Adapting optimization models to better inform energy planning decisions

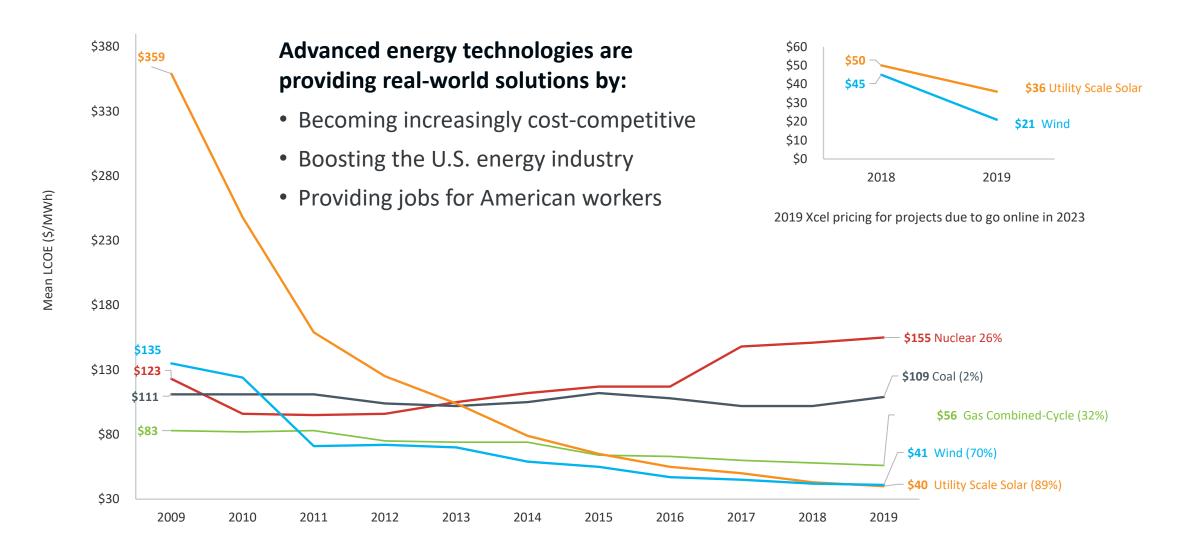
Kate Anderson Advanced Energy Systems, Colorado School of Mines Energy Systems Integration, National Renewable Energy Laboratory February 4, 2021







Cost for Renewables are Falling



NREL at-a-Glance

2,926

Workforce, including

219 postdoctoral researchers 60 graduate students 81 undergraduate students

World-class

facilities, renowned technology experts **Partnerships**

More than

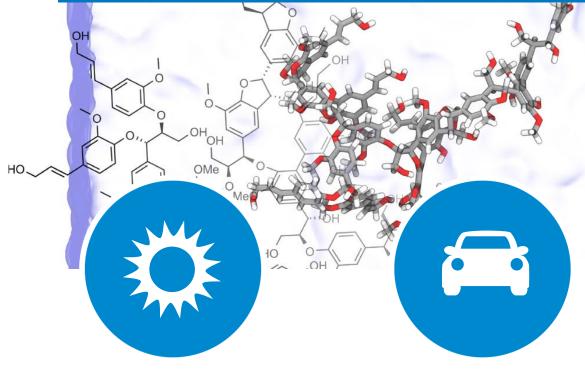
900

with industry, academia, and government

Campus

operates as a living laboratory

NREL Science Drives Innovation



Renewable **Power**

Solar

Wind

Water

Geothermal

Sustainable **Transportation**

Bioenergy

Vehicle Technologies

Hydrogen

Energy Efficiency

Buildings

Advanced Manufacturing

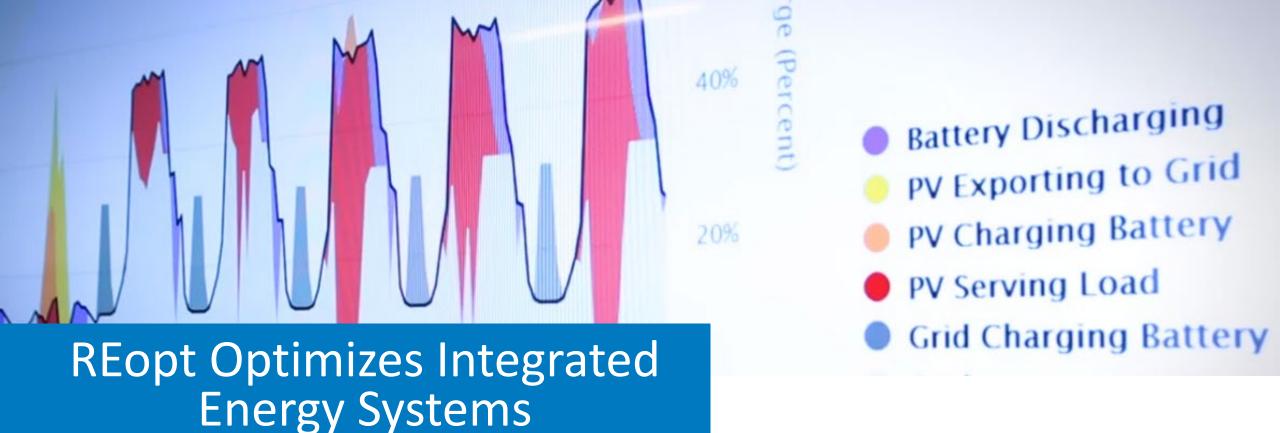
Government Energy Management

Energy Systems Integration

Grid Integration

Hybrid Systems

Security and Resilience



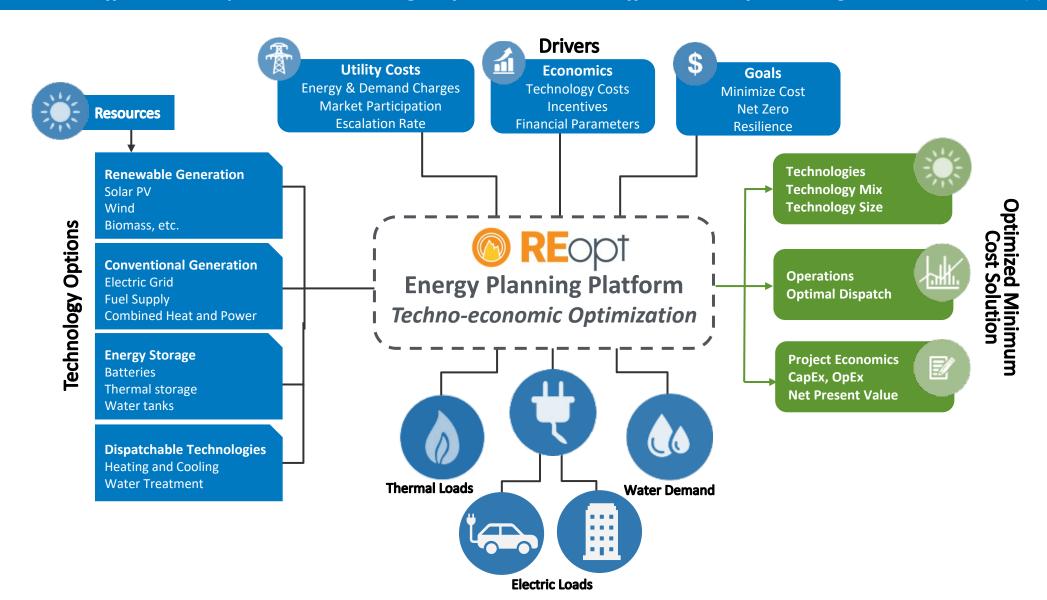
- NREL's REopt™ platform optimizes planning of generation, storage, and controllable loads to maximize the value of integrated systems
- It transforms complex decisions into actionable results for building owners, utilities, developers, and industry
- REopt analysis guides investment in economic, resilient, sustainable energy technologies



Many factors affect whether distributed energy technologies can provide cost savings and resilience to your site, and they must be evaluated concurrently.

REopt

Formulated as a mixed integer linear program, REopt considers the integration of multiple technologies and evaluates the trade-off between capital costs and savings to find the most cost-effective mix of technologies to meet the load(s)



REopt Objective Function

The objective function minimizes the lifecycle cost of energy, including capital costs, operation and maintenance costs, energy costs, and maximizes incentives.

$$\underbrace{\sum_{t \in \mathcal{T}, k \in \mathcal{K}^{c}, s \in \mathcal{S}_{tk}} \left(c_{ts}^{cm} \cdot X_{tks}^{\sigma s} + c_{ts}^{cb} \cdot Z_{tks}^{\sigma s} \right)}_{\text{Total Technology Capital Costs}} + \underbrace{\sum_{b \in \mathcal{B}} \left(c_{b}^{kW} \cdot X_{b}^{bkW} + (c_{b}^{kWh} + c_{b}^{omb}) \cdot X_{b}^{bkWh} \right)}_{\text{Total Storage Costs}} + \underbrace{\left(\sum_{t \in \mathcal{T}, k \in \mathcal{K}^{c}, s \in \mathcal{S}_{tk}} \left(c_{ts}^{cm} \cdot X_{tks}^{\sigma} + c_{ts}^{cb} \cdot Z_{tks}^{\sigma} \right)}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} \right)}_{\text{Total Storage Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{omp} \cdot X_{th}^{rp}}_{\text{Variable O&M Costs}} + \underbrace{\sum_{t \in \mathcal{T}^{f}, h \in \mathcal{H}} c_{ts}^{o$$

$$(1 - f^{\text{tot}}) \cdot \left(\underbrace{\Delta \cdot \sum_{f \in \mathcal{F}} c_f^{\text{u}} \cdot \sum_{t \in \mathcal{T}_f, h \in \mathcal{H}} f_t^{\text{pf}} \cdot X_{th}^{\text{f}}}_{\text{Total Production Costs}} \right) + (1 - f^{\text{tot}}) \cdot f^{\text{e}} \cdot \left(\underbrace{\Delta \cdot \sum_{u \in \mathcal{U}^{\text{p}}, h \in \mathcal{H}^{\text{g}}} c_{uh}^{\text{g}} \cdot X_{uh}^{\text{g}}}_{\text{Peak Ratchet Charges}} + \underbrace{\sum_{r \in \mathcal{R}, e \in \mathcal{E}} c_{re}^{\text{r}} \cdot X_{re}^{\text{de}}}_{\text{Peak Monthly Demand Charges}} + \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{mn}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{N}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{\sum_{m \in \mathcal{M}, n \in \mathcal{M}} c_{re}^{\text{rm}} \cdot X_{mn}^{\text{dn}}}_{\text{Peak Monthly Demand Charges}} - \underbrace{$$

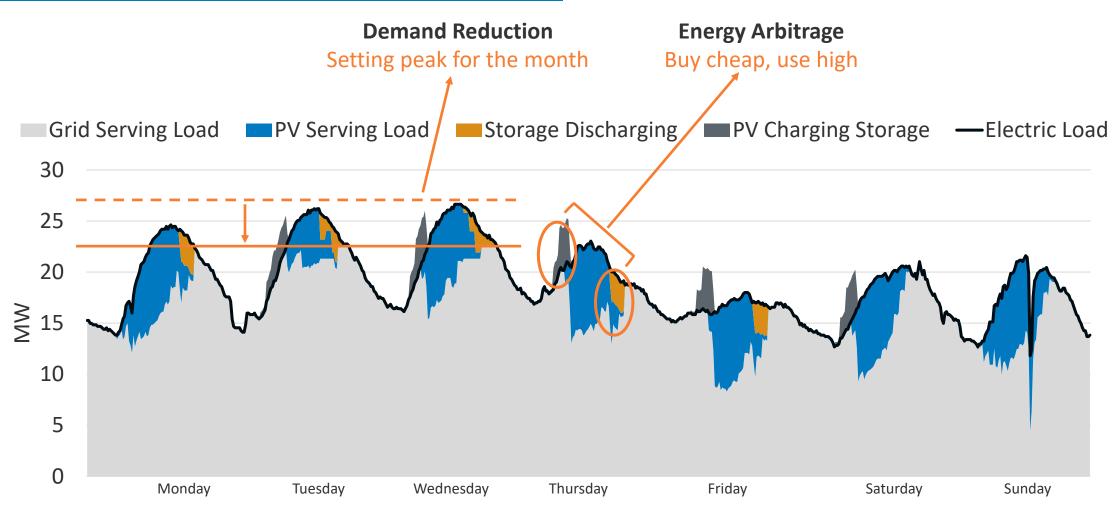
$$\underline{\Delta \cdot \left(\sum_{h \in \mathcal{H}^{g}} \left(\sum_{u \in \mathcal{U}^{\text{sb}}} c_{uh}^{\text{e}} \cdot X_{uh}^{\text{stg}} + \sum_{t \in \mathcal{T}, u \in \mathcal{U}_{t}^{\text{s}}} c_{uh}^{\text{e}} \cdot X_{tuh}^{\text{ptg}} \right) \right)} + \underbrace{c^{\text{afc}} + X^{\text{mc}}}_{\text{Total Fixed Charges}} - (1 - f^{\text{tow}}) \cdot \underbrace{\sum_{t \in \mathcal{T}} X_{t}^{\text{pi}}}_{\text{Production Incentives}}$$

REopt Lite Constraints

- Fuel constraints
- Switch constraints
- Storage size, state of charge, and operational constraints
- Production incentive cap
- Power rating
- Load balancing and grid sales
- Rate tariff constraints
- Minimum utility charge
- Non-negativity and integrality

How Does REopt Work?

REopt considers the trade-off between ownership costs and savings across multiple value streams to recommend optimal size and dispatch.



REopt Provides Solutions for a Range of Users

Including researchers, developers, building owners, utilities, and industry



What is the optimal size of distributed energy resources (DERs) to minimize my cost of energy?



What will it cost to meet my sustainability or resilience goal?



What is the most costeffective way for me to survive a grid outage?



How do I optimize system control across multiple value streams to maximize project value?



Where do market opportunities for DERs exist? Now and in the future?



Description: NREL used REopt to independently verify the predicted utility savings estimated by the project developer from battery peak shaving.

Technology: Li-ion battery storage

Impact: 4.2 M; 8.5-MWh battery installed at Ft. Carson under an ESPC. Largest battery in the Army at time of installation, saving Ft. Carson \$500,000 per year in utility costs.

Partner: Army, AECOM

Design Tradeoffs between Economics and Resilience

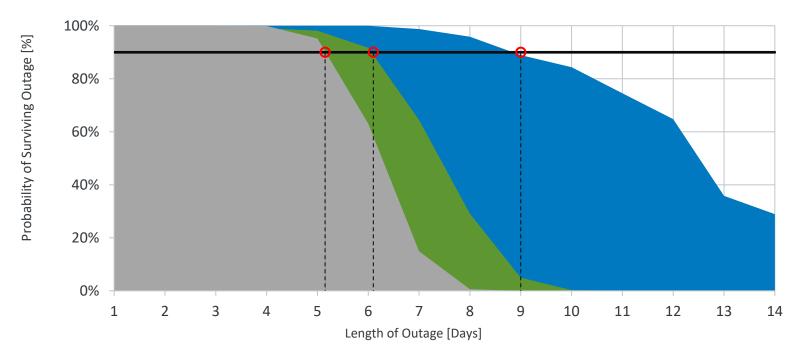
Description: NREL used REopt to evaluate how long existing and proposed backup energy systems could sustain the critical load during an outage at an Army National Guard base. REopt evaluated thousands of random grid outage occurrences and durations and compared hours survived with diesel gensets vs. gensets augmented with PV and battery.

Technology: Solar, storage, diesel generation

Impact: PV and battery can provide savings and resilience. Site can achieve 4 extra days of resilience with no added cost.

Partner: Army National Guard

	<u>Generator</u>	<u>Solar PV</u>	<u>Storage</u>	<u>Lifecycle Cost</u>	<u>Outage</u>
1. Base case	2.5 MW			\$20 million	5 days
2. Lowest cost	2.5 MW	625 kW	175 kWh	\$19.5 million	6 days
3. Proposed system	2.5 MW	2 MW	500 kWh	\$20 million	9 days



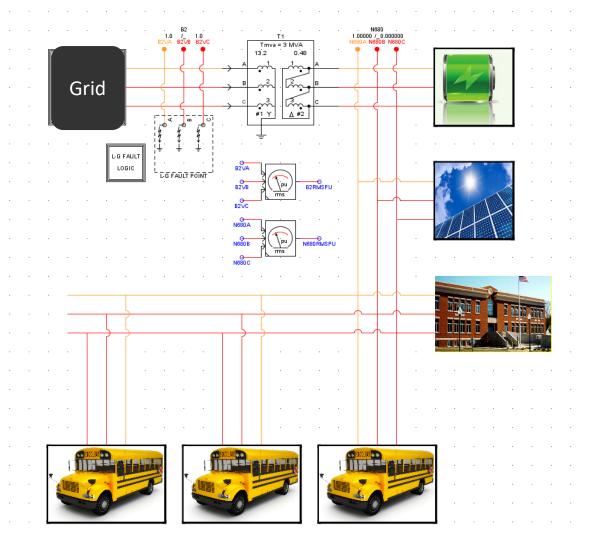
Integrating EV Fleets With DER and Grid

Description: NREL evaluated opportunities for synergistic integration and control of electrified transportation fleets with flexible buildings loads, RE, and stationary storage.

Technologies: Mobility, storage, buildings, solar, advanced system integration controls

Impact: Demonstrated optimal control of integrated RE, building loads, storage, and EV system in laboratory testing. Integrated system provided increased value to the site owner.

Partners: Eaton (funding partner), Holy Cross Energy, SDG&E, Duke Energy, UPS, EPRI



The Gap Between Modeling and Deployment

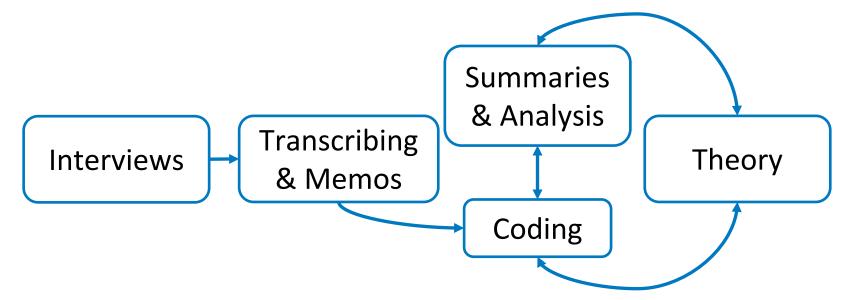
- A gap exists between actual and modeled optimal clean energy deployment.
- Qualitative values and practical deployment barriers are not always captured in models.
- This can lead decision makers down paths that will ultimately fail.
- This research explores how models can be adapted to inform more realistic energy solutions.

Drivers of energy deployment and their inclusion in models

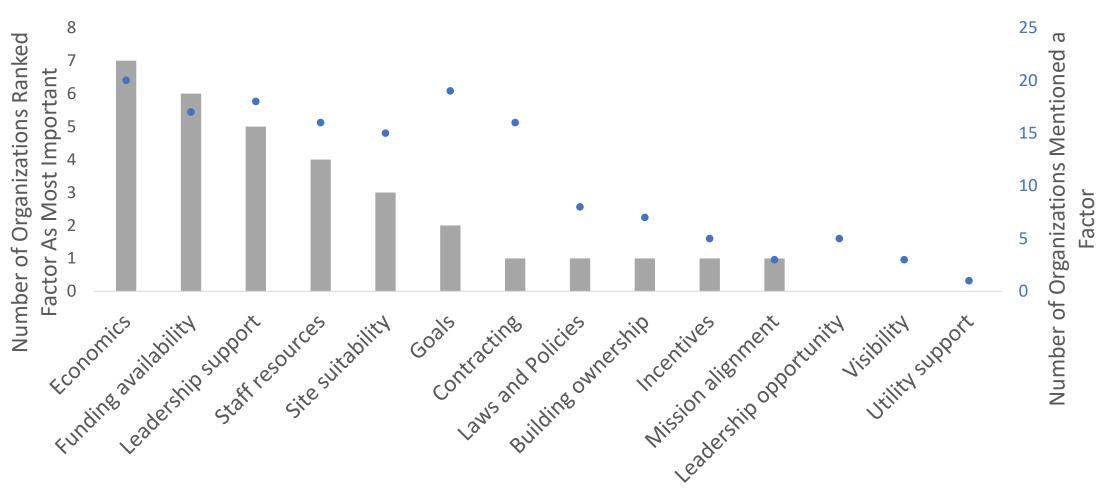
Туре	Driver	Included in energy models
Technical	Energy generation or savings Site suitability	X
Economic	Energy price Discount rates Incentives	x
Regulatory	Unenforced, conflicting, unstable policy Land ownership Ease of permitting	
Organizational	Alignment with corporate strategy Organizational divisions of labor & power Capacity to act	
Social and Behavioral	Aversion to risk and uncertainty Non-monetary costs of information Heterogeneity of preference Peer effects Social acceptance Perceived status, recognition, and pride Perceived fairness in decision-making Trust between community and developer Individual values Aesthetics, branding, perceived reliability, comfort, quality, design	

Approach

- Research questions
 - 1. What are the drivers of and barriers to renewable energy deployment?
 - 2. How do decision tools impact deployment decisions?
 - 3. How could a tool or resource be adapted to increase deployment?
- Comparative case study methodology to develop grounded theory



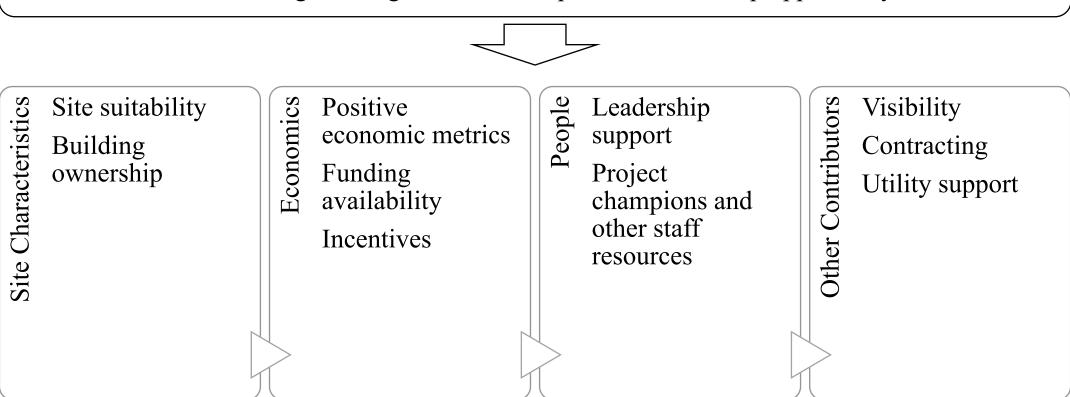
Results: Factors in RE Deployment



Anderson, K., Nevrly, M., Elgqvist, E. & Bazilian, M. (2021). Closing the Gap Between Renewable Energy Decision Models and Deployment. Submitted for publication in *Energy Research and Social Science*.

Results: Factors Present in Stage Gates

Organizational Motivation
Mission alignment, goals, laws and policies, leadership opportunity



Anderson, K., Nevrly, M., Elgqvist, E. & Bazilian, M. (2021). Closing the Gap Between Renewable Energy Decision Models and Deployment. Submitted for publication in Energy Research and Social Science.

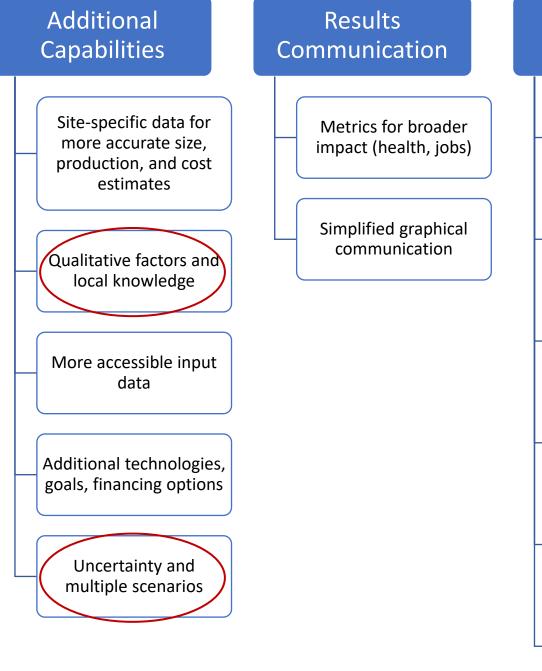
Results: The Role of Tools in Deployment Decisions

Factor	Provided by Tool	Not Provided by Tool
Site Suitability	-Estimate renewable energy resources	-Estimate space available
	-Estimate system size	-Assess historical or cultural resource impacts
Building Ownership		-Assess ownership of building or land
Economics	-Calculate cost-effectiveness of RE, as measured by	-Gather site-specific load and utility data
	metrics such as net present value	-Provide local cost estimates
Funding Availability	-Estimate system size, costs, and economic metrics for	-Identify funding sources
	funding applications	-Apply for funding
Staff Resources	-Calculate metrics required to make a decision	-Increase staff availability
	-Increase staff knowledge of RE opportunities	-Create project champion
		-Provide decision authority
Leadership Support	-Provide metrics to use in gaining support of leaders	-Gain leadership support
		-Provide legitimization through expert credibility
Goals	-Calculate contribution of RE toward goals	
Laws & Policies	-Estimate impact of interconnection and net metering	-Identify laws that govern RE deployment
	limits	-Assess environmental compliance
Utility Support		-Identify if utility supports RE deployment
Mission Alignment		-Identify if project aligns with mission
Visibility		-Increase visibility
Leadership Opportunity		-Identify if project is new and innovative
Contracting	-Calculate economics of different options	-Develop contracting documents and execute contract
Incentives	-Calculate impact of incentives on economics	-Apply for incentives

Anderson, K., Nevrly, M., Elgqvist, E. & Bazilian, M. (2021). Closing the Gap Between Renewable Energy Decision Models and Deployment. Submitted for publication in *Energy Research and Social Science*.



Results: Improvements to Tools and Resources to Increase RE Deployment



Peer network

Example projects and contacts

Vendor recommendations

Funding opportunities list

Example procurement specifications

Training resources

21

Uncertainty in Energy Models

- Accounting for uncertainty is a major challenge of optimization models.
- Parametric uncertainty arises from lack of knowledge about model inputs.
- Structural uncertainty results from inability to model certain factors.

Uncertainty

Parametric

- Sensitivity Analysis
- Monte Carlo Simulation
- Stochastic Programming
- Robust Optimization

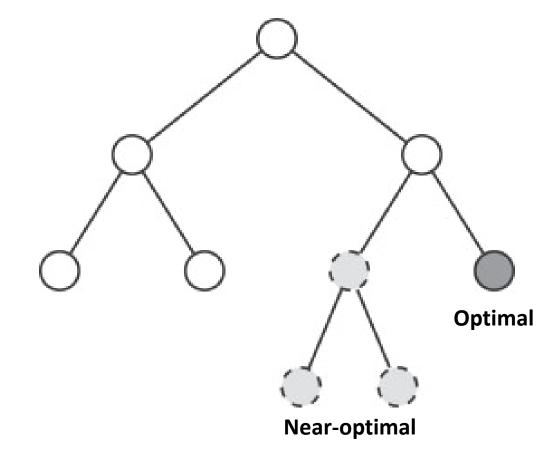
Structural

 Modeling to Generate Alternatives

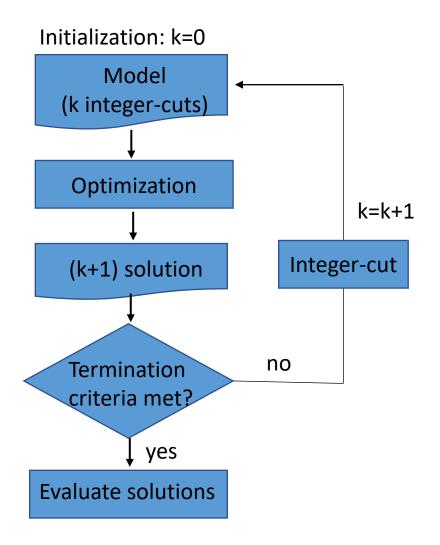


Method #1: Branch-and-Bound Tree

- Integer programs are solved through branch-and-bound trees, which eliminate sub-optimal branches for efficiency.
- We explore alternate solutions by retaining feasible, but near-optimal, solutions.
- The user defines the number of solutions, the maximum gap between alternate solutions and the optimal, and the diversity of solutions.



Method #2: Integer-Cut Constraints



We iteratively solve the optimization model, each time adding a constraint to exclude the previous solution.

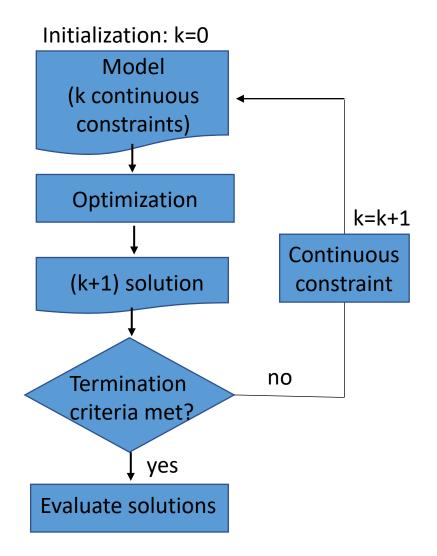
$$Z_{th}^{\text{to}} \leq y_t^{\text{to}} \quad \forall t \in \mathcal{T}, h \in \mathcal{H} \quad \succeq \text{Ensures binary is 1 if the technology operates in any hour}$$

$$\sum_{t \in \mathcal{T}'} y_t^{\text{to}} \le |\mathcal{T}'| - n$$

- Sums over all technologies that operate in the optimal solution and requires the alternate solution to be different from the optimal by at least *n* technologies

Where T= set of all technologies, T'= set of all technologies operating in the base case, y_t^{to} = 1 if technology t ever operates and 0 otherwise, Z_{th}^{to} = 1 if technology t operates in timestep h and 0 otherwise, and n = the number of technologies that must be different.

Method #3: Continuous Constraints



We iteratively solve the optimization model, each time adding a constraint to restrict the size of technologies to be at least some percent different from the sizes given in previous solutions.

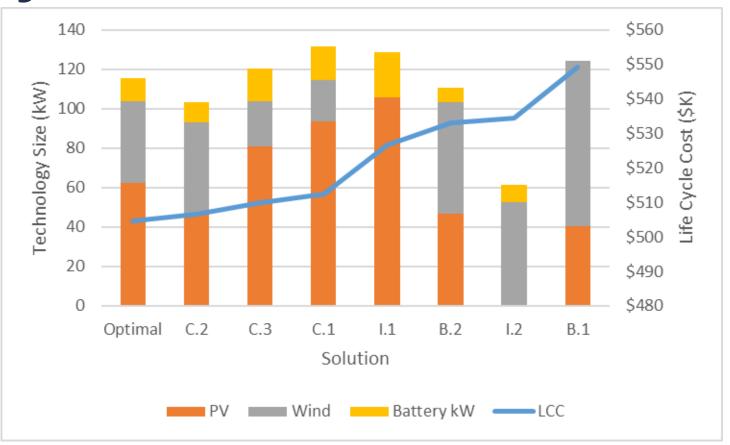
$$X \ge (1+n)X^* - M\alpha$$
$$X \le (1-n)X^* + M(1-\alpha)$$

➤ Restrict the size of technologies to be some percentage greater than or less than their size in the previous solution

Where X= size of technology, X*= size of technology in the previous case, n= decimal percent difference, M= a big number, and α = variable that enforces binary logic (1 if some fraction of technology X* is greater than or equal to X and 0 otherwise).

Results Summary

- Seven alternate solutions are within 10% of the optimal objective function value.
- These provide the decision maker with a useful set of nearoptimal choices to consider, along with qualitative factors not represented in the model when making an investment decision.



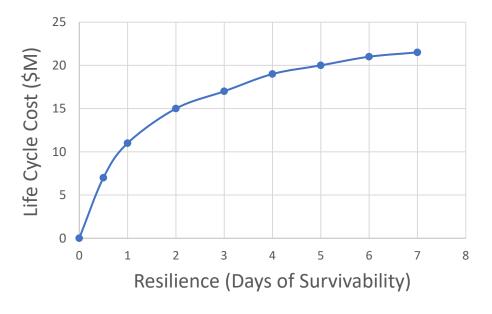
Comparison of optimal solution to the set of near-optimal choices (B=Branch and Bound; I=Iterative Constraint; C=Continuous Constraint)



Co-Optimization

We use two techniques to co-optimize cost and resilience goals and develop solutions that balance multiple competing objectives:

- a) Efficient frontier: Minimize cost while parametrically varying the grid outage length to develop an efficient frontier of pareto optima solutions for different levels of resilience
- b) Goal programming: Set target cost and resilience goals, and then minimize the amount the solution falls short of these.



Efficient frontier of solutions for varying resilience levels

Value of Resilience

- Resilience benefits are difficult to quantify and value, and therefore are often not included in energy decision modeling.
- This work develops a method for valuing resilience and integrates it in two energy decision models at microgrid and macrogrid scales.
- We test whether including a value of resilience changes investment and/or operational decisions.

Campus Planning and Operation Case Study

Research Question: If a site owner understands the duration-dependent magnitude of losses they will incur during an outage, will they make different investment and operational decisions to minimize their lifecycle cost of energy?

- **Method:** We incorporate a duration-dependent value of lost load in REopt to optimize system size and dispatch to minimize lifecycle energy costs for a site, including outage costs.
- Results: Knowledge of duration-dependent value of lost load allows a site owner to reduce outage costs and overall lifecycle energy costs using larger PV and storage systems to provide longer duration backup power.

Anderson, K., Murphy, C., Hotchkiss, E., Barrows, C., Dalhi, S., Li, X., Ericson, S., Lisell, L. Integrating the Value of Electricity Resilience in Energy Planning and Operations Decisions. IEEE Systems Journal January 2020.

Outage Cost Functions

	Resilience Value		
	Constant Duration-dependent		
Fixed cost	\$0/kW	\$16/kW	
Flow cost	\$13/kW	\$8/kW	
Stock cost	\$0/kW	\$0/kW	

Optimal System Sizing and Cost Results

	Resilience Value		
	None	Constant	Duration- Dependent
PV size (kW)	265	283	321
Battery size (kWh)	300	599	692
Outage survival (hours)	0.24	0.66	0.87
Total outage cost (\$)	\$315,319	\$238,788	\$214,853
Outage cost reduction (%)	-	24%	32%
Value of resilience (\$)	-	\$76,531	\$100,466



Accessing REopt Lite

- Web tool: reopt.nrel.gov/tool
- API: https://developer.nrel.gov/docs/energy- optimization/reopt-v1/
- Open Source code: https://github.com/NREL/REopt Lite API

Step 1: Choose Your Focus

Do you want to optimize for financial savings or energy resilience?





\$ Financial

Step 2: Enter Your Site Data

Enter information about your site and adjust the default values as needed to see your results.



Step 3: Select Your Technologies

Which technologies do you wish to evaluate?



Acknowledgments

- National Renewable Energy Laboratory
 - Dr. Adam Warren, REopt team, Dr. Alex Zolan, Josiah Pohl, Maggie Nevrly, Emma Elgqvist
- Colorado School of Mines
 - Dr. Alexandra Newman, Dr. Tulay Flamand, Dr. Rob Braun, Dr. Morgan Bazilian, Seun Ogunmodede, Jamie Grymes, Dr. Jesse Wales, Jusse Hirwa, Chris Hampel, Valerie Holt, Suzanne Beach
- Department of Energy Advanced Manufacturing Office and Federal Energy Management Program
 - Rachel Shepherd, Bob Gemmer, Patti Garland, Bruce Hedman

Thank you!

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