Can simulation results be trusted?

Fried Augenbroe, fried@gatech.edu
Georgia Tech
A preliminary answer

Etienne and his PhD students engaged in building energy simulation

LOCIE-CNRS
Sensible questions

1. How uncertain are current simulation results?

2. How do they impact our use in practice and our decisions?

3. Can they be made transparent?

4. Can they be reduced by using higher fidelity models?

5. Can we translate them into measures of risk and adapt our decision models?
A high level view at models

1. NEED: Models need to be there for a reason

2. GOAL: Support a decision with necessary level of confidence

COROLLARY:
- Sometimes no model exists (early design support fallacy)
- Confidence needs to be transparent and symmetric (Akerlof)
- High fidelity models may be over-engineered for certain problems
  - Reduced order models are back!
  - Calibration of reduced order models sometimes the best of both worlds
- Example: work by Yeonsook Heo on retrofit decisions in BS11 proceedings
Background

Origins of uncertainty in building simulations

- Physical parameters \(\leftarrow\) Not as easy as you think
- Model discrepancy \(\leftarrow\) “Dark Matter”
- Observation errors
- Deterioration effects
- Surprise
- Modeler’s ignorance (indifference)

Needs for uncertainty analysis

- To support risk-conscious decision making
- To explore the true variability and sensitivity of outcomes
Early work: de Wit (TU Delft), McDonald (ESRU)

Technique:

- Uncertainty Quantification (Underdeveloped)
- Monte Carlo Sampling
- Sensitivity Analysis, Parameter Ranking
- Screening (dominant parameters)

Outcome:

Traditional outcome:

Based on design idealization
TO = 143.5 (lucky shot)
Work over last decade

Tremendous progress in propagation techniques:
- Spectral methods
- Intrusive methods

Statistics society: SAMSI workshops
Last week SIAM-UQ conference

For buildings:
- Raising awareness: OK (from 0 to 30% in BS proc.)
- Rigorous UQ: little progress
- UQ framework: non existent
- Penetration in practice: zero
Risk conscious design and retrofit of buildings for low energy

2 M$, 8/2010- 08/2014

Godfried Augenbroe (PI)
Jeff Wu
Chris Paredis
John Peponis
Ali Malkawi
Overarching objectives

1. The scientific community will acknowledge that current tools are inadequate vis-à-vis the complexity, unpredictability and “messiness” of buildings
2. Risk-conscious design methods will lead to systematically better performing buildings and large energy savings
3. Uncertainties at the macro, meso and micro scales of influence will be better understood and quantified
4. Picking winners and losers among proposed building energy solutions will be enhanced by comprehensive risk analyses
5. Benchmarking building energy technologies at the whole building scale under uncertainty will become routine in design evolution
6. The introduction of risk-conscious design measures will forever change our thinking about how we integrate energy systems in buildings
7. New fields of building science will emerge that study the correlation between architectural and system features, and underperformance risks
Project Plan

YEAR 1: DATA ANALYSIS

1. “Building stock”
   Building data base
   240 buildings

2. Simulation
   Model bank

YEAR 2: THEORY and METHODS

3. Risk measures and
   risk-conscious design
   criteria

4. Uncertainty analysis
   methodology

5. Risk conscious
   decision framework

6. Energy Benchmarking
   With Uncertainty

YEAR 3: APPLICATION

7. Application 1:
   Large Scale Energy Retrofit

8. Application 2:
   (Near) Zero Energy Building

YEAR 4: IMPLEMENTATION

DISSEMINATION

Broader Impact

A. Reports
B. Workshops
C. Benchmarking
D. Design Feedback
E. Education
F. Outreach

Computational methods &
Stochastic simulation

Risk conscious decision
framework

Policy making

Energy Auditing &
Retrofit practice

System Design Practice

Smart grid developers

Energy Auditing &
Retrofit practice

“Building stock”

Building data base

240 buildings

Uncertainty Quantification

Architectural and system
Design Theory

Reports

Workshops

Benchmarking

Design Feedback

Education

Outreach

Application 1:
Large Scale Energy Retrofit

Application 2:
(Near) Zero Energy Building

A. Reports
B. Workshops
C. Benchmarking
D. Design Feedback
E. Education
F. Outreach
Immediate targets

- Acknowledge the inadequacy of current tools given the complexity, unpredictability and “messiness” of buildings
- Pick winners and losers among proposed building energy solutions by comprehensive risk analyses

Applications:

- (Near) Zero energy buildings
- Large scale energy retrofit
Task 1: Model base

122 UPenn and 30 Georgia Tech buildings:
- Modeled at 4 levels of fidelity
- GT buildings monitoring in-use data
Augmented by DOE database of prototype buildings
Multi fidelity model base
Task 1: Simulation Results

**DesignBuilder/EnergyPlus**
- **Thermal Energy Need**
- **Delivered Energy**

**eQuest**
- **Thermal Energy Need**
- **Delivered Energy**

**Normative Model**
- **Thermal Energy Need**
- **Delivered Energy**
Building energy modeling

• State of the art
  ▫ Idealized Model (design spec)
    Large level of indifference and/or ignorance
    Suspected model discrepancy, but where?
  ▫ Space discretization: finite element model
    DAE system $M \frac{dx}{dt} + S(x, u) x = f(u)$
    State variables $x$
    Control variables: $u$
  ▫ Computer code for numerical time integration and post-processing of state variables
Use of model base

1. Basis of Uncertainty Analysis in 2\textsuperscript{nd} year (Task 4, 5, 6)
   - Step 1: UQ
   - Step 2: model uncertainty
2. Estimate model discrepancy for each model
3. Test-cases for UA methods for different measures (Task 4)
4. Regression into statistical black box models (ongoing)
   - UPenn buildings used for development
   - GT buildings used as test set
   - Follows in tradition of Phil Steadman
5. Discovery of extraneous factors in consumed energy prediction
   - Which non-energy factors make buildings underperform?
6. Creation of generic effect categories of uncertainties for design and retrofit scenarios
Task 2: UQ

Step 1: UQ at meso-scale level
• 8 microclimate pars

Step 2: UQ at the material systems level
• Mostly physical parameters and modeling assumptions
• System module with uncertainty in performance curves
• Approx 80 pars

Step 3: UQ at the people and processes level
• 5 parameters based on occupancy analytics
• Occupant behavior (stochastic processes)
• Fundamental discussion: scenario or uncertainty?
UQ Framework

Accessible urban detail
- Low
- Middle
- High

Modeler’s choice
- \( \delta_1 \)
- \( \delta_2 \)

Low fidelity Model (Standard Model)

High fidelity Model (Meso-scale Model)

Weather Data (TMY)

Urban variance

Microclimate

Building

\[ \varepsilon_{\text{dis}}^{hf-if} + \varepsilon_{\text{agg}} + \delta_2 \]
Challenges and purpose of UQ:

- Module inadequacy in models
- Insufficient knowledge (e.g., early stage)

Major purpose of our UQ outcomes:

- to propagate uncertainty through the model.
- to rank the impacts of all parameters
- to rank the impacts of model inadequacy;
UQ of Building Microclimates

Microclimate variables:
- Wind speed
- Temperature
- Wind pressure
- Solar irradiation

Meteorological Stations
High level of model sophistication + High knowledge about the urban environments (one particular case)

Inputs

**Urban Geometry:**
Coordinates for urban surface geometry
- 8 coordinates for a building

**Thermal Properties:**
1. Emissivity
2. Solar reflectance
3. Heat transfer coefficient
- One set of properties for each surface

**Boundary Conditions:**
1. Temperature Profile
2. Turbulent energy profile
3. Wind Profile
4. Solar Radiation
High level of model sophistication

A number of Particular Cases

\[ V_z = F_i(M) \]

Uncertainty in model parameters

How to aggregate simulation results?
Local Wind Speed

**Standard model** ← ASHRAE Fundamentals

\[ V_z = V_{met} \left( \frac{\delta_{met}}{z_{met}} \right)^{\alpha_{met}} \left( \frac{z}{\delta} \right)^{\alpha} \]

**Meso-scale model** ← High Fidelity

Community Land Model

Urban parameterization scheme
Local Wind Speed

Procedures to compute local wind speeds from TMY data

\[ V_{\text{me}} \text{ at } 10 \text{ m} \]

Meteorological Stations

Urban Environment

Atmospheric Layer
## Local Wind Speed

### Setup for experimental designs

<table>
<thead>
<tr>
<th></th>
<th>H</th>
<th>H/W</th>
<th>B_{L/B_w}</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>max</td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>Open Country</td>
<td>3</td>
<td>3</td>
<td>0</td>
<td>0.3</td>
</tr>
<tr>
<td>Urban/Suburban</td>
<td>99 cases</td>
<td>0.25</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Large City centers</td>
<td>26 cases</td>
<td>0.25</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

### Sample size using Latin Hypercube sampling

- 260 from large city centers
- 990 from urban and suburban areas
- 50 from open country
- 20 from meteorological stations
Local Wind Speed

Statistical model

\[
\text{Diff} = \begin{cases} 
\beta_0 + \beta_1 z + \epsilon & \epsilon \sim N(0, \sigma^2) \quad z \leq \tau \\
\beta_0 + \beta_2 z + \epsilon & \epsilon \sim N(0, \sigma^2) \quad z > \tau 
\end{cases}
\]

The $R^2$ for all the situations is above 0.95.

Histograms of unknown parameters
Statistical Model and Prediction

• Purpose: Model the difference in local wind speed between standard model and meso-scale model.

• The statistical model is as follows:

\[
\text{Diff} = \begin{cases} 
\beta_0 + \beta_1 z + \epsilon & \epsilon \sim \mathcal{N}(0, \sigma^2) \quad z \leq \tau \\
\beta_0 + \beta_1 z + \epsilon & \epsilon \sim \mathcal{N}(0, \sigma^2) \quad z > \tau 
\end{cases}
\]

• This regression model fits the difference data very well \( (R^2 \text{ all above } 0.95) \) good prediction accuracy.

• Significance of results: gives an accurate emulator of the meso-scale model to predict the local wind speed at any height \( z \) in different terrains; providing UQ of prediction.
Urban Heat Island (UHI)

Standard models do not consider the UHI effect

Meso-scale model (TEB Model)

• Urban Parameterization
Urban Heat Island (UHI)

Standard models do not consider the UHI effect

Meso-scale model (TEB Model)

- Urban canyon concept
- Hourly air temperatures with a resolution \(\geq 500\) m

Procedures to compute urban heat island effect
Urban Heat Island

Setup for experimental designs

<table>
<thead>
<tr>
<th>Terrain</th>
<th>$\alpha_{\text{roof}}$</th>
<th>$\alpha_{\text{perv}}$</th>
<th>H(m)</th>
<th>H:W</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cities</td>
<td>min 40%</td>
<td>12.5%</td>
<td>60</td>
<td>W=25m</td>
</tr>
<tr>
<td></td>
<td>max 85%</td>
<td>71.4%</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>min 5%</td>
<td>10%</td>
<td></td>
<td>99 Cases</td>
</tr>
<tr>
<td></td>
<td>max 90%</td>
<td>80%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Urban Heat Island

Statistical model

\[ \Delta T_j = \hat{\beta}_0 + \hat{\beta}_{1j}(z_1 - \bar{z}_1) + \cdots + \hat{\beta}_{pj}(z_p - \bar{z}_p) \]  
(1)

\[ \beta_i^{RIDW}(w_0) = \tilde{\alpha}_0 + \sum_{j=1}^{p} \tilde{\alpha}_j w_{0j} + \frac{\sum_{j=1}^{N} r_{ij} \left\{ (w_0 - w_j)^T \text{diag}(\theta)(w_0 - w_j) \right\}^{-1}}{\sum_{j=1}^{N} \left\{ (w_0 - w_j)^T \text{diag}(\theta)(w_0 - w_j) \right\}^{-1}} \]  
(2)

where \( z \) is urban geometric variables and \( w \) weather variables.

Model evaluation

- Linear model (Eq. (1)) fits the data very well.

- Cross validation suggests that models (1) and (2) combined give good prediction accuracy.
Wind Pressure Coefficient

Standard model: ASHRAE Fundamental

- Wind-tunnel experiments for a stand-alone building.

\[ P_W = C_p \frac{V_z^2}{2} \]

\[ C_p = 0.6 \ln \left( 1.248 - 0.703 \sin \left( \frac{\theta}{2} \right) - 1.175 \sin^2(\theta) + 0.131 \sin^2(2\alpha G) + 0.769 \cos \left( \frac{\theta}{2} \right) + 0.07 \cos^2 \left( \frac{\theta}{2} \right) \right) \]

\( \theta \), wind incident angle and \( G \) the natural log of the building ratio.

High-Fidelity model (TNO \( C_p \) generator)

- Based on experimental data
- Require urban context
Wind Pressure Coefficient

Urban parameterization:

<table>
<thead>
<tr>
<th>Model parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate</td>
</tr>
<tr>
<td>Wind direction</td>
</tr>
<tr>
<td>Terrain roughness</td>
</tr>
<tr>
<td>Obstacle basepoint</td>
</tr>
<tr>
<td>Obstacle azimuth</td>
</tr>
<tr>
<td>Obstacle width</td>
</tr>
<tr>
<td>Obstacle length</td>
</tr>
<tr>
<td>Obstacle height</td>
</tr>
</tbody>
</table>

Setup for experimental designs

<table>
<thead>
<tr>
<th></th>
<th>H</th>
<th>H/W</th>
<th>H/BL</th>
<th>BW/BL</th>
<th>Roughness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>max</td>
<td>min</td>
<td>max</td>
<td>min</td>
</tr>
<tr>
<td>Low-rise Building</td>
<td>99 cases</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>
Wind Pressure Coefficient

Statistical model

\[
\text{Diff} = \begin{cases} 
  f_1(\theta) + \varepsilon_1 & \varepsilon_1 \sim \text{N}(0, \sigma_1^2) \quad \text{for} \quad \frac{B_W}{B_L} = 1 \\
  f_2(\theta) + \varepsilon_2 & \varepsilon_2 \sim \text{N}(0, \sigma_2^2) \quad \text{for} \quad \frac{B_W}{B_L} = 2 \\
  f_3(\theta) + \varepsilon_3 & \varepsilon_3 \sim \text{N}(0, \sigma_3^2) \quad \text{for} \quad \frac{B_W}{B_L} = 4
\end{cases}
\]

To estimate the \( f_i(\theta) \)'s, we tried

- Smoothing spline;
- Local polynomial regression;
- Stochastic kriging
Wind Pressure Coefficient

Finally, \( f_i(\theta) = \beta_{0i} + \beta_{1i}\theta + \beta_{2i}\theta^2 + \beta_{3i}\theta^3 + \beta_{4i}\theta^4 \), where \( i = \frac{B_W}{B_L} \)

\[ B_W/B_L = 1 \]

\[ B_W/B_L = 2 \]

- \( B_W/B_L \) has a significant effect on \( \beta' \)'s and \( \sigma' \)'s.
- As for the other values of \( B_W/B_L \), we will use a linear interpolator.
Solar Irradiation

Solar irradiation

- Direct (Standard model is accurate enough)
- Diffuse (UQ of Perez model-ongoing)
- Ground reflected

UQ of ground reflectance
Standard : 0.2
High fidelity: $\rho_{\text{ground}} = \rho_{\text{prvd}} f_{\text{prvd}} + \rho_{\text{imprvd}} (1 - f_{\text{prvd}})$

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Large Cities</th>
<th>Urban/Suburban Areas</th>
<th>Open Country</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>$f_{\text{prvd}}$</td>
<td>5%</td>
<td>25%</td>
<td>5%</td>
</tr>
<tr>
<td>$\rho_{\text{imprvd}}$</td>
<td>0.072</td>
<td>0.44</td>
<td>0.072</td>
</tr>
<tr>
<td>$\rho_{\text{prvd}}$</td>
<td>0.05</td>
<td>0.4</td>
<td>0.05</td>
</tr>
</tbody>
</table>
In the presence of snow

\[ \rho_{ground} \in [0.16, 0.49] \] based on literature review.
Outcomes first year

- **UQ:**
  - Rigorous UQ of multi scale parameters
  - Putting the built environment on the map of UQ
- Unique multi fidelity building model base to run uncertainty tests across discipline
- Identification and verification of low fidelity models as viable alternatives for certain applications; several PhD theses at Georgia Tech deal with this:
  - Retrofit decision making under uncertainty (PhD thesis)
  - Campus energy topology modeling (PhD thesis)
  - Large scale building stock modeling with uncertainty (PhD thesis)
AGENT-BASED MODELING OF COMMERCIAL BUILDING STOCKS FOR POLICY SUPPORT

Fei Zhao¹, Ignacio J. Martinez-Moyano²,³, and Godfried Augenbroe¹
¹Georgia Institute of Technology, Atlanta, GA, USA
²Argonne National Laboratory, Argonne, IL, USA
³The University of Chicago, Computation Institute, Chicago, IL, USA

Impact Level: Aggregated Indices

Agent Level: Aggregated Building Stocks

Building Level: Individual Buildings

Component Level: Building Systems
RIGHT SIZING AN OFF-GRID SOLAR HOUSE

Huafen Hu\textsuperscript{1}, Godfried Augenbroe\textsuperscript{1}

\textsuperscript{1}College of Architecture, Georgia Institute of Technology
Atlanta, GA, 30332

\textit{Figure 2 A front view of the GT solar house}
<table>
<thead>
<tr>
<th>Performance measure</th>
<th>Description</th>
<th>Typical design criterion</th>
<th>Risk based performance measure</th>
<th>Risk conscious design criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>U</td>
<td>% of time that power service is not available</td>
<td>$U \leq 1%$ for critical loads</td>
<td>Risk($U$) = $Pr(U &gt; 1%)$</td>
<td>Risk($U$) $\leq 10%$</td>
</tr>
<tr>
<td>Percentage $T_e$</td>
<td>% of exceeding hours of thermal comfort range</td>
<td>Percentage $T_e \leq 10%$</td>
<td>Risk($T_e$) = $Pr(Percentage T_e &gt; 10%)$</td>
<td>Risk($T_e$) $\leq 10%$</td>
</tr>
<tr>
<td>Percentage $T_c$</td>
<td>% exceeding hours of extreme temp range</td>
<td>Percentage $T_c \leq 1.5%$</td>
<td>Risk($T_c$) = $Pr(Percentage T_c &gt; 1.5%)$</td>
<td>Risk($T_c$) $\leq 10%$</td>
</tr>
<tr>
<td>R</td>
<td>% energy reduction compared to benchmark</td>
<td>$R \geq 10%$ for new buildings (LEED)</td>
<td>Risk($R$) = $Pr(R &lt; 10%)$</td>
<td>Risk($R$) $\leq 5%$</td>
</tr>
<tr>
<td>E</td>
<td>Annual electric consumption per area</td>
<td>$E \leq 6.0\text{kWh/sq.ft.}$</td>
<td>Risk($E$) = $Pr(E &gt; 6.0)$</td>
<td>Risk($E$) $\leq 5%$</td>
</tr>
<tr>
<td>PY</td>
<td>Payback year of an investment</td>
<td>$PY &lt; 15$</td>
<td>Risk($PY$) = $Pr(PY &gt; 20)$</td>
<td>Risk($PY$) $&lt; 10%$</td>
</tr>
</tbody>
</table>
Figure 6 The reduced cost impact if power interruption is noticed to customers 24 hours ahead (Willis, Welch et al. 2001)

Figure 1 The concept of value-based planning (Kaur, Singh et al. 2004)
RISK ANALYSIS OF ENERGY-EFFICIENCY PROJECTS BASED ON BAYESIAN CALIBRATION OF BUILDING ENERGY MODELS

Yeonsook Heo$^{1,2}$, Godfried Augenbroe$^1$, and Ruchi Choudhary$^3$

$^1$College of Architecture, Georgia Institute of Technology, Atlanta, USA
$^2$Decision and Information Sciences, Argonne National Laboratory, Argonne, USA
$^3$Engineering Department, University of Cambridge, Cambridge, UK
Bayesian Calibration

- Bayesian approach updates our prior beliefs on true values of uncertain parameters $\theta$ in a computer model given observations.
Whole Retrofit Analysis Procedure

1. Prior Uncertainty Quantification
2. Parameter Screening
3. Bayesian Calibration
4. Validation
5. Model Predictions

- Prior Distribution for selected parameters
- Utility Data
- Normative Model
- Uncertainty from Retrofit
- Posterior Distributions
Step 3: Bayesian Calibration

- Intercept C for Window Opening
- Indoor Temperature during Heating
- Infiltration Rate
- Discharge Coefficient
Model Prediction

- Candidate Energy Conservation Measures

<table>
<thead>
<tr>
<th>ECM</th>
<th>Model Parameters</th>
<th>Base</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM1: Insulation Addition</td>
<td>U-value (W/m²K)</td>
<td>0.30</td>
<td>0.27</td>
<td>0.33</td>
</tr>
<tr>
<td>ECM2: Window Replacement</td>
<td>U-value (W/m²K)</td>
<td>1.41</td>
<td>1.27</td>
<td>1.55</td>
</tr>
<tr>
<td></td>
<td>Solar Transmittance</td>
<td>0.65</td>
<td>0.63</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>Emissivity</td>
<td>0.05</td>
<td>0.04</td>
<td>0.06</td>
</tr>
<tr>
<td>ECM3: Air-tightness</td>
<td>Infiltration Rate Reduction (%)</td>
<td>11</td>
<td>1</td>
<td>31</td>
</tr>
</tbody>
</table>

- Simple Payback Time Predictions

![Graphs showing simple payback time predictions for ECM1, ECM2, and ECM3.](image)
The New Methodology in the Chicago Loop Project

Policy & Scenario Evaluation
( Normative Model)

ECM Decisions
(Calibrated Normative Model)

Scenarios

Aggregate-level

Finance Tool
ECMs Database

Individual-level

Model base

Calibration Process

STC
Ongoing research in 2\textsuperscript{nd} year

- **Task 3: Risk measures in design and retrofit, driven by:**
  - Performance risks: energy, comfort, LOL,
  - Investment risks: ESCO-led, Vendor-led, Investment models
  - Commission (Cx) and diagnostics practices

- **Task 4: Uncertainty Analysis: Propagation**
  - Tools and methods for sampling and propagation
  - MC approach: “Anytool” wrappers (with some level of intrusion)
    - Sampling techniques
  - Intrusive methods: PC method with newest approaches may be breakthrough (but fully intrusive)

- **Task 5: Risk conscious decision framework**
  - Combining the outcomes of Tasks 3 and 4
  - Embedded in Workbench where new buildings or building technologies can be tested under uncertainty
Task 4: UA Tools and methods

- Structural error is very difficult to characterize
  - Requires large numbers of actual observations

→ Reduce structural error as much as possible by:
  - Quantifying uncertainty in inputs & parameters
  - Improving & Extending Building Energy model

\[
y = f(x, \theta) + \varepsilon(x, \theta)
\]

\[
y = f(x_D, \theta_D) + \varepsilon_D
\]

\[
y = f(x_P, \theta_P) + \varepsilon_P
\]

\[
y = f^+(x_P, \theta_P) + \varepsilon_E
\]
Monte Carlo with ModelCenter

Probabilistic Analysis Tool

Monte Carlo Simulator

Uncertainties

- Draw a sample
- Evaluate $E^{+++}$
- Store Outcome

Define Distribution of Outcomes

Do $N$ times

- $x_P(i)$
- $\theta_P(i)$
- $\varepsilon_1(i)$
- $\varepsilon_2(i)$
- $\varepsilon(i)$
- $y_P(i)$

Monte Carlo with ModelCenter

Probabilistic Analysis Tool

Energy Plus

ModelCenter 10.0

PHOENIX INTEGRATION

CenterLink

Cumulative Distribution Function

Total Cost

Amazon Web Services
Year 3 and 4: Applications

- Reality check
- Looking for suitable projects (partnering)
- Decision making in the real world
  - Investment models (symmetric risks)
  - PPA
  - Commissioning/auditing
  - Rating (with confidence interval)
  - “Extreme” buildings: expression of damage to evaluate risk = \( P(\text{event}) \times (\text{damage|event}) \)
  - Some of these require long tail accuracy of weather (TMY data unusable)
Current related PhD theses:

- Power simulation: connection to PNNL smart grid simulator
- Stochastic weather simulator: long tail representation
- Façade retrofit study: different underperformance risks for owner and tenant
Conclusions

- Rewriting the book on building performance simulation
  - Recognizing the limitations of energy predictions
  - Model discrepancy vs. limitations of use
  - Compare different model fidelities
- Elevating building energy profession to recognize the importance of UQ
  - Changing the way we interpret energy performance
  - Changing the way we do commissioning and retrofit
- Making energy system development and investment risks transparent
  - Supporting investment decisions under risk
  - Choosing renewable technology winners
THANK YOU!

Many questions ....
..... not enough answers

fried@gatech.edu