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A Robust Design Approach to Cost Estimation: Solar Energy for Marine Corps Expeditionary Operations

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A ROBUST DESIGN APPROACH
TO COST ESTIMATION:
SOLAR ENERGY FOR MARINE CORPS
EXPEDITIONARY OPERATIONS

S.M. Sanchez, M.M. Morse, S.C. Upton, M.L. McDonald, D.A. Nussbaum

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- Assessing life cycle cost and risk are important
 - and tricky – problems!
- Motivation: USMC Expeditionary Energy
 - E2O initiatives
 - HOMER model
 - Sources of variability
- Designed experiments can help
- Find out more...

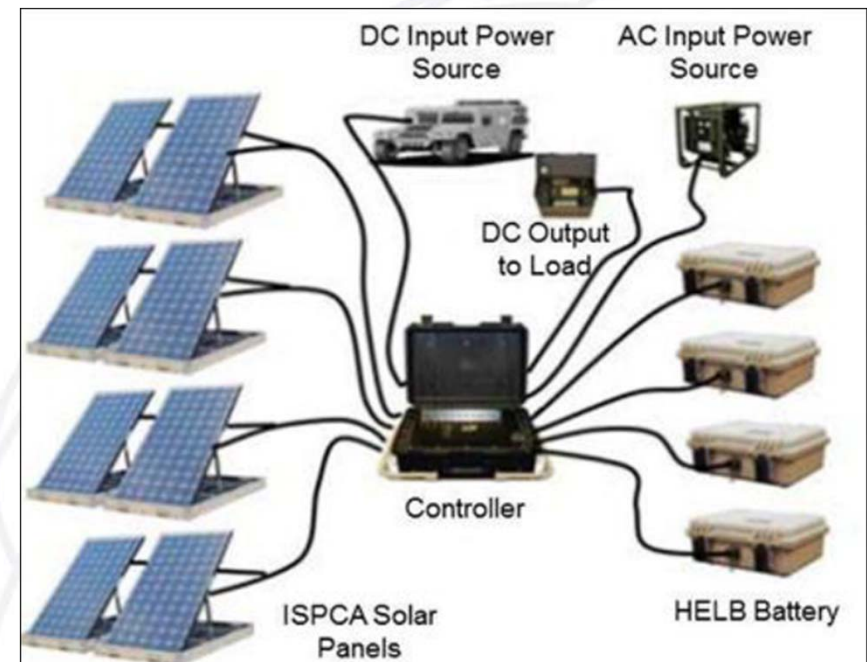


- Cost estimates underpin many important decisions in the Marine Corps, DoD, and beyond.
- Computational models may provide useful insights—but they are typically too complex to study with brute-force methods
- “Robust design” incorporates many sources of uncertainty that can influence life cycle costs, in terms of expected cost and the risk of exceeding or falling under a threshold.
- NPS’s SEED Center specializes in new methods for designing and conducting computational experiments—leading to revolutionary changes in the way we can leverage computational models



2011 USMC E²O Strategy

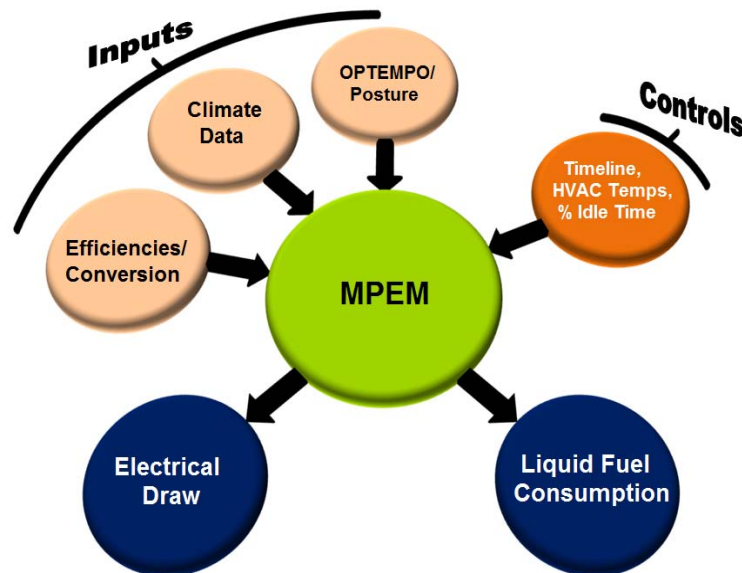
- Goal: 50% of bases “net-zero” by 2020
- First focus: forward operating bases
 - 32% of fuel consumed by MEB (2009, Afghanistan) used for electric power generation (Schwartz et al., 2012)
 - Ground Renewable Energy System (GREENS) one successful renewable energy asset





MPEM (MAGTF Power and Energy Model)

- Mission-level model used to assess potential impact of energy investments on fuel consumption.
- Inputs include unit type and size (e.g. MEU, MEB, etc.), length of the operation and OPTEMPO phases, equipment type and efficiencies, and environmental conditions (solar, wind, temperature).



Outputs include:

- daily requirement for liquid fuel and electricity (kW) to sustain the operation
- secondary measures (days of supply, number/weight of batteries required, ...)

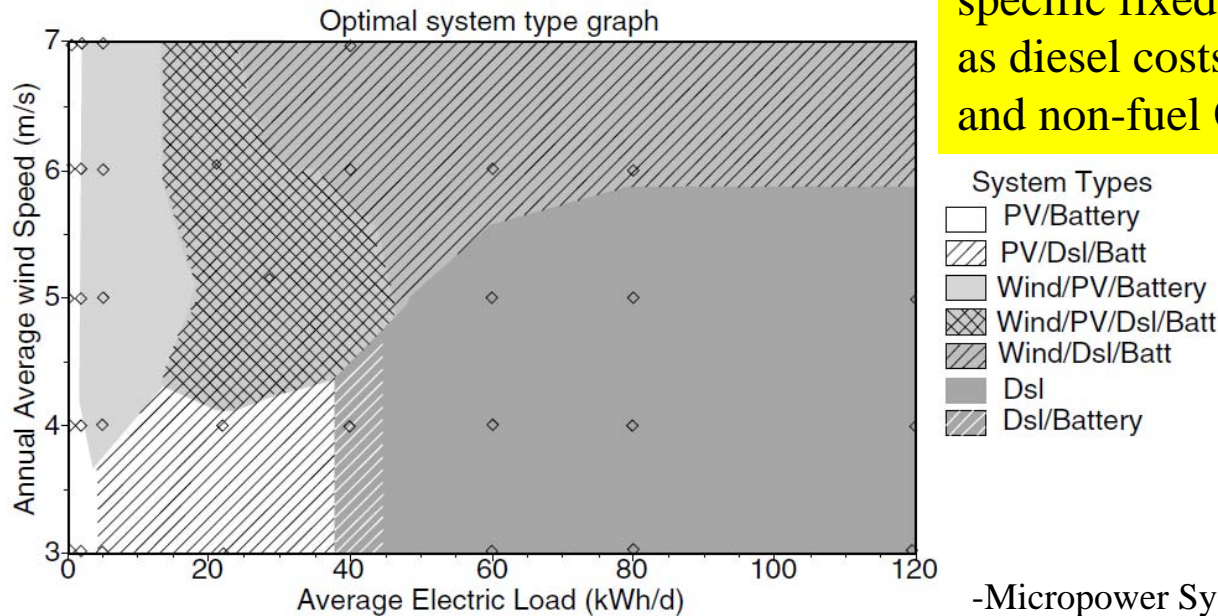
Outputs depend on the inputs, could be converted to costs for direct comparison with other alternatives and acquisition costs



HOMER (Hybrid Optimization Model for Electric Renewables)

- Assists in identifying the optimal composition of a power system for decreasing life cycle fuel consumption when given a specified load profile and location
- Power system assets considered include generators, battery banks, solar arrays and wind turbines

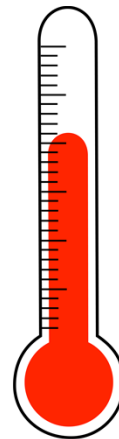
“Optimal” results depend on specific fixed cost inputs, such as diesel costs, capital costs, and non-fuel O&M costs



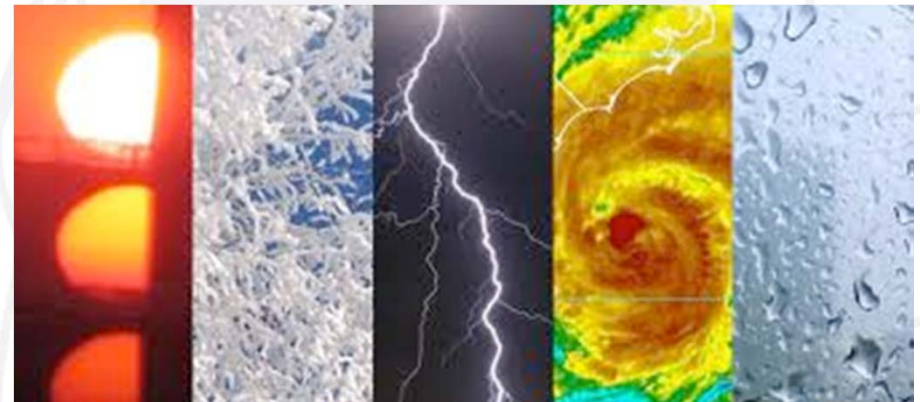
-Micropower System Modeling
With HOMER

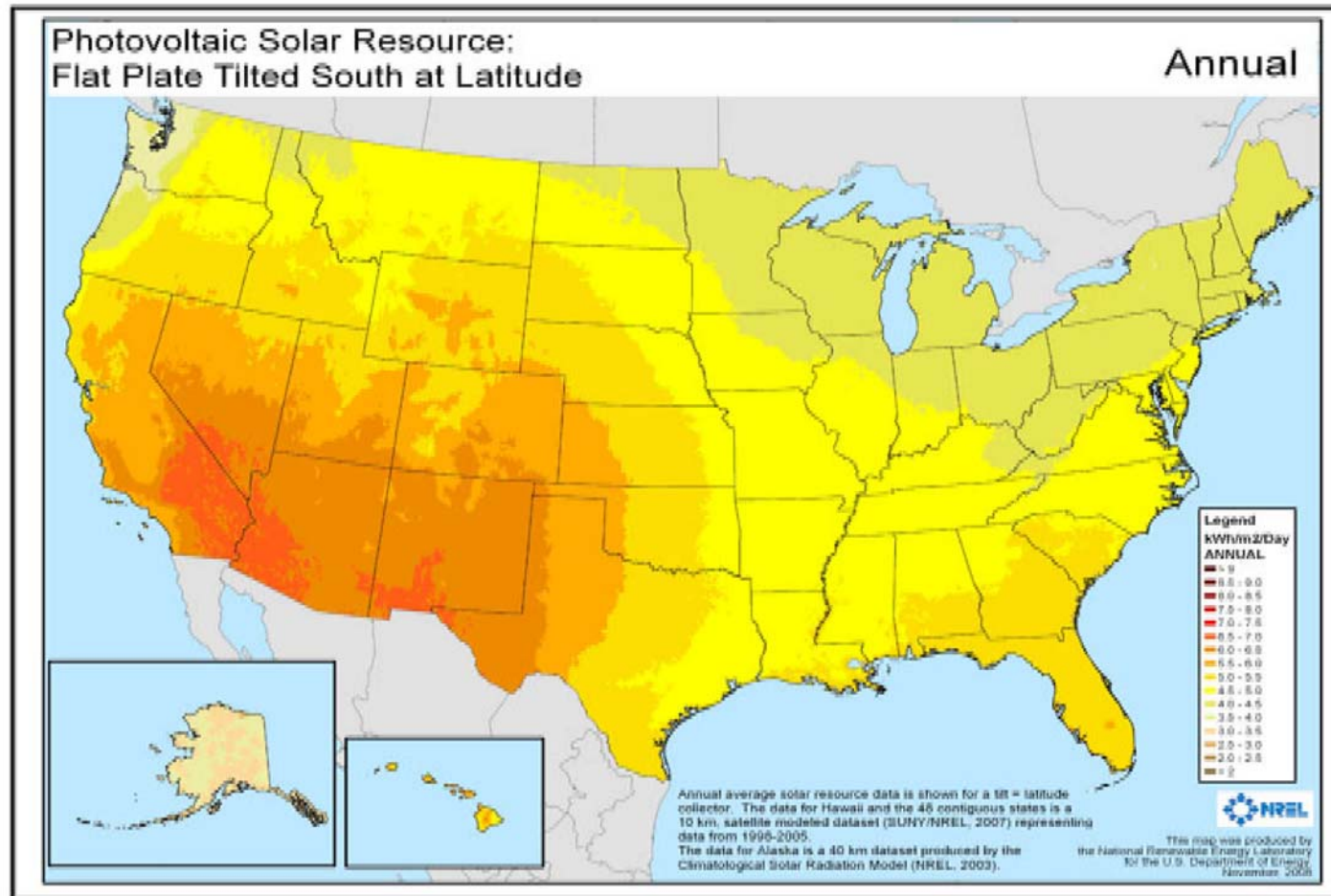


Model inputs: operational, environmental, and cost



Equipment	Average Hourly Power Required (W)	Peak Power Required (W)
GBOSS Heavy (w/2 40" LCDs)	961	800
VRC-110 w/Blue Force Tracker	165	440
PRC-150	57	375
Coffee Pot	45	975

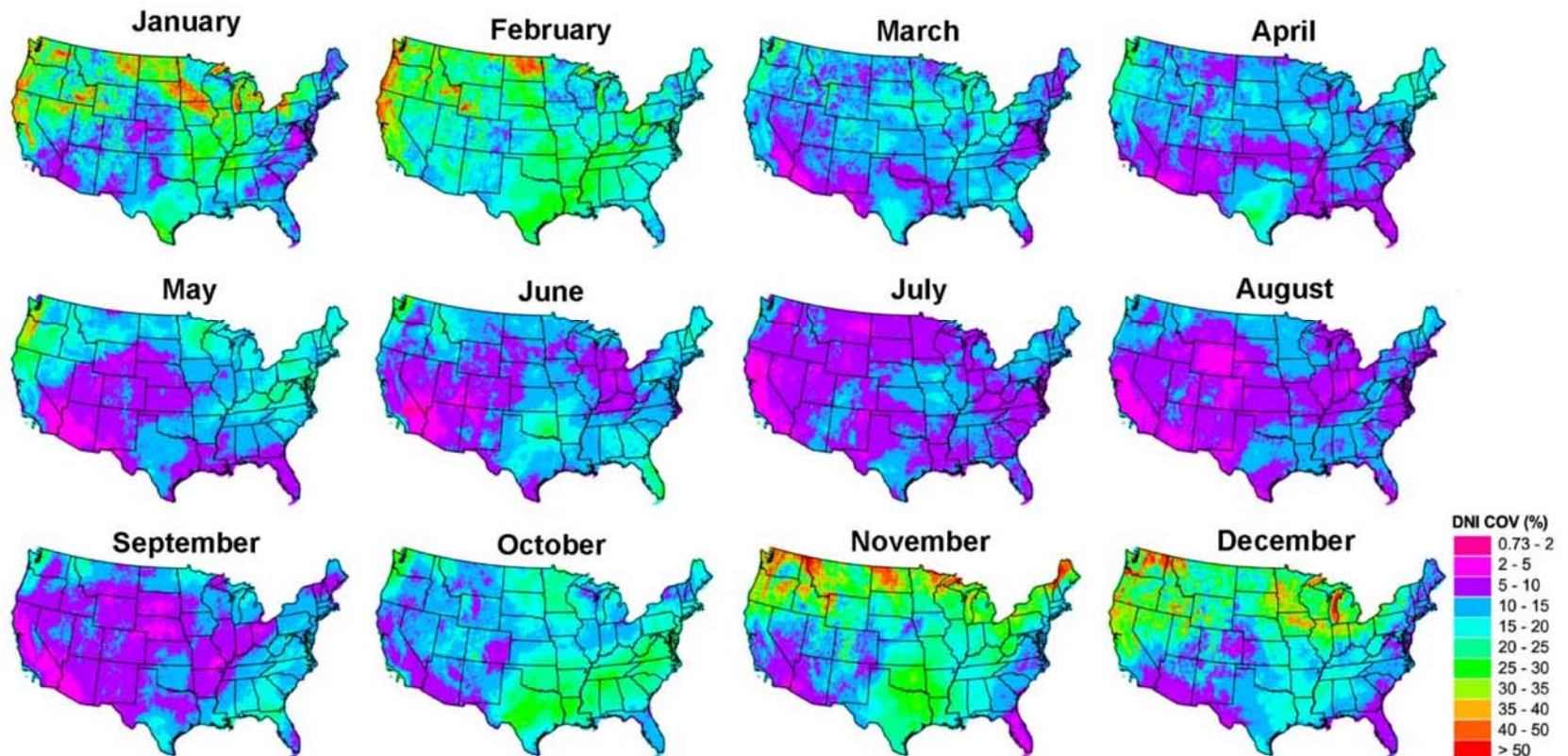




Annual solar irradiance in the United States (from USEIA, 2013).



Monthly DNI Interannual COV (%) 1998-2005

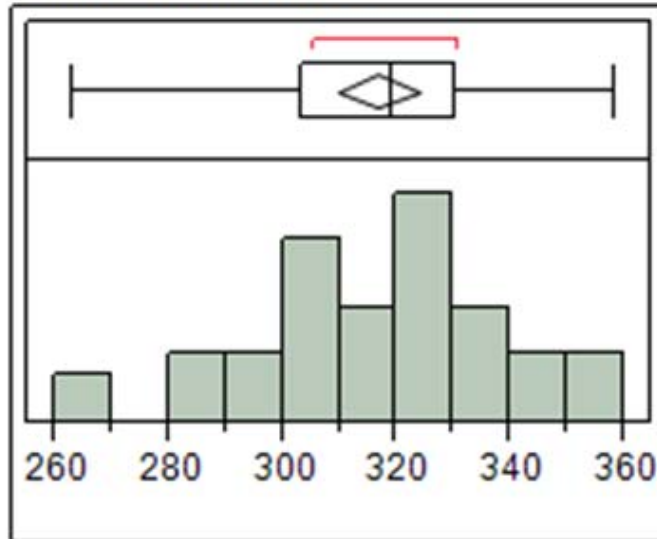


Monthly direct normal irradiance (DNI) interannual coefficient of variation (COV) in the United States (Gueymard & Wilcox, 2011)



Temporal variability: Salt Lake City

SumOfIrradiance



Quantiles

100.0%	maximum	358.708
99.5%		358.708
97.5%		358.512
90.0%		347.913
75.0%	quartile	330.528
50.0%	median	319.15
25.0%	quartile	303.436
10.0%		284.379
2.5%		263.346
0.5%		262.891
0.0%	minimum	262.891

Summary Statistics

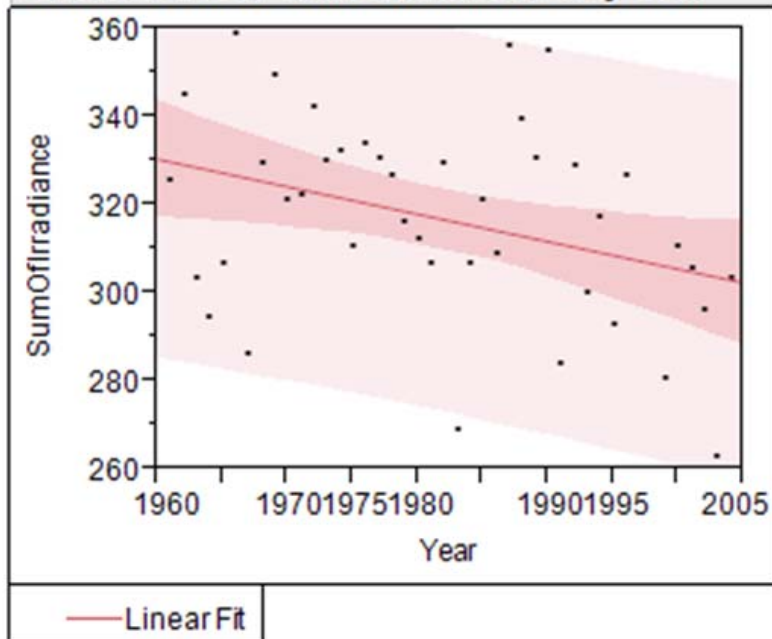
Mean	316.84362
Std Dev	22.616746
Std Err Mean	3.4898397
Upper 95% Mean	323.89149
Lower 95% Mean	309.79574
N	42

**Histogram of total solar irradiation over days 75-134
for Salt Lake City, by year, 1961-2010**



Temporal variability: Salt Lake City

Bivariate Fit of SumOfIrradiance By Year



Linear Fit

$$\text{SumOfIrradiance} = 1551.8297 - 0.6231683 * \text{Year}$$

Summary of Fit

RSquare	0.122638
RSquare Adj	0.100704
Root Mean Square Error	21.44773
Mean of Response	316.8436
Observations (or Sum Wqts)	42

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2571.995	2572.00	5.5912
Error	40	18400.210	460.01	Prob > F
C. Total	41	20972.205		0.0230*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	1551.8297	522.2965	2.97	0.0050*
Year	-0.623168	0.263543	-2.36	0.0230*

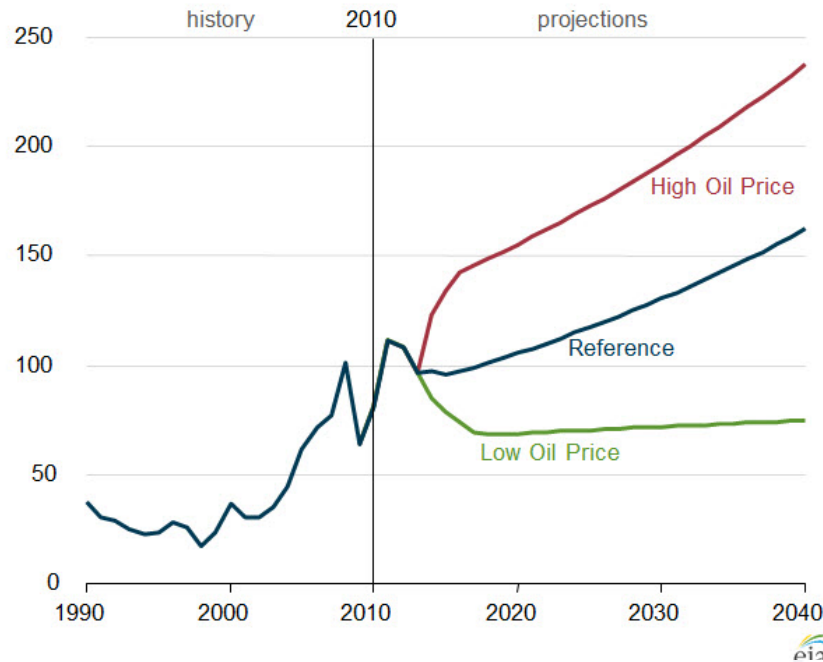
Scatterplot of total solar irradiance over days 75-134 for Salt Lake City, by year, 1961-2010



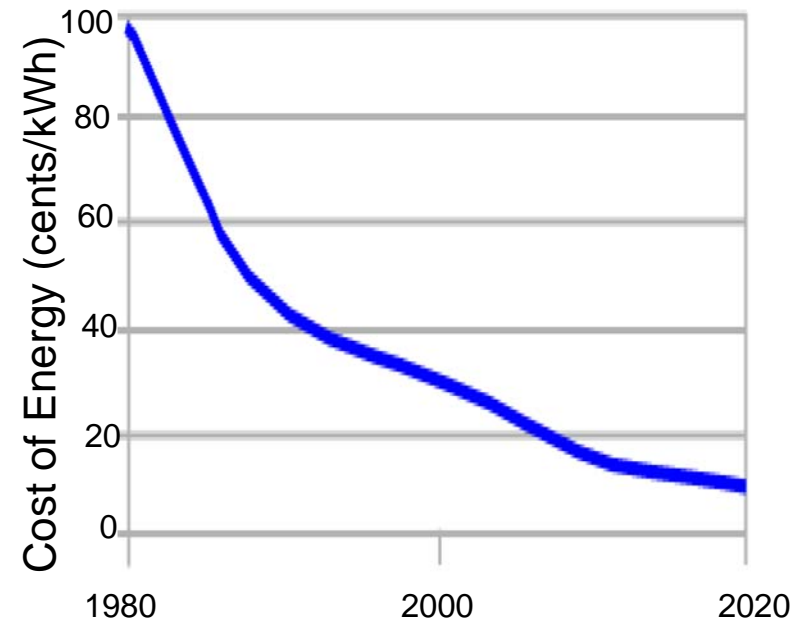
Cost projections: oil and solar

(a) World oil prices in three cases, 1990-2040

2011 dollars per barrel, Brent crude oil



(b) PV Cost of Energy

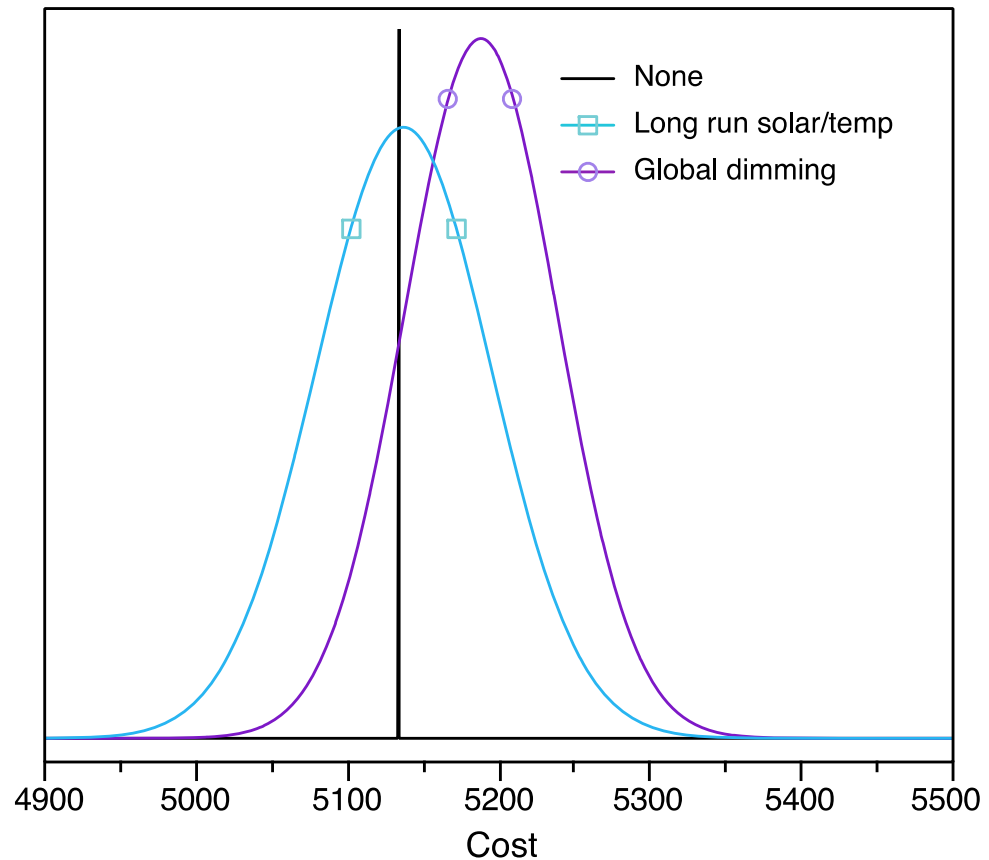


**Oil cost projections (from USEIA, 2014) and
PV array cost projections (adapted from USDOE, 2014)**



Replace fixed
cost estimates
with
distributions

*Reveal risk of
exceeding a
target budget*

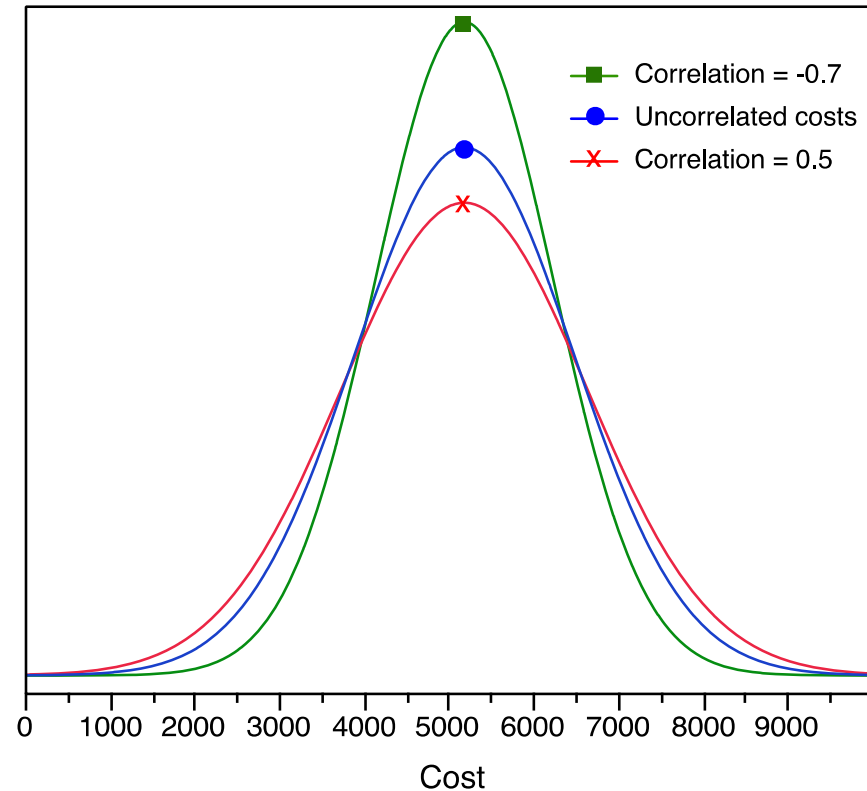


(a) Cost distributions based on different assumptions regarding uncertainties in solar and temperature data



Examine impact
of correlated
submodel costs
on overall cost

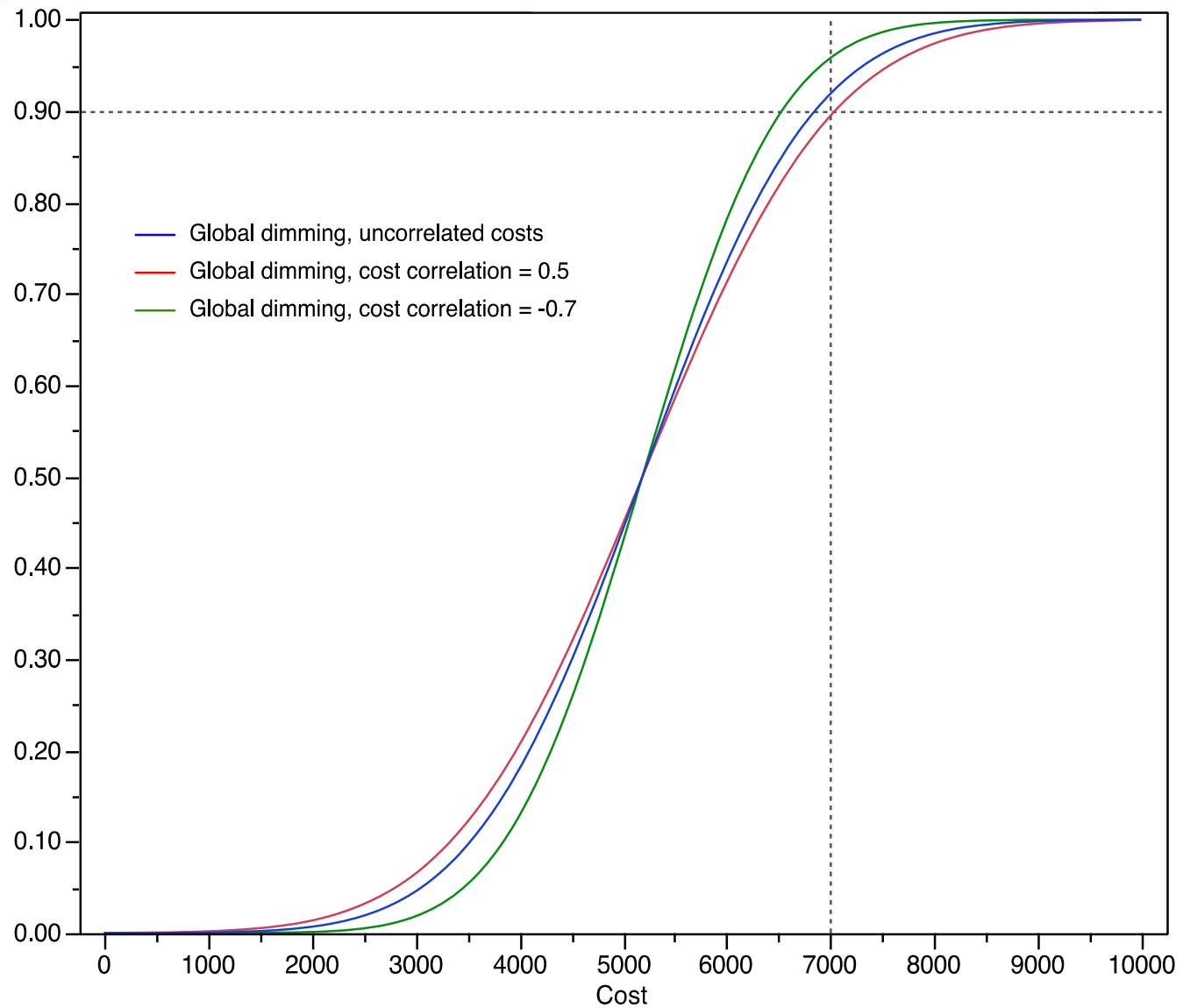
*Note that
variability is
much larger*



(b) Cost distributions based on global dimming, with different assumptions regarding correlations in future costs of PV arrays and diesel fuel



Exploring robustness of cost estimates





- For simple models with few input factors, we can use Monte Carlo simulation
- For models with many factors that have interactions, or nonlinear effects, this doesn't work
- Fortunately, not all factors / sources of variation are equally important. Structured exploration helps identify driving factors, knees in the curve, “robust” alternatives, etc.
- Large-scale models will require large-scale experiments.



Behind the scenes: Design of Experiments

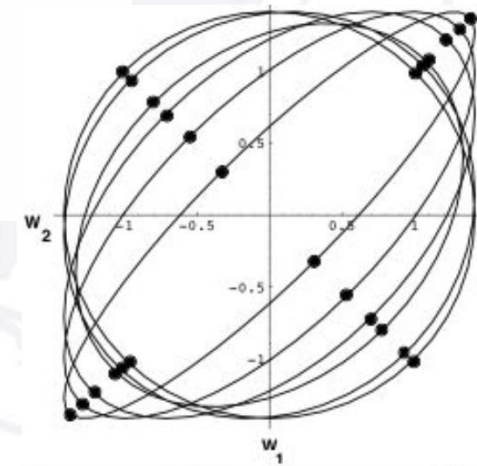
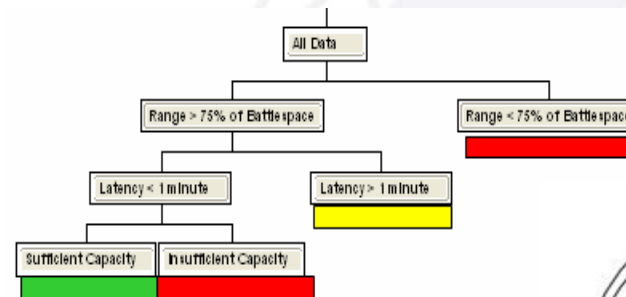
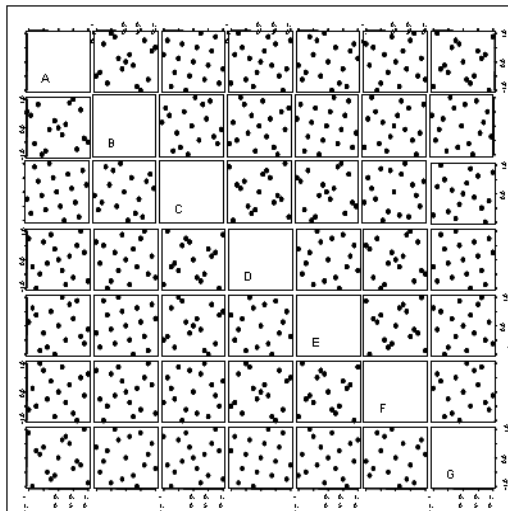
- Consider a model with 100 factors
- Study each factor at only 2 levels
- This would require 2^{100} experiments, approximately
1,000,000,000,000,000,000,000,000,000,000,000,000,000,000

...not good enough to be of practical use!



Behind the scenes: Design of Experiments

- Designed experiments (developed by NPS's SEED Center) allow 100's of factors to be explored in days or weeks
- Analysis makes use of a variety of statistical data mining techniques
- A revolution in capabilities for gaining insights from computational models





- Effects of (correlated) uncertainties in submodel costs
 - *What if high fuel prices tend to increase O&M transportation/spare part costs, but also tend to hasten economies of scale for new energy technologies?*
- Incorporate with operational simulations
 - *How robust are particular energy strategies over a set of likely MAGTF mission types and AORs?*



- Details and references for this study

Acquisition Research Symposium Proceedings

- Much broader study of energy modeling in HOMER, use of renewable energy for USMC expeditionary ops

Morse, M. (2014). *An analysis of the HOMER energy micropower optimization model's robustness for Marine Corps expeditionary operations* (Master's thesis, Naval Postgraduate School). In process.

- More on large-scale design of experiments

Sanchez, S. M., T. W. Lucas, P. J. Sanchez, C. J. Nannini, and H. Wan (2012). "Designs for large-scale simulation experiments, with application to defense and homeland security." Chapter 12 in *Design of Experiments, V. 3* (ed. K. Hinkelmann).

<http://harvest.nps.edu> (SEED Center website)



Questions?



Simulation
Experiments &
Efficient
Designs

Center for Data Farming

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