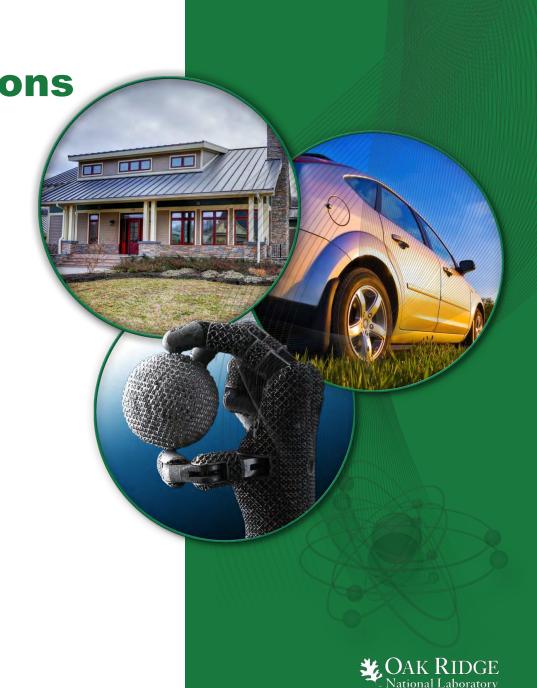
Visualization and Software Simulations for Actualized Energy Savings

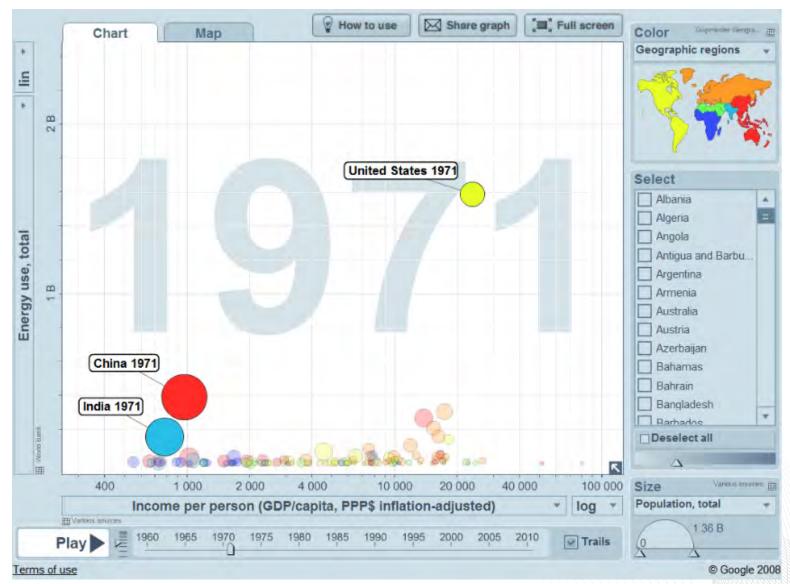
ASHRAE Local Chapter Jan. 21, 2015

Joshua New, Ph.D. 865-241-8783

newjr@ornl.gov



40 Years: Energy and Quality of Life



A brief history of energy and life quality





Sustainability is the defining challenge

Buildings in U.S.

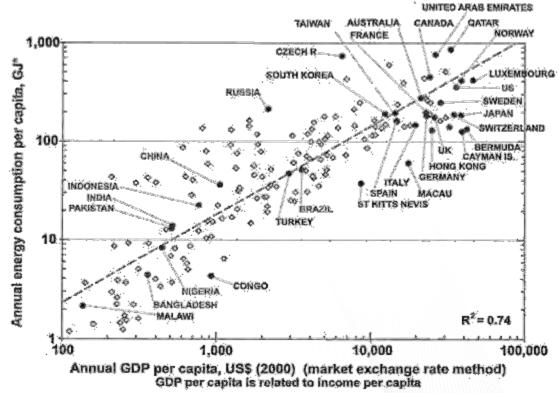
41% of primary energy/carbon 73% of electricity, 34% of gas

Buildings in China

60% of urban building floor space in 2030 has yet to be built

Buildings in India

67% of all building floor space in 2030 has yet to be built

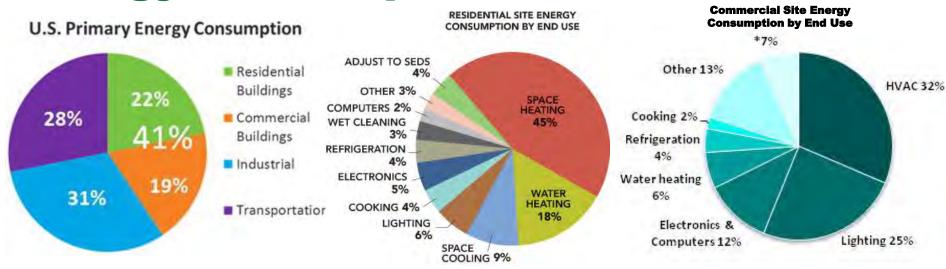


T:000,000,000 GJ ≈ 1 EJ

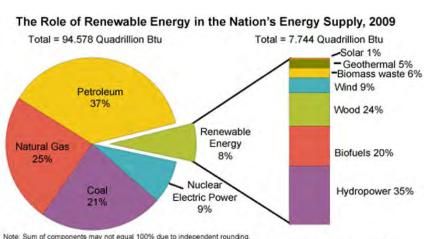
Source: Spengy follorestion Administration



Energy Consumption and Production

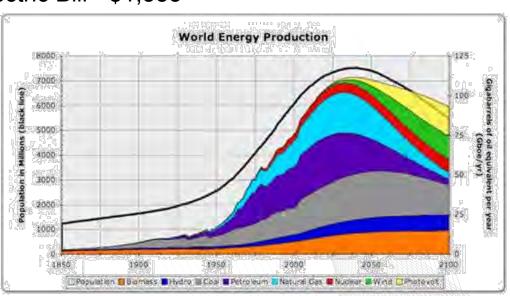


TN 2012 Electric Bill - \$1,533



Note: Sum of components may not equal 100% due to independent rounding.

Source: U.S. Energy Information Administration, Annual Energy Review 2009, Table 1.3, Primary Energy Consumption by Energy Source, 1949-2009 (August 2010).



Presentation summary

- Scientific Paradigms
- Roof Savings Calculator
- Visual Analytics
- Knowledge Work
- Autotune
- Publications



Presentation summary

- Scientific Paradigms (context)
- Roof Savings Calculator
- Visual Analytics
- Knowledge Work
- Autotune
- Publications

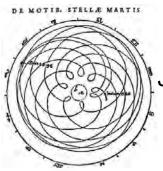


4th Paradigm – The Science behind the Science

- Empirical guided by experiment/ observation
 - In use thousands of years ago, natural phenomena
- Theoretical based on coherent group of principles and theorems
 - In use hundreds of years ago, generalizations
- Computational simulating complex phenomena
 - In use for decades
- Data exploration (eScience) unifies all 3
 - Data capture, curation, storage, analysis, and visualization
 - Jim Gray, free PDF from MS Research

Tycho Brahe





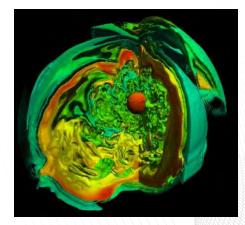
Johannes Kepler

$$\oint \mathbf{E} \cdot d\mathbf{A} = q / \varepsilon_{0}$$

$$\oint \mathbf{B} \cdot d\mathbf{A} = 0$$

$$\oint \mathbf{E} \cdot d\mathbf{S} = -d\Phi_{\mathbf{B}} / dt$$

$$\oint \mathbf{B} \cdot d\mathbf{S} = \mu_{0}i + \mu_{0}\varepsilon_{0}d\Phi_{\mathbf{E}} / dt$$

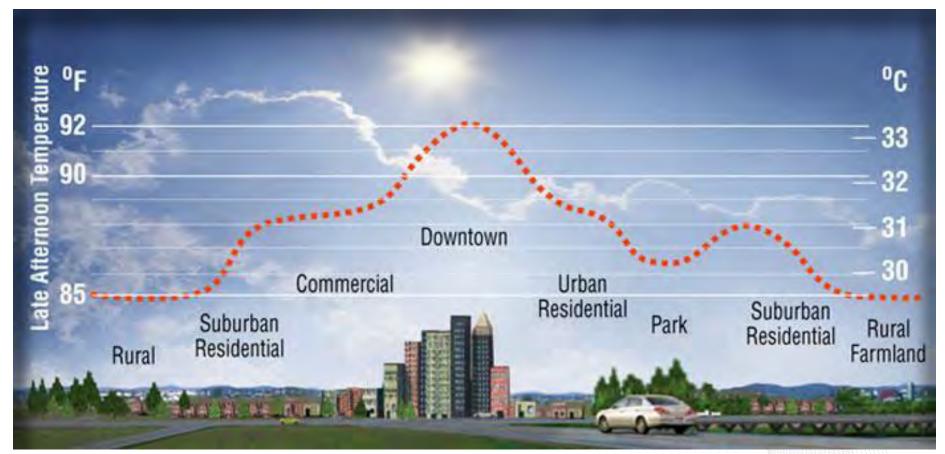


Presentation summary

- Scientific Paradigms
- Roof Savings Calculator
- Visual Analytics
- Knowledge Work
- Autotune



Urban Heat Island Effect and Albedo Engineering

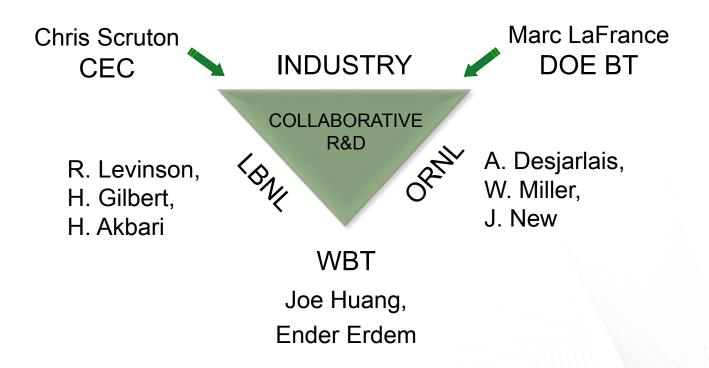






Computer tools for simulating cool roofs

Roof Savings Calculator (RSC)





Roof Savings Calculator

Replaces:

- EPA Roof Comparison Calc
- DOE Cool Roof Calculator
- Minimal questions (<20)
 - Only location is required
 - Building America defaults
 - Help links for unknown information

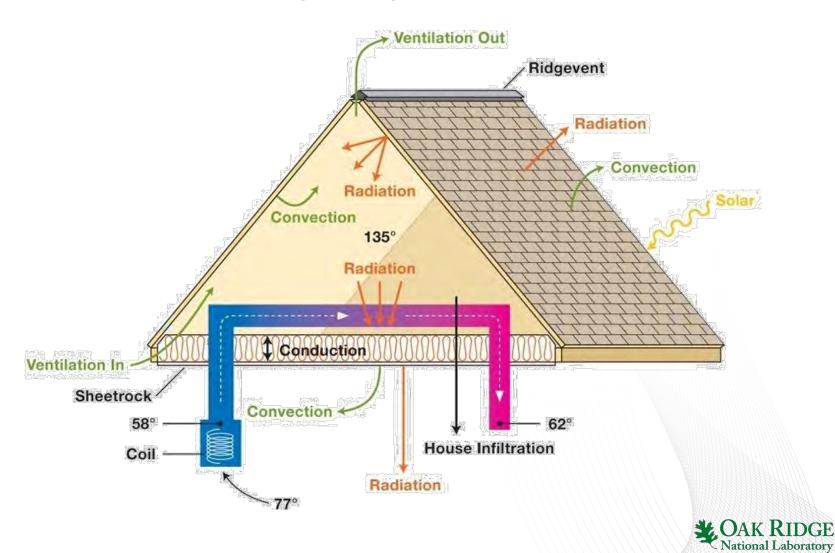
Calculator Input Comparison Chart

	RSC1	PAC Slides ²	PAC QRpt ³	EPA4	DOE
Building Type	4	4	4	4	
Location	4	4		4	4
Days of Operation per week		-	-	4	
Building stock	~	~		4	
Cooling system efficiency (SEER)	~	4	4	4	4
Type of heating	~	4	~	~	-
Heating system efficiency	~	4	1	4	4
Duct location	-	-	~		
Level of roof/ceiling insulation	4	-	4	4	4
Above-sheathing ventilation	4	4			
Radiant barrier	~	4			
Roof thermal mass	4	4			
Roof solar reflectance	4	4	4	4	4
Roof solar reflectance (black compare)	4		1	1	
Roof thermal emittance	4	4	4		4
Roof thermal emittance (black compare)	4		4		
Internal load		4			
Conditioned space under roof		4			
Gas and electricity costs	~	4	4	4	4
Inclination / Roof Area	4			4	
HVAC Schedule			4		
Conditioned space (ft²)	4			4	
Number of floors	4				
Window-to-wall ratio	1				



RSC = AtticSim + DOE-2.1E

AtticSim - ASTM C 1340 Standard For Estimating Heat Gain or Loss Through Ceilings Under Attics



Commercial building types

Office

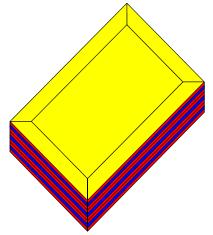


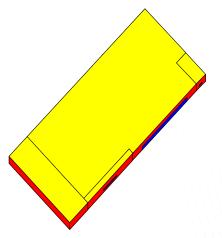
Warehouse

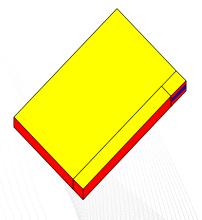






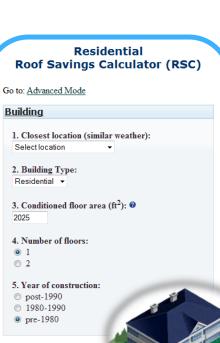






Torcellini et al. 2008, "DOE Commercial Building Benchmark Models", NREL/CP-550-43291, National Renewable Energy Laboratory, Golden CO.





Heating/Cooling

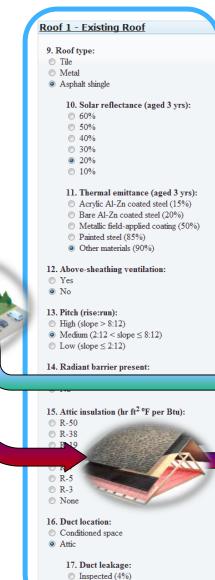
- 6. Heating equipment:
- Electric heat pump
- Natural gas furnace
- Oil furnace
 - P1. Electricity price (cents per kWh): 0
 - P2. Natural gas price (dollars per 1000 ft³): 11.65

7. Heating system efficiency (AFUE): 0

- High-efficiency (90%)
- Mid-efficiency (83%)
- Low-efficiency (70%)
- Custom

8. Cooling system efficiency (SEER): 0

- High-efficiency (15)
- Mid-efficiency (13)
- Low-efficiency (10)
- Custom



Uninspected (14%)

Roof 2 - Cool Roof Comparison 18. Roof type:

- Metal
- Asphalt shingle

19. Solar reflectance (aged 3 yrs):

- 50%
- 40%
- © 30% © 20%
- © 10%

20. Thermal emittance (aged 3 yrs):

- Acrylic Al-Zn coated steel (15%)
- Bare Al-Zn coated steel (20%)
- Metallic field-applied coating (50%)
- Painted steel (85%)
- Other materials (90%)

21. Above-sheathing ventilation:

- Yes
- No

22. Pitch (rise:run):

- Migh (slope > 8:12)
- Medium (2:12 < slope ≤ 8:12)
 </p>
- Low (slope ≤ 2:12)
- 23. Radiant barrier pr



- © R-38
- © R-19
- © R-5
- R-3
- None

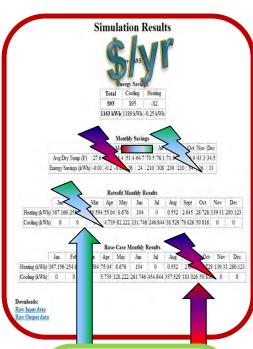
25. Duct location:

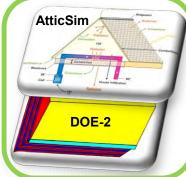
- Conditioned space
- Attic

26. Duct leakage:

- Uninspected (14%)

Calculate







RoofCalc.com impact

79

66

1.52

00:01:07

00:01:33

70.89%

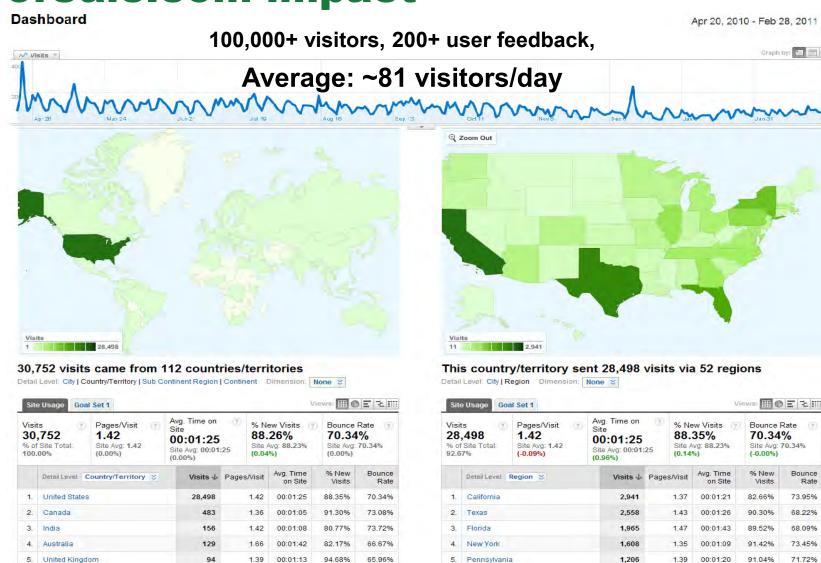
89.39%

68.35%

63.64%

Illinois

7. Georgia





89.41%

90.50%

73.79%

69.09%

00:01:12

00:01:18

1.36

1.40

1.114

1,032

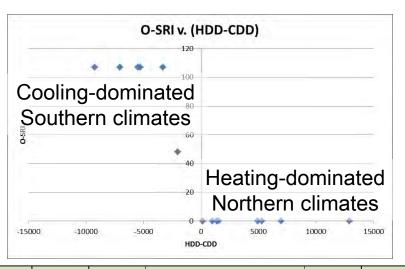
South Korea

7. Italy

Nationwide results

Cost savings for offices - 14 cities, local utility prices, 22 roof types

	Reflect		0.5	Houston	1.0
Description	ance	sivity	SRI	\$ saved	13
BUR No Coating	10	90	6	42	
Mineral Mod Bit	25	88	25	103	
Single Ply	32	90	35	230	
Mineral Mod Bit	33	92	35	197	
Metal	35	82	35	60	
Aluminum Coating	43	58	35	279	
Mineral Mod Bit	45	79	55	291	
Coating over BUR	49	83	55	433	
Metal	49	83	55	208	
14					

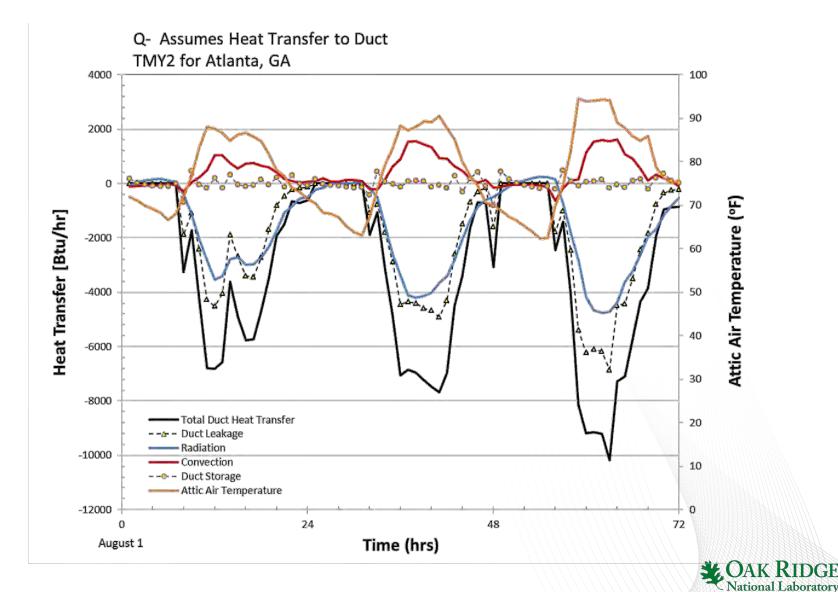


	Trend	Maximum			
	Desired	Observed		Related	Slope
Location	SRI	Savings, \$	Best Observed System	SRI	Difference
Atlanta	107	1080	Aluminum Coating over BUR	65	Reversed
Austin	107	2680	Coating over BUR (White)	107	Same
Baltimore	107	1000	Single Ply /Coating over BUR	103.5	Reversed
Chicago	64.95	360	Aluminum Coating over BUR	48	Same
Fairbanks	42.68	680	Aluminum Coating over BUR	48	Same
Fargo	40.58	160	Aluminum Coating over BUR	48	Same
Houston	107	1840	Coating over BUR (White)	107	Same
Kansas City	107	800	Coating over BUR (White)	107	Reversed
Los Angeles	107	440	Aluminum Coating over BUR	65	Same
Miami	107	4440	Coating over BUR (White)	107	Same
Minneapolis	47.05	360	Aluminum Coating over BUR	48	Same
New York	107	560	Aluminum Coating over BUR	65	Reversed
Phoenix	107	3000	Coating over BUR (White)	107	Same
San Francisco	39.31	200	Aluminum Coating over BUR	48	Same

Mellot, Joseph W., New, Joshua R., and Sanyal, Jibonananda. (2013). "Preliminary Analysis of Energy Consumption for Cool Roofing Measures." In *RCI Interface Technical Journal*, volume 31, issue 9, pp. 25-36, October, 2013

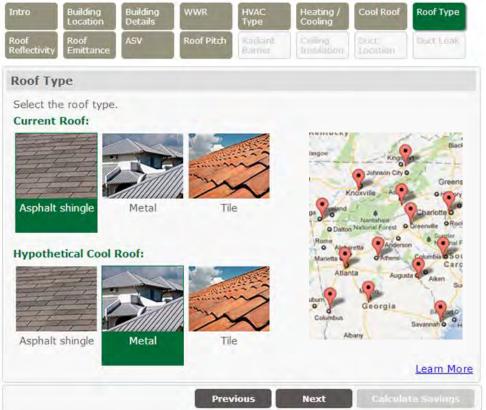
National Laboratory

Summer operation of HVAC duct in ASHRAE climate zone 3



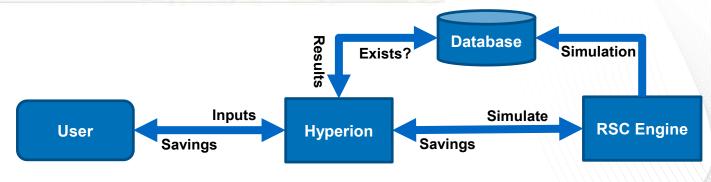
Enhanced RSC Site

Input Parameter GUI



Result Output





AK RIDGE National Laboratory

Quote

"We speak piously of ... making small studies that will add another brick to the temple of science. Most such bricks just lie around the brickyard."

-J.R. Platt, Science 1964, 146:347-53



RSC Service Example (Python)

```
client = suds.client.Client('URL/TO/WEB/SERVICE/rsc.wsdl')
print(client)
sm = client.factory.create('schema:soapmodel')
load soap model from xml('../examplemodel.xml', sm)
sr = client.service.simulate(sm)
print(sr)
sm = client.factory.create('schema:soapmodel')
load soap model from xml('../examplemodel.xml', sm)
print(sm)
contents = client.service.test(sm)
with open('pytest.zip', 'wb') as outfile:
    outfile.write(base64.b64decode(contents))
```

...download example building and batch script from rsc.ornl.gov/web-service.shtml



Update 1 line of code to change servers

```
import base64
      import suds
      import xml.dom.minidom
 3
4
      import logging
 5
 6
7
    Hdef load soap model from xml(xmlfilename, soapmodel):
18
19
    Hdef load soap results from xml(xmlfilename, soapresults):
34
35
36
      logging.basicConfig()
37
38
      test type = ['simulate', 'test', 'upload', 'download']
39
40
     print ("hello there, initializing client")
      client = suds.client.Client('http://evenstar.ornl.gov/RSC/service/rsc.wsdl')
41
42
      print ("printing client")
43
      print(client)
      raw input('Press Enter to continue...'+'\n')
44
```

Millions of simulations visualized for DOE's Roof Savings Calculator and deployment of roof and attic technologies through leading industry partners

DOE: Office of Science

CEC & DOE EERE: BTO

Industry & Building Owners

Engine (AtticSim/DOE-2) debugged using HPC Science assets enabling visual analytics on 3x(10)⁶ simulations





Roof Savings Calculator (RSC) web site/service developed and validated [estimates energy and cost savings from roof and attic technologies]



Leveraging HPC resources to facilitate deployment of building energy efficiency technologies



77,577 visits came from 112 countries

Personal story behind one of DOE's RSC images

RoofCalc.com 14. Radiant barrier present: O Yes · No **Duct Leakage** 15. Attic insulation (hr Leaky ducts in unconditioned spaces are effectively costing you @ R-50 money to condition the planet, not your house. Commercial buildings have typical leakage rate of 10-20%; likewise, residential @ R-38 buildings typically have duct leakage rates near 14%. The CEC's O R-19 Title 24 target leakage rate for inspected ducts is 4% and requires @ R-11 no greater than 6%. This calculator supports duct leakage rates of @ R-7 4% and 14%. @ R-5 **Leaky Connection** Damaged Duct Sealed Ducts 0 R-3 None 16. Duct location: Conditioned space Attic 17. Duct leakare:



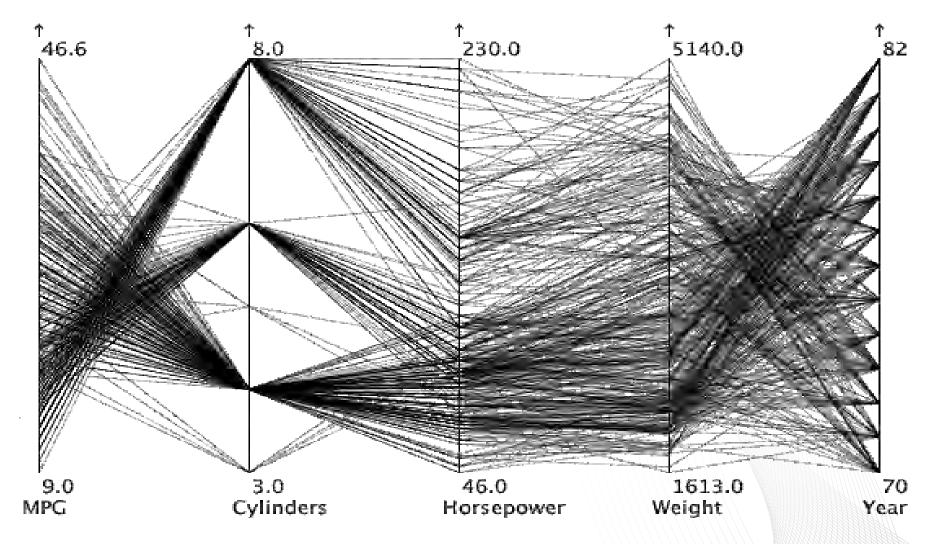
Inspected (4%)
 Uninspected (14%)

Presentation summary

- Scientific Paradigms
- Roof Savings Calculator
- Visual Analytics
- Knowledge Work
- Autotune

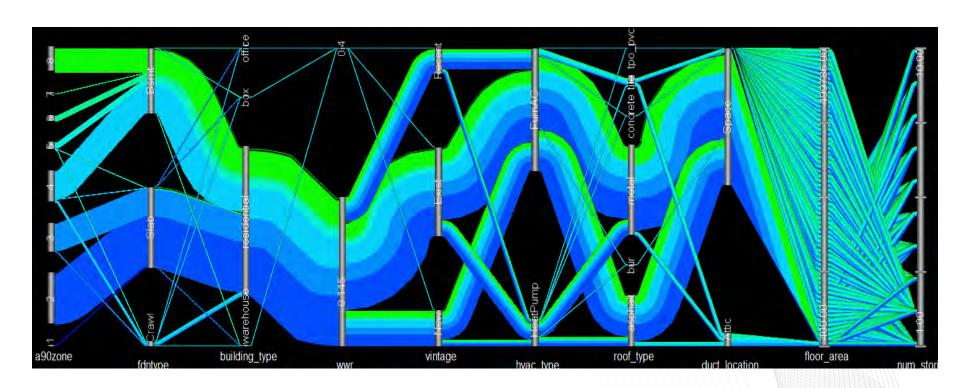


PCP - car data set



PCP bin rendering (data)

- Transfer function coloring:
 - Occupancy or leading axis





The power of "and" – linked views (info)



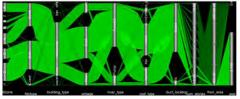
Roof Savings Calculator

www.roofcalc.com

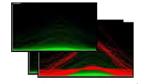


Dr. Joshua New (ORNL) and Chad Jones (UC-Davis)
Dr. William A. Miller (ORNL), A. Desjarlais (ORNL), Yu Joe Huang (WhiteBox), Ender Erdem (WhiteBox)

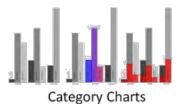
Multivariate Visualization of Large-Scale Parameter Sweeps





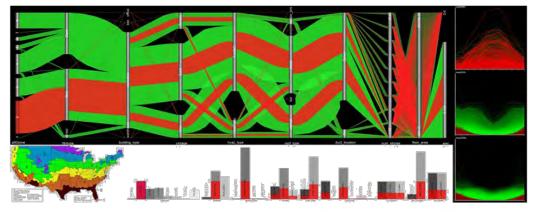


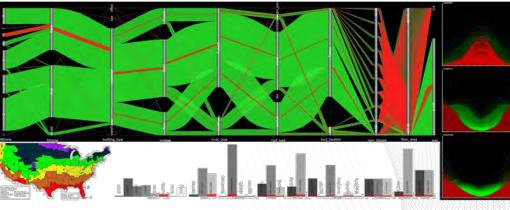
Time-variant Function Plots



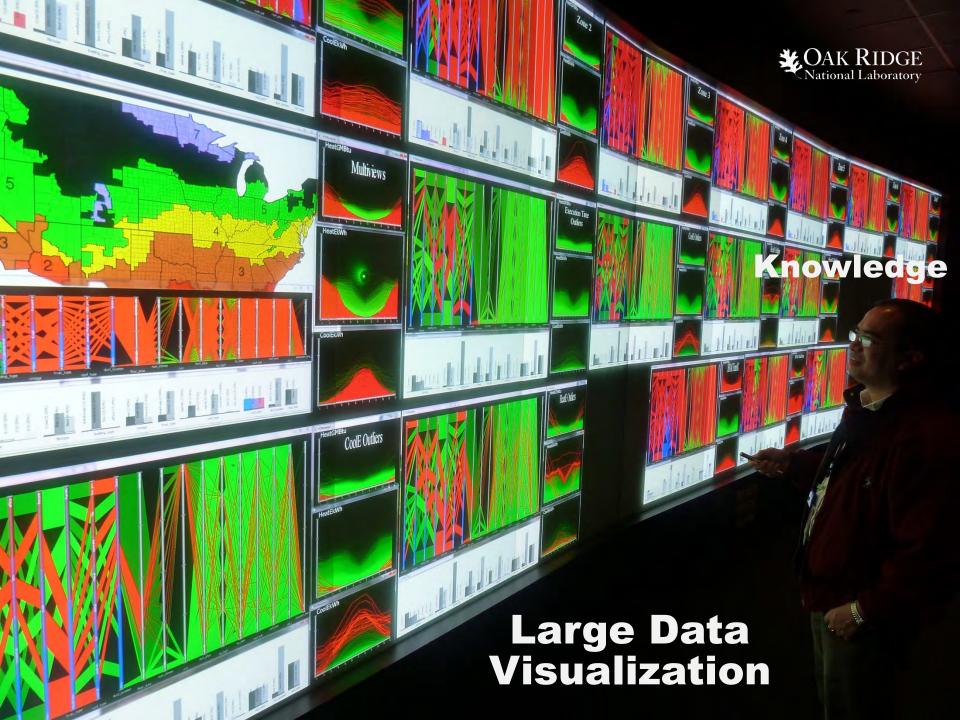


Climate Zone Map



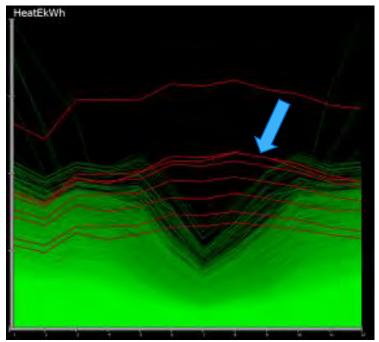


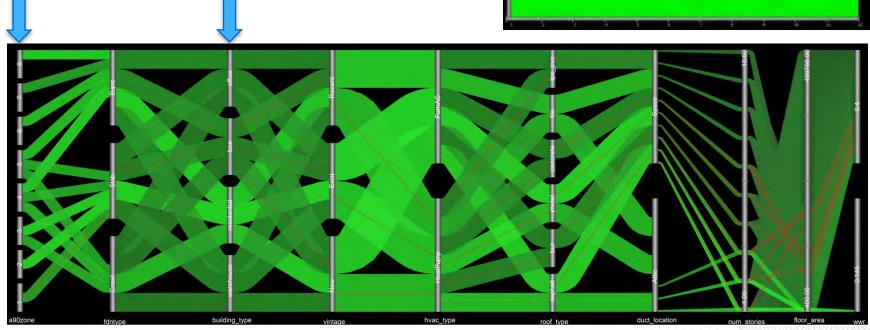




Outliers (wisdom)

- Selection of heating outliers
- Find all have box building type and in Miami





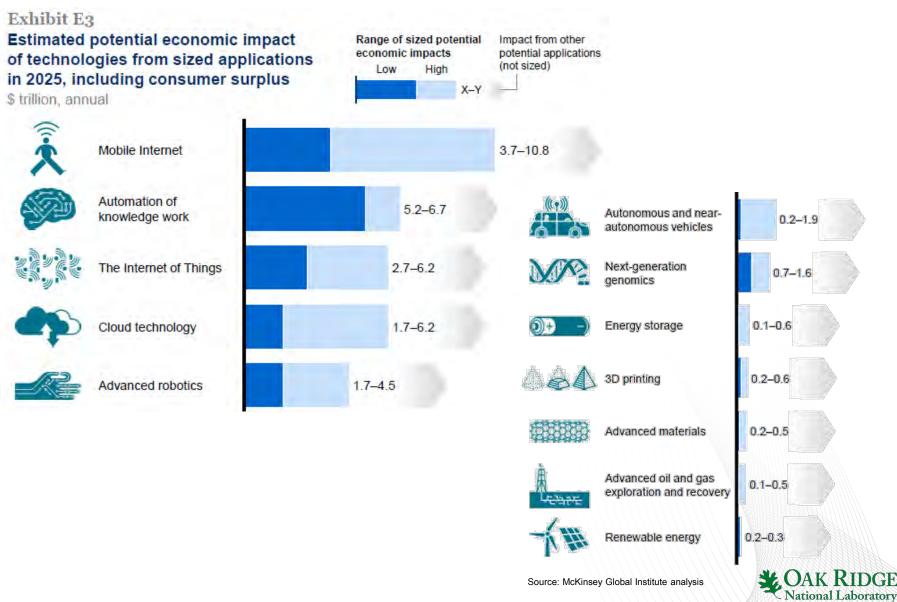


Presentation summary

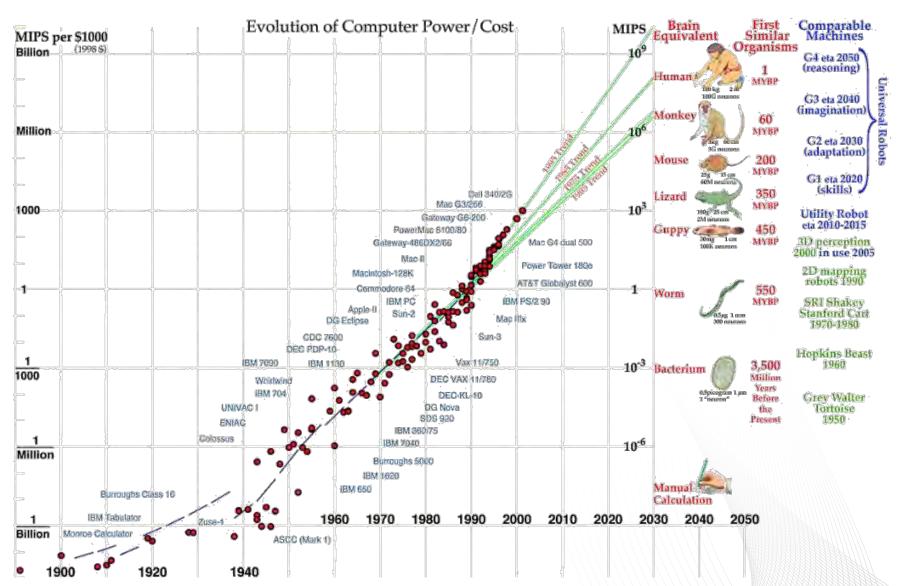
- Scientific Paradigms
- Roof Savings Calculator
- Visual Analytics
- Knowledge Work (context)
- Autotune



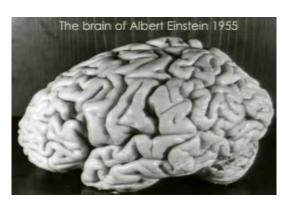
McKinsey Global Institute Analysis



\$1000 machine helping meat machines



Humans and computers



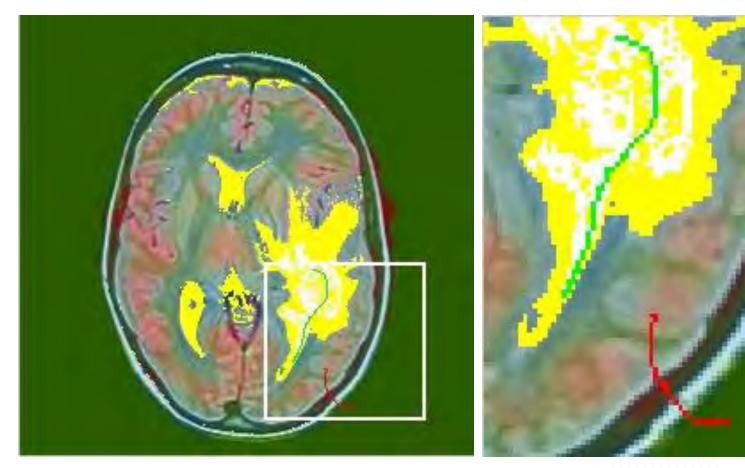
- 3 lbs (2%), 20 watts (20%)
- 120-150 billion neurons
- 100 trillion synapses
 - Firing time ~milliseconds
- 11 million bits/second input
 - Consciousness 40 bits/second
- Working memory 4-9 words
- Long-term memory 1-1k TB
- Complex, self-organizing



- PC 40 lbs, 500 watts
- 4 cores
- 3 billion Hz
 - Firing time ~nanoseconds
- 100 million bits/second
 - Not yet
- 62,500,000 words
- Disk 3TB, perfect recall
- "Dumb", Artificial Intel.



Learning associations



Full Results

Detailed Results

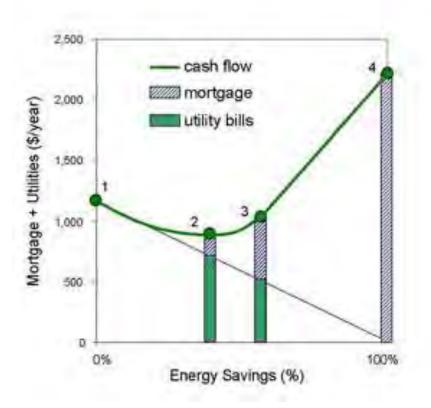


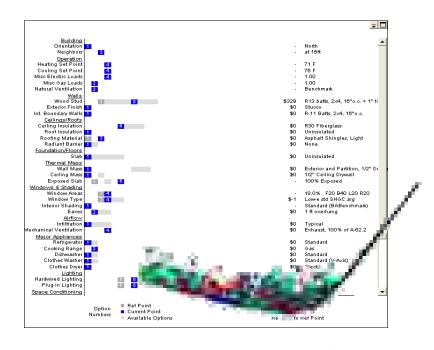
Presentation summary

- Scientific Paradigms
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Existing tools for retrofit optimization





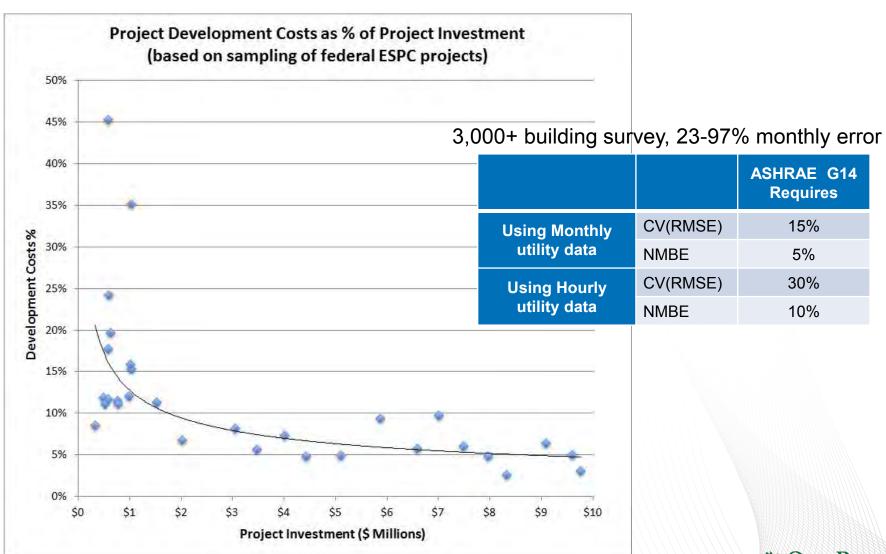
Simulation Engine DOE-\$65M (1995-?)



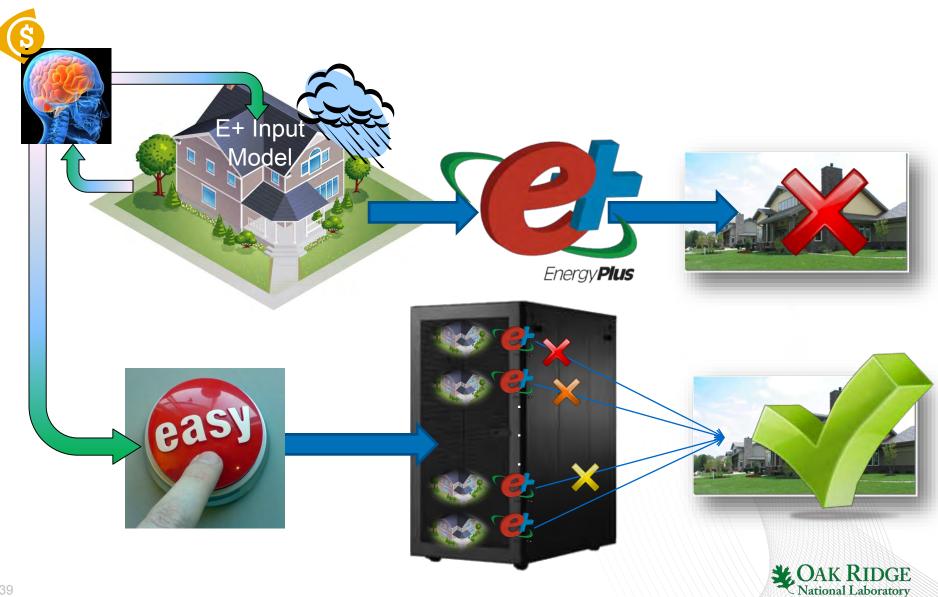




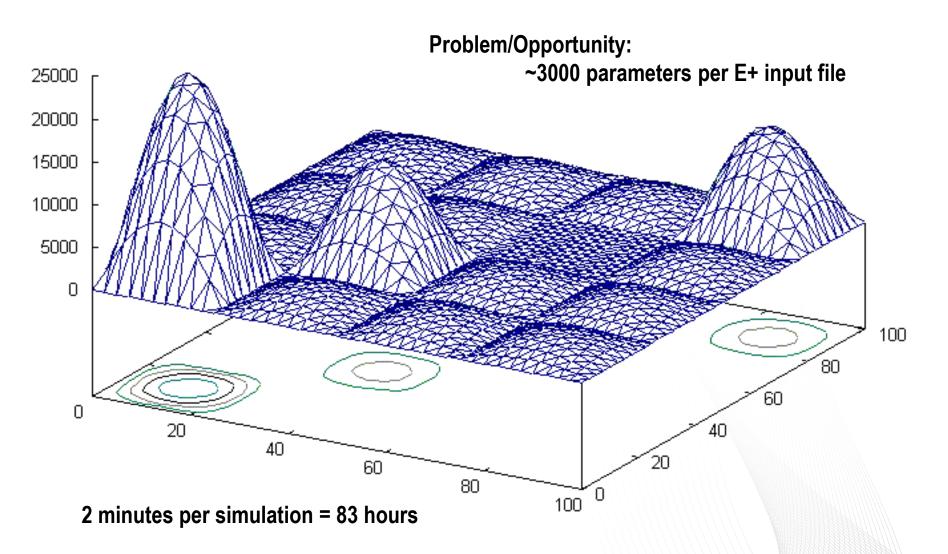
Business limitations for M&V



The Autotune Idea Automatic calibration of software to data



The search problem



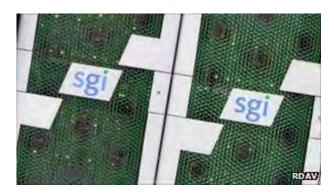
ORNL High Performance Computing Resources



Titan:
299,008 CPU cores
18,688 GPU cores
710TB memory, distributed

Jaguar: 224,256 cores 360TB memory

Nautilus: 1024 cores 4TB shared-memory





Kraken: 112,896 cores



Gordon: 12,608 cores SSD

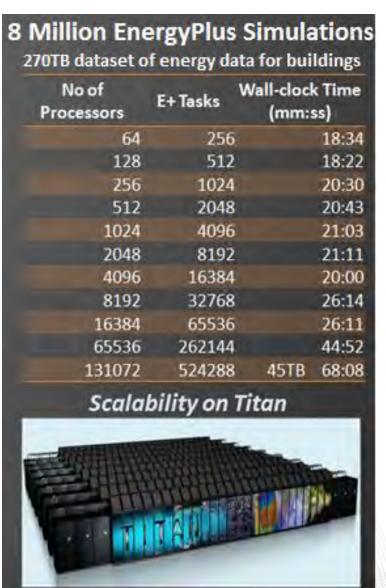




HPC scalability for desktop software

- EnergyPlus desktop app
- Writes files during a run
- Uses RAMdisk
- Balances simulation memory vs. result storage
- Works from directory of input files & verifies result
- Bulk writes results to disk

Acknowledgment: Jibo Sanyal, ORNL R&D Staff



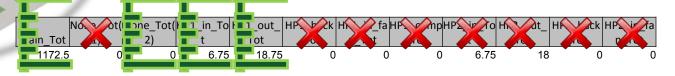
Computational complexity

E+ Input Model

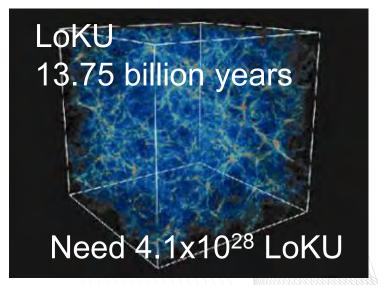


Domain experts chose to vary 156 Brute-force = 5x10⁵² simulations

E+ parameters



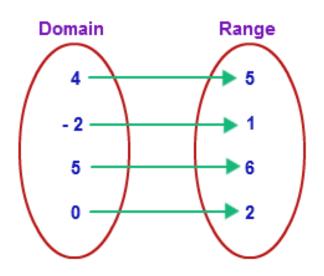






What is artificial intelligence?

- Give it (lots of) data
- It maps one set of data to another
- Paradigms
 - Unsupervised (clustering)
 - Reinforcement (don't run into wall)
 - Supervised (this is the real answer)
- Methods for doing that...
 biologically motivated or not



act	act
human	rational
think	think
human	rational



MLSuite: HPC-enabled suite of machine learning algorithms

- Linear Regression
- Feedforward Neural Network
- Support Vector Machine Regression
- Non-Linear Regression
- K-Means with Local Models
- Gaussian Mixture Model with Local Models

- Self-Organizing Map with Local Models
- Regression Tree (using Information Gain)
- Time Modeling with Local Models
- Recurrent Neural Networks
- Genetic Algorithms

Ensemble Learning

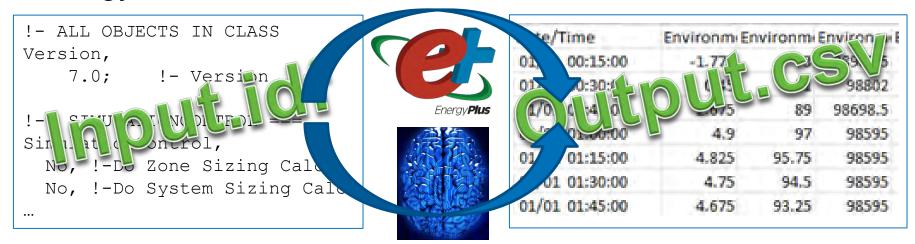


Acknowledgment: UTK computer science graduate graduate Richard Edwards, Ph.D. (advisor Dr. Lynne Parker); now Amazon

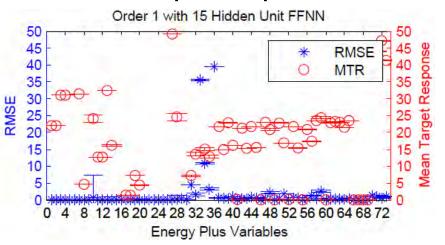


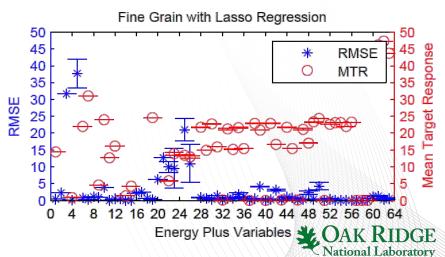
MLSuite example

EnergyPlus – 2-10 mins for an annual simulation



 ~E+ - 4 seconds AI agent as surrogate model, 90x speedup, small error, brittle

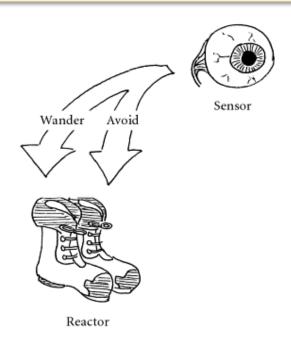




Quote

"the world is the best model of itself."

-Rodney Brooks, 1990, Elephants and nouvelle AI



Nouvelle AI. A robot should sense and then move according to simple rules such as "Avoid collisions" or "Wander."



Source of Input Data

- 3 Campbell Creek homes (TVA, ORNL, EPRI)
- ~144 sensors/home, 15-minute data:
 - Temperature (inside/outside)
 - Plugs
 - Lights
 - Range
 - Washer
 - Radiated heat







Dishwasher



- Heat pump air flow
- Shower water flow
- Etc.

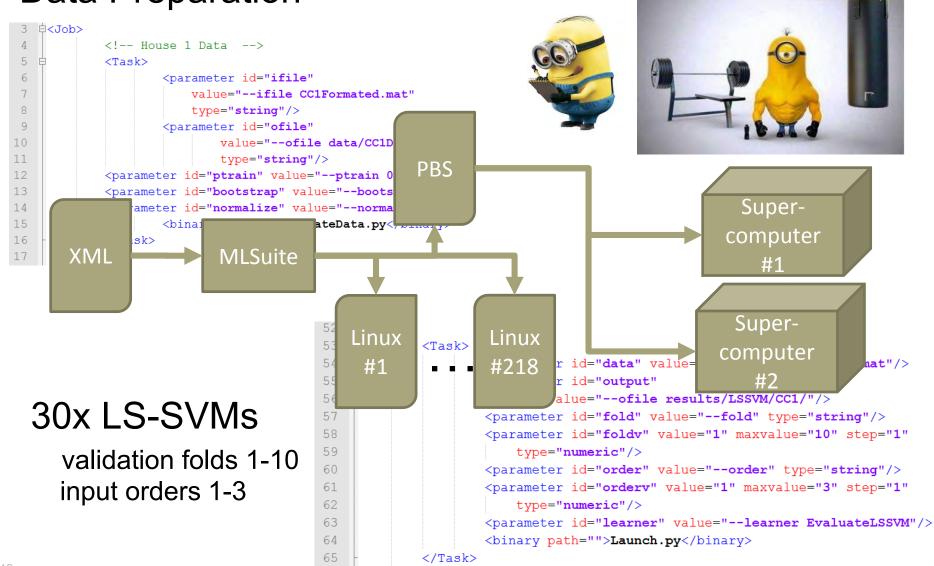






MLSuite Architecture

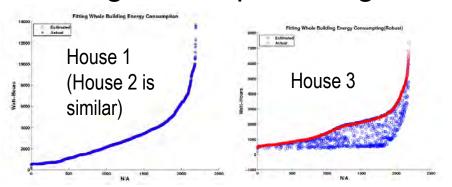


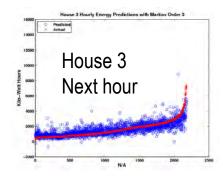


</Job>

Applications of machine learning

Linear Regression predicting whole building energy use





Accuracy Metrics for best subset of sensors

Root Mean Squared Error(RMSE):

$$RMSE = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (y_i - p_i)^2}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - p_i|}{y_i}$$

$$CV = \frac{RMSE}{y_{mean}} \times 100$$

Mean Bias Error(MBE):

$$\frac{1}{N-1} \sum_{i=1}^{N} (y_i - p_i)$$

	HME FFNN	HME LS-SVM	SVR	FCM
RMSE(Watt-Hours)	569.96±50.13	582.61±33.97	603.85±40.55	581.87±41.67
MAPE(%)	17.07±1.19	15.94±0.92	15.48±0.67	17.37±1.02
CV(%)	20.14±1.65	20.59 ± 1.12	21.32±1.32	20.56±1.37
MBE(%)	0.42±1.17	-0.07±0.89	-1.50±0.80	0.01 ± 0.99

	Best Four Sensors	Best Model	Top 10 Sensors
RMSE	1127.88±33.00	942.25±26.14	1129.04±32.38
MAPE	41.17±1.12	30.53±1.03	40.4483±1.29
CV	39.76±1.02	33.21±0.73	39.80±0.96
MBE	-0.04±0.90	-0.06±0.92	-0.05±1.05
ICOMP(IFIM)	2166.3±1.54	1845.88±21.25	2125.50 ± 2.72



MLSuite: HPC-enabled Suite of Machine Learning algorithms

- Linear regression
- Feedforward neural network
- Support vector machine regression
- Non-linear regression
- K-means with local models
- Gaussian mixture model with local models

- Self-organizing map with local models
- Regression tree (using information gain)
- Time modeling with local models
- Recurrent neural networks
- Genetic algorithms
- Ensemble learning





Evolutionary computation

How are offspring produced?

	Thickness	Conductivity	Density	Specific Heat
Bldg1	0.022	0.031	29.2	1647.3
Bldg2	0.027	0.025	34.3	1402.5
(1+2) ₁	0.0229	0.029	34.13	1494.7
(1+2) ₂	0.0262	0.024	26.72	1502.9

- Average each component
- Add Gaussian noise
- ... "Al inside of Al"



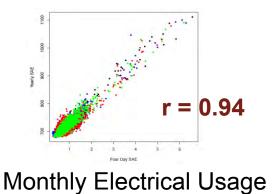
Getting more for less

- EnergyPlus is slow
 - Full-year schedule
 - 2 minutes per simulation



Energy**Plus**

- Use abbreviated 4-day schedule instead
 - Jan 1, Apr 1, Aug 1, Nov 1
 - 10 20 seconds per simulation



r = 0.9666 68 70 72 74 76 78
FOULDRY SAE

Hourly Electrical Usage



Evolutionary combination













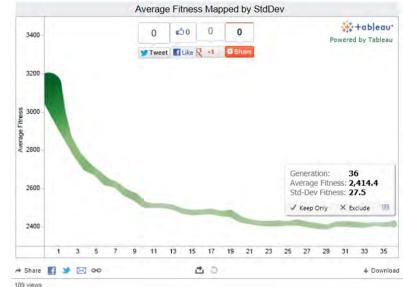




4 of 19 experiments

- 1. Surrogate Modeling
- 2. Sensor-based Energy Modeling (sBEM)
- 3. Abbreviated Schedule
- 4. Island-model evolution





Automated M&V process Autotune calibration of simulation to measurements

XSEDE and DOE Office of Science

DOE-EERE BTO

Industry and building owners





Features:

Works with "any" software Tunes 100s of variables Customizable distributions Matches 1+ million points

Commercial Buildings

		ASHRAE G14 Requires
Monthly	CVR	15%
utility data	NMBE	5%
Hourly	CVR	30%
utility data	NMBE	10%

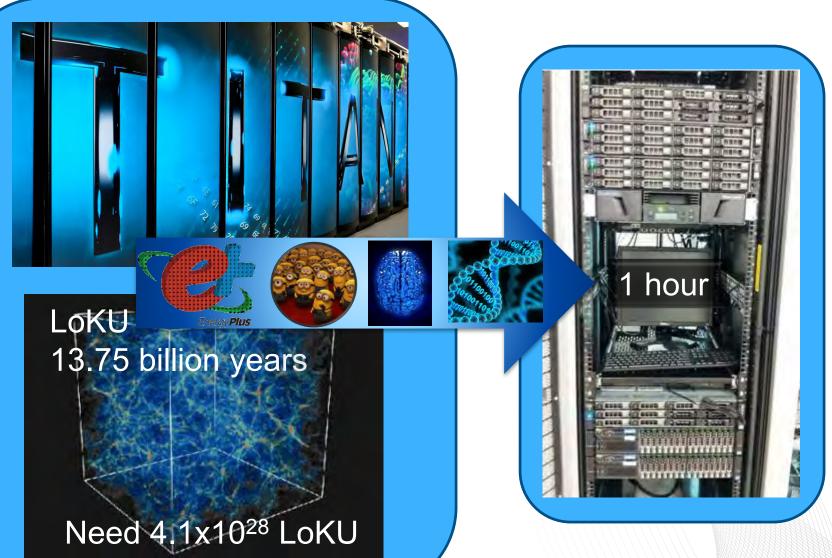
Residential	Tuned input
home	avg. error
Within 30¢/day	Hourly – 8% Monthly – 15%
(actual use \$4.97/day)	

10+ companies interested

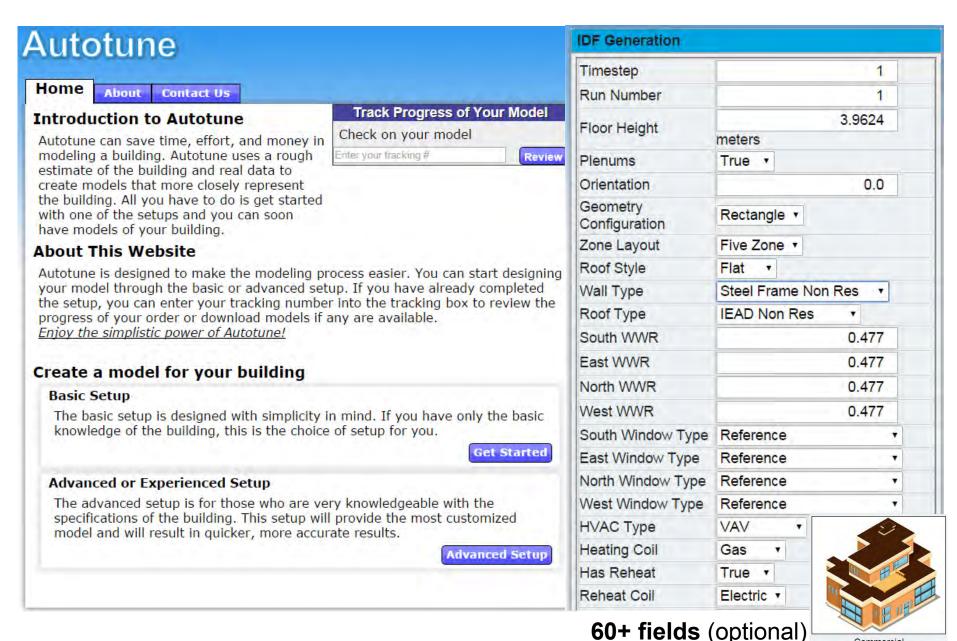
Leveraging HPC resources to calibrate models for optimized building efficiency decisions



HPC-informed algorithmic reduction... to commodity hardware



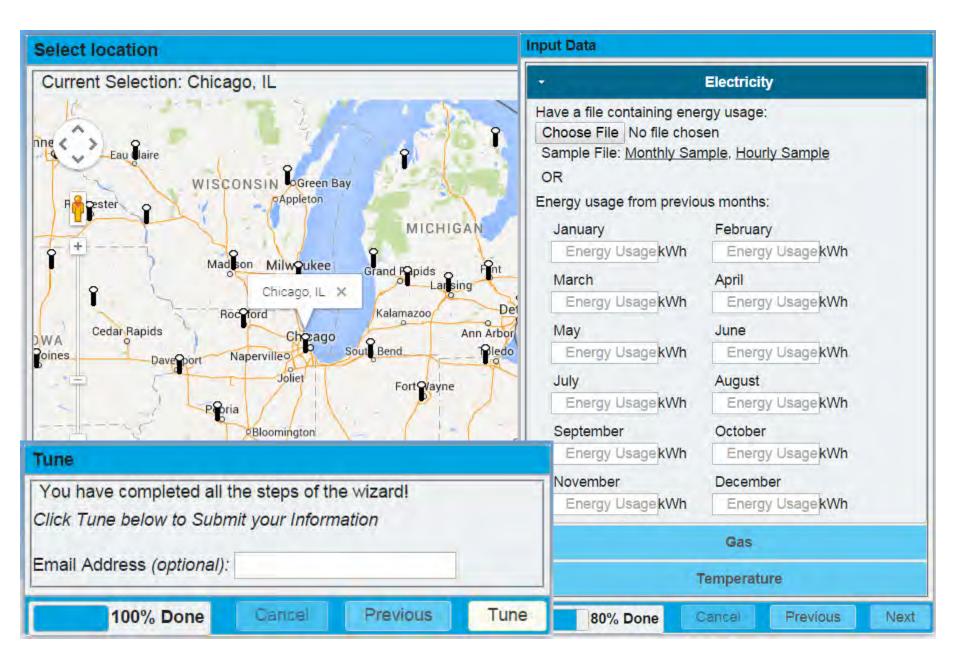
That's great, but how can I use it?



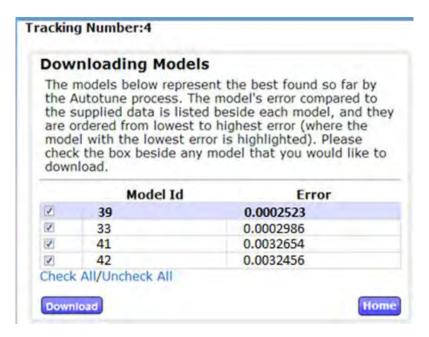
Determine inputs to calibrate

		Restaur t	ran	Hospital	Large Hotel	Large Office	Medi Offic			drise rtment		rimar choo	-	Quick Service
#Iı	nputs	49		227	110	85	81		,	155		166		54
#0	Froups	49		146	71	45	38			82		113		54
		Seconda Schoo	ary ol	Small Hotel	Small Office	Stand- alone Retail	Strip I	Mall		uper arket	Waı	rehou	ıse	TOTAL
#lı	nputs	231		282	72	59	113	3		78		47		1809
#0	Groups	128		136	61	56	89)		73		45		1143
4	Α			В	С	D	Е		F	G		Н	- 1	J
	Class		Obje		Field	Default							Group	Constraint
2	Lights		Bake	ery_Lights	Watts per Zor	ie 18.29	12.803	2	23.777	uniform		float		
3	Lights		Deli	_Lights	Watts per Zor	e 18.29	12.803	2	23.777	uniform		float		
4	ElectricEquip	ment	Bake	ery_MiscPlug_E	Design Level	11244	7870.8	14	1617.2	uniform		float		
5	ElectricEquip	ment	Deli	_MiscPlug_Equ	ii Design Level	12105	8473.5	15	736.5	uniform		float		
6	GasEquipme	nt	Bake	ery_MiscGas_E	Design Level	5622	3935.4	7	7308.6	uniform		float		
7	GasEquipme	nt	Deli	_MiscGas_Equi	p Design Level	6053	4237.1	. 7	7868.9	uniform		float		
8	Exterior:Ligh	ts	Exte	rior Facade Lig	h Design Level	13577	9503.9	17	7650.1	uniform		float		
9	ZoneInfiltrat	ion:Desig	Bake	ery_Infiltration	Flow per Exte	ri 0.000302	0.000211	0.0	00393	uniform		float	G0001	
LO	ZoneInfiltrat	ion:Desig	Deli	_Infiltration	Flow per Exte	ri 0.000302	0.000211	0.0	00393	uniform		float	G0001	
11	Schedule:Co	mpact	CLG	SETP_SCH	Field 4	30	21		39	uniform		float	CA1	
12	Schedule:Co	mpact	CLG	SETP_SCH	Field 7	30	21		39	uniform		float	CA2	HA2 - CA2 <
13	Schedule:Co	mpact	CLG	SETP_SCH	Field 9	24	16.8	1	31.2	uniform		float	CA3	HA3 - CA3 <
L4	Schedule:Co	mpact	CLG	SETP_SCH	Field 11	30	21		39	uniform		float	CA4	HA4 - CA4 <
15	Schedule:Co	mpact	HTG	SETP_SCH	Field 4	15.6	10.92		20.28	uniform		float	HA1	
16	Schedule:Co	mpact	HTG	SETP_SCH	Field 7	15.6	10.92		20.28	uniform		float	HA2	
17	Schedule:Co	mpact	HTG	SETP_SCH	Field 9	21	14.7	,	27.3	uniform		float	HA3	
18	Schedule:Co	mpact	HTG	SETP SCH	Field 11	15.6	10.92		20.28	uniform		float	HA4	

Provide actual data



Autotune returns calibrated model



1532	中	<material></material>	
1533	中	<name></name>	IDF + CSV = XML
1534		Metal S	iding
1535	-		
1536	中	<roughness></roughness>	
1537		Smooth	
1538	-	<td>></td>	>
1539		<thickness< td=""><td>tuneType="float"</td></thickness<>	tuneType="float"
1540			tuneMin="0" tuneMax="0.5"
1541			tuneDistribution="uniform"
1542			tuneGroup="A"
1543	中		<pre>tuneConstraint="A+B<1"></pre>
1544		0.005	
1545	-	<td>></td>	>

Metric	Value					
Input error average	24.38					
Input error maximum	66.12					
Input error minimum	0.09					
Input error variance	228.53					
CV(RMSE)						
CH4:Facility [kg](Monthly)	9.95					
CO2:Facility [kg](Monthly)	15.42					
CO:Facility [kg](Monthly)	20.40					
Carbon Equivalent:Facility [kg](Monthly)	14.42					
Cooling:Electricity [J](Hourly)	1577.96					
Electricity:Facility [J](Hourly)	10.48					
NMBE						
CH4:Facility [kg](Monthly)	-9.57					
CO2:Facility [kg](Monthly)	-14.78					
CO:Facility [kg](Monthly)	-19.52					
Carbon Equivalent:Facility [kg](Monthly)	-13.83					
Cooling:Electricity [J](Hourly)	592.77					
Electricity:Facility [J](Hourly)	-9.52					
Electricity:Facility [J](Monthly)	-9.52					
143+ outputs						

Performance and availability

		ASHRAE G14 Requires	Autotune Results
Monthly	CVR	15%	0.32%
utility data	NMBE	5%	0.06%
Hourly	CVR	30%	0.48%
utility data	NMBE	10%	0.07%

		ASHRAE G14 Requires	Autotune Results
Monthly	CVR	15%	1.20%
utility data	NMBE	5%	0.35%
Hourly	CVR	30%	3.65%
utility data	NMBE	10%	0.35%

Results from 24 Autotune calibrations (3 building types - 8, 34, 79 tuned inputs each)

Results from 20,000+ Autotune calibrations (15 types – 47-282 tuned inputs each)

FY15 project to begin integration of Autotune web service as an OpenStudio application Free to use. Pay for cloud computing.

