [W] Ground Temp February
- [M] Gypsum Thickness
- [M] Gypsum Conductivity
- [M] Gypsum Density
- [M] Gypsum Specific Heat
- [M] Carpet Thickness
- [M] Carpet Conductivity
- [M] Carpet Density
- [M] Carpet Specific Heat
- [H] Heating SP
- Window U-Factor

Cor.Bot. Int. Mass: Surface Area
Cor.Mid. Int. Mass: Surface Area
Cor.Top. Int. Mass: Surface Area
Per.Bot1. Int. Mass: Surface Area
Per.Bot2. Int. Mass: Surface Area
Per.Mid1. Int. Mass: Surface Area
Per.Mid2. Int. Mass: Surface Area
Per.Mid3. Int. Mass: Surface Area
Per.Mid4. Int. Mass: Surface Area
Per.Top1. Int. Mass: Surface Area
Per.Top2. Int. Mass: Surface Area
Per.Top3. Int. Mass: Surface Area
Per.Top4. Int. Mass: Surface Area

Top Floor Plen. Infiltration Cnst.

0.7
0.6
0.5
0.4
0.3
0.2
0.1
Top 5 out of 624 parameters includes outdoor air conditions as well as setpoints

Sensitivity of Bandwidth

Bandwidth Sensitivity [HVAC Supply Temperature to Zone Temperature]

-H- Heating SP
-H- OA Damper until 18:00 Sat
-H- Seasonal-Reset-Supply-Air-Temp-Sch
-H- Cor.Mid.Reheat Constant Min. Air Flow Fraction
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Model Reduction

- Sensitivity Index vs. Parameter Number
- Probability Density of Comfort (PMV) and Energy (GJ)
- Meta-Model for 1009 parameters: $f(x)$

1009 parameters: Comfort, Energy
Model Reduction

Meta-Model

\[ f(x) \]

1009 parameters

Comfort, Energy

E+ Data
All 1009 Parameters
Nominal

Comfort [PMV]

Energy [GJ]

Probability Density

-0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1 1.2 1.4

0
0.01
0.02
0.03
0.04
0.05

3500 4000 4500 5000 5500 6000

0
0.01
0.02
0.03
0.04
0.05

0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9

Sensitivity Index

Sorted Parameters

100 200 300 400 500 600 700 800 900 1000
Model Reduction

![Graphs showing model reduction results](image)

Meta-Model

\[ f(x) \]

1009 parameters

Comfort, Energy

Graphs illustrating sensitivity indices and probability density distributions for comfort and energy metrics.
Model Reduction

- Sensitivity Index vs Sorted Parameters
- Probability Density of Comfort [PMV]
- Probability Density of Energy [GJ]

Meta-Model

20 parameters

\[ f(x) \]

Comfort, Energy
Model Reduction

Meta-Model

\[ f(x) \]

7 parameters

Comfort, Energy

Sorted Parameters

\[
\begin{array}{ccccccccccc}
10 & 20 & 30 & 40 & 50 & 60 & 70 & 80 & 90 & 100 \\
0 & 0.1 & 0.2 & 0.3 & 0.4 & 0.5 & 0.6 & 0.7 & 0.8 & 0.9 \\
\end{array}
\]

Sensitivity Index

E+ Data
All Parameters
Top 20
Top 7
Nominal

3500 4000 4500 5000 5500 6000

Comfort [PMV]

Energy [GJ]
Model Reduction

Meta-Model

5 parameters

\( f(x) \)

Comfort, Energy
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Optimization

More energy

All building designs

Less comfort

Best building design

Not feasible but ideal solution

Energy Costs

Thermal Comfort
Discontinuity & Uncertainty
Discontinuity & Uncertainty

Last iterates.
No decrease in cost along coordinate directions due to a discontinuity.

First iterations.

Domain in which the cost function is differentiable.

\[ x^2 = w_{\text{cost}} \ln m \]

\[ x^1 = w_{\text{cost}} \ln m \]

Wetter & Polak 2004
Uncertainties in meta-model dealt with by uncertain cost function weights

\[ \text{Cost} = \alpha_1 \text{Comfort} + \alpha_2 \text{Energy} \]

Methods:
1. **IPOPT** - Primal-Dual Interior Point algorithm with a filter line-search method for nonlinear programming *(Wachter - Carnegie Melon / IBM)*
2. **NOMAD** - Derivative free Mesh Adaptive Direct Search (MADS) algorithm *(Digabel - Ecole Polytechnique de Montréal)*
Optimization Results

- Energy model created
- 1009 parameters sampled
- Subsets of parameters selected for different optimization experiments
- Different cost functions evaluated
- Compared to traditional optimization methods

Model reduction based on parameter type or parameter influence

Rank ordering of parameter sensitivity

Parameters collected by type

[Eisenhower, E&B 2012]
Optimization Results

![Graph showing annual energy (GJ) vs. average comfort (PMV). The Baseline point is marked with a red circle. There is a blue curve connecting the baseline point to another point, indicating the energy savings from improvements.]
Optimization Results

Cost = $\alpha_1$ Comfort + $\alpha_2$ Energy

- Full Model [1009,C1]
- Baseline

Annual Energy [GJ]

Average Comfort | PMV |

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
3
3.5
4
4.5
5
5.5
Optimization Results

Cost = $\alpha_1 \text{Comfort} + \alpha_2 \text{Energy}$
Optimization Results

Cost = $\alpha_1$ Comfort + $\alpha_2$ Energy

Full Model [1009,C1]
Full Model [1009,C2]
Full Model [1009,C3]
Baseline
Optimization Results

![Graph showing optimization results](image)

- Full Model [1009,C3]
- Top 20 [20,C3]
- Top 7 [7,C3]
- Baseline

The graph illustrates the relationship between annual energy consumption [GJ] and average comfort (PMV) for different models and scenarios. The Full Model [1009,C3] appears to offer a balance between energy efficiency and comfort compared to the Baseline and other models.
Optimization Results

![Graph showing annual energy vs. average comfort (PMV). Points represent different models: Baseline, Full Model [1009,C3], Top 20 [20,C3], Top 7 [7,C3], and Top 5 [5,C3].]
Optimization Results

It takes seconds to obtain each of these results!

Using the traditional method took 3 days for one result.
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- **Calibration**
- Failure Mode Effect Analysis
Model Calibration (assimilation)

Examples of 3 Scales:
Utility meter level
Weekly trends
Dynamics (e.g. 5 Min)
Utility Bill Assimilation

Critical Parameters

Assimilation Cost = $\sqrt{\sum (\text{model} - \text{data})^2}$

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Before Calibration</th>
<th>After Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chiller reference capacity W</td>
<td>190800</td>
<td>215287.776</td>
</tr>
<tr>
<td>Chiller reference COP °C</td>
<td>2.85</td>
<td>2.200</td>
</tr>
<tr>
<td>Chiller off outside air temperature</td>
<td>14</td>
<td>12.794</td>
</tr>
<tr>
<td>Room temperature daytime cooling set-point °C</td>
<td>24.4</td>
<td>22.996</td>
</tr>
<tr>
<td>FL2 Zone5 plug load power density W/m²</td>
<td>20</td>
<td>19.234</td>
</tr>
<tr>
<td>FL2 Zone15 plug load power density W/m²</td>
<td>14</td>
<td>14.212</td>
</tr>
<tr>
<td>FL0 Zone5 plug load power density W/m²</td>
<td>600</td>
<td>620.550</td>
</tr>
<tr>
<td>FL2 Zone11 plug load power density W/m²</td>
<td>14</td>
<td>13.347</td>
</tr>
<tr>
<td>FL1 Zone4 plug load power density W/m²</td>
<td>14.5</td>
<td>13.347</td>
</tr>
<tr>
<td>AHU1 supply fan efficiency</td>
<td>0.44</td>
<td>0.353</td>
</tr>
</tbody>
</table>

Error | Plug Electricity | Total Electricity |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NMBE</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>

Chiller malfunction predicted by calibrated model

[O’Neill and Eisenhower, Building Simulation 2013]
Envelope Assimilation

Wireless sensor installation

85 wireless sensors

85 model zones

\[ T_s \xrightarrow{e} PID \xrightarrow{\dot{Q}_{ID}} \text{Energy Plus} \xrightarrow{T_m} \]

[Bhamornsiri & Eisenhower, Submitted 2013]
Control-oriented Modeling

Physics-based Modeling

Dynamic assimilation of time constants

Static assimilation of flow network

Uncertainty in phase margin of control loop

[Eisenhower, Simbuild 2012]
Assimilation

Open topic: We know which parameters influence output metrics most, but which are the correct parameters to tune
Create Energy Model E+, TRNSYS, Modelica

Identify key parameters, perform sampling

Calculate simulation results, study uncertainty in output

Calculate full order meta-model

Perform Sensitivity Analysis
- Model Reduction
- Optimization
- Calibration
- Failure Mode Effect Analysis
Modeling Failures

Example failures:

Envelope
- Envelope breach
- Shades inoperable
- Inadequate insulation

HVAC Equipment
- Flow restriction / leaks
- Motor / impeller failures
- Surface fouling (HEX, collectors, etc.)
- Stuck valves, dampers

HVAC Controls
- Miscalibrated sensors
- Improper programming

Internal
- Unexpected internal loads

[Otto & Eisenhower, Simbuild 2012]
Modeling Failures

Example failures:

- Envelope
  - Envelope breach
  - Shades inoperable
  - Inadequate insulation

- HVAC Equipment
  - Flow restriction / leaks
  - Motor / impeller failures
  - Surface fouling (HEX, collectors, etc.)
  - Stuck valves, dampers

- HVAC Controls
  - Miscalibrated sensors
  - Improper programming

- Internal
  - Unexpected internal loads

Energy model created

533 individual component failures postulated

Failure modes mapped to real parameters

Failures sampled and critical failures identified

Failure distributions have long tails compared to typical UQ

[Otto & Eisenhower, Simbuild 2012]
Modeling Failures

**Example failures:**

- **Envelope**
  - Envelope breach
  - Shades inoperable
  - Inadequate insulation

- **HVAC Equipment**
  - Flow restriction / leaks
  - Motor / impeller failures
  - Surface fouling (HEX, collectors, etc.)
  - Stuck valves, dampers

- **HVAC Controls**
  - Miscalibrated sensors
  - Improper programming

- **Internal**
  - Unexpected internal loads

**Energy model created**

533 individual component failures postulated

Failure modes mapped to real parameters

Failures sampled and critical failures identified

Critical single-effect failures on heating consumption:

- AHU2 Economizer OA damper fails open
- Boiler gas/air flow restricted/leaks
- Lighting not turned off at night
- Zone 7 Thermostat improperly located
- Nightsetpoint temperature set incorrectly

*Sensitivity Index*

*Output Num. 9  heating.sum*

[Otto & Eisenhower, Simbuild 2012]
Example failures:

1. **Envelope**
   - Envelope breach
   - Shades inoperable
   - Inadequate insulation

2. **HVAC Equipment**
   - Flow restriction / leaks
   - Motor / impeller failures
   - Surface fouling (HEX, collectors, etc.)
   - Stuck valves, dampers

3. **HVAC Controls**
   - Miscalibrated sensors
   - Improper programming

4. **Internal**
   - Unexpected internal loads

---

### Output 9: Heating Annual Consumption

<table>
<thead>
<tr>
<th></th>
<th>Boiler gas/air flow restricted/leaks</th>
<th>AHU2 Economizer OA damper fails open</th>
<th>Zone 7 Thermostat improperly located</th>
<th>Nightsetpoint temperature set incorrectly</th>
<th>Lighting not turned off at night</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Sensitivity</td>
<td>0.09</td>
<td>0.05</td>
<td>0.81</td>
<td>0.84</td>
<td>0.12</td>
</tr>
<tr>
<td>First Order</td>
<td>0.02</td>
<td>0.04</td>
<td>0.08</td>
<td>0.08</td>
<td>0.04</td>
</tr>
<tr>
<td>Boiler gas/air flow restricted/leaks</td>
<td>0.01</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>AHU2 Economizer OA damper fails open</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Zone 7 Thermostat improperly located</td>
<td>0.01</td>
<td>0.67</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Nightsetpoint temperature set incorrectly</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Lighting not turned off at night</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

---

### Combinatorial-effect failures are most critical

**[Otto & Eisenhower, Simbuild 2012]**
We want to test the effect of multiple failures at once.
We estimate that the building operates in a unfailed state ~90% of the time.
We seek a transformation between a uniform distribution and a long tail distribution that gives decent concurrence probability.

“when the threshold is low (0.1), it is not likely that only 1-5 FM’s are active....”
Open topic: What is the best prior for failure occurrence?
Clustering essential dynamics
Clustering essential dynamics

Reasons:
- Control architecture
  - Robustness to faults, identification of weak links
  - Ease in implementation
- Model computation / modularity

Approaches:
- Static – propagation of uncertainty
- Static - Topology of dynamics
- Dynamic
Clustering essential dynamics

Uncertainty at each node and pathway flow identified for a heterogeneous building

Table A1. Variables for the nodes of the sensitivity decomposition of Facility Electricity (Figure 7).

<table>
<thead>
<tr>
<th>Level 3</th>
<th>Level 2</th>
<th>Level 1</th>
</tr>
</thead>
</table>

Circles: Uncertainty at each node
Line Thickness: ‘conductance’
Sorting Dynamics

Detailed Whole-Building Model

Unsorted $A$-matrix interconnections

Sorting based on Laplacian eigenvector

Sorted based on interconnection matrices

State-space dynamics

Detailed Energy Software

Unsorted $A$-matrix interconnections

\[ C \frac{dT_c}{dt} = \sum_{i=1}^{N_{\text{surfaces}}} Q_{\text{conv}} + \sum_{i=1}^{N_{\text{conex}}} Q_{\text{mixing}} + \sum_{i=1}^{N} Q_{\text{sol}} + Q_{\text{in}} + Q_{\text{HVAC}}. \]

\[ \dot{x} = A(x_0, p)x + B_u(x_0)u + B_w(x_0, p)w \]

\[ y = Cx \]
Uncertainty in spectral gap of the graph Laplacian illustrates robustness of interconnectivity of energy dynamics.
Sorting Dynamics

A-matrix (color coded by state type)

Sorted based on clustering using Laplacian Eigenvector
Clustering with frequency

Multivariable analysis highlights at what frequency zones communicate

\[ \text{RGA} = \text{G.} \cdot \text{pinv(G)} \cdot \text{G} \]
Clustering with frequency
High dimensional parametric analysis has been proven on large building energy models with successful optimization, assimilation, sensitivity and failure analysis studies

- Needs include: Analysis at much larger scales, e.g. 300,000 buildings. Better understanding of failure distributions, computationally manageable dynamic uncertainty analysis

Different approaches to decomposition and clustering have been explored

- Needs include: Decomposition methods for design and operation strategies that are robust to temporal variation and other disturbance at many different scales
Funding & Collaborators

Funding: NSF, DOE, AFOSR, ARO, UTC, UTRC, UCSB

Collaborators (chronological order...)
Satish Narayanan
Scott Bortoff
Michael Wetter
Igor Mezic
Vladimir Fonoberov
Zheng O’neill
T. Maile, M. Fischer
Kevin Otto
P. Gomez, T. Wilson, M. Georgescu

UTC Systems and Control Engineering
Mitsubishi Electric Research Labs
LBNL
UCSB
AimDyn
University of Alabama
Stanford
MIT & Singapore Uni. of Tech. and Design
UCSB