Probabilistic Resource Adequacy Suite (PRAS)

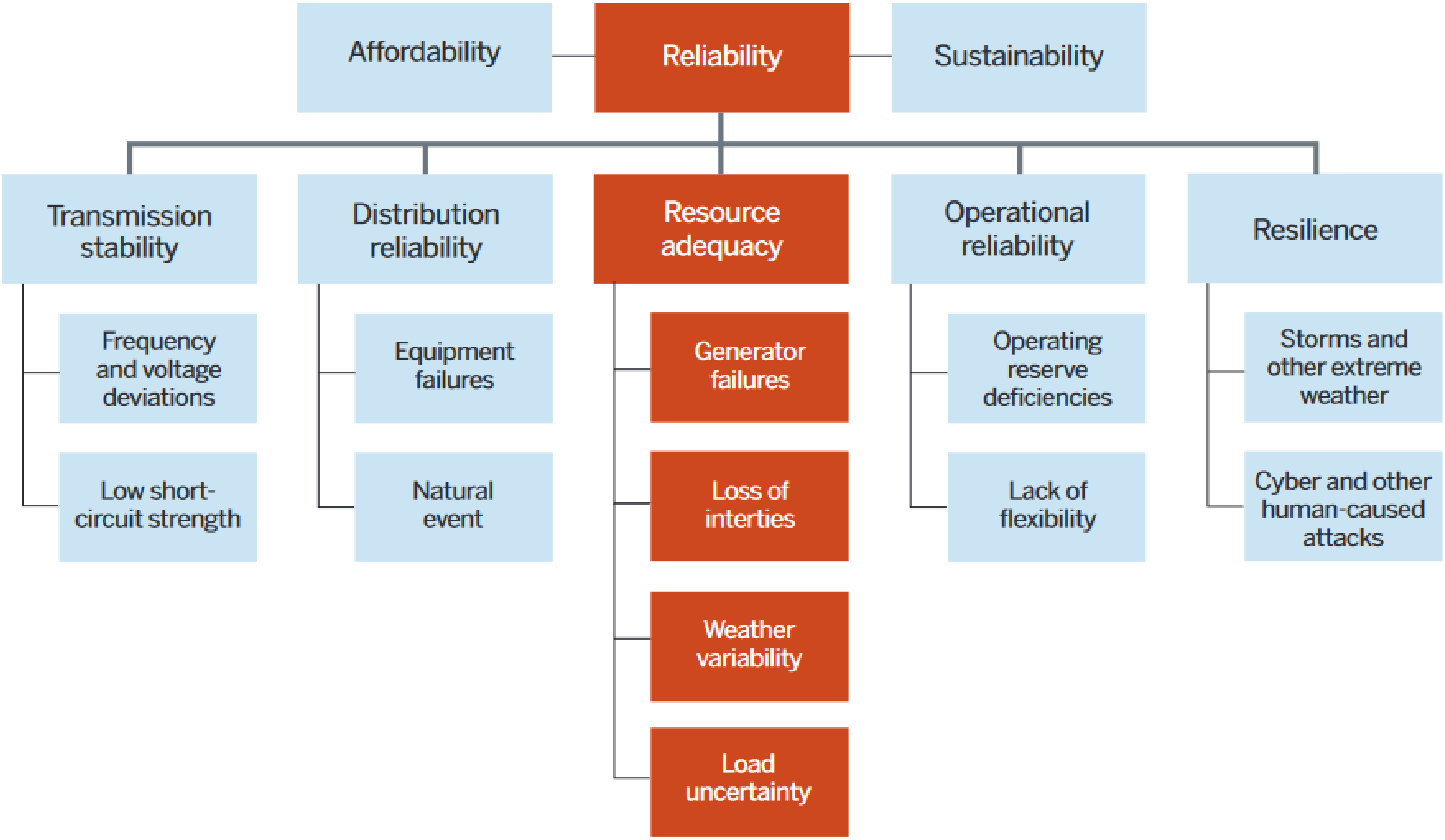
Gord Stephen
National Renewable Energy Laboratory

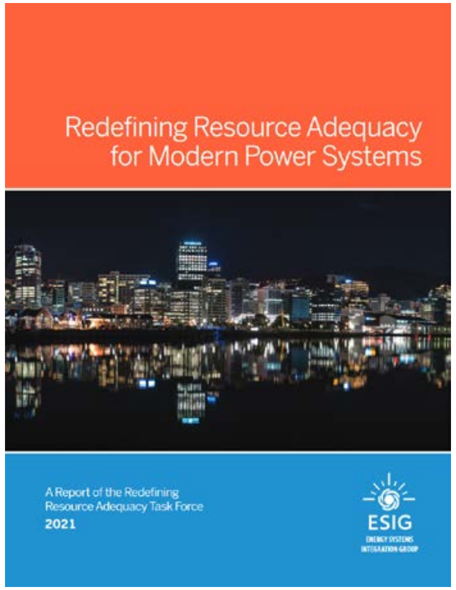
Sept. 10, 2024

What Is Resource Adequacy?

Photo by Dennis Schroeder, NREL 18980

What Is Resource Adequacy?





https://www.esig.energy/resource-adequacy-for-modern-power-systems/

Core Drivers of Modern Adequacy Assessment

Uncertainty

Resources are subject to unplanned outages

Variability

Time-varying availability decouples peak risk from peak demand

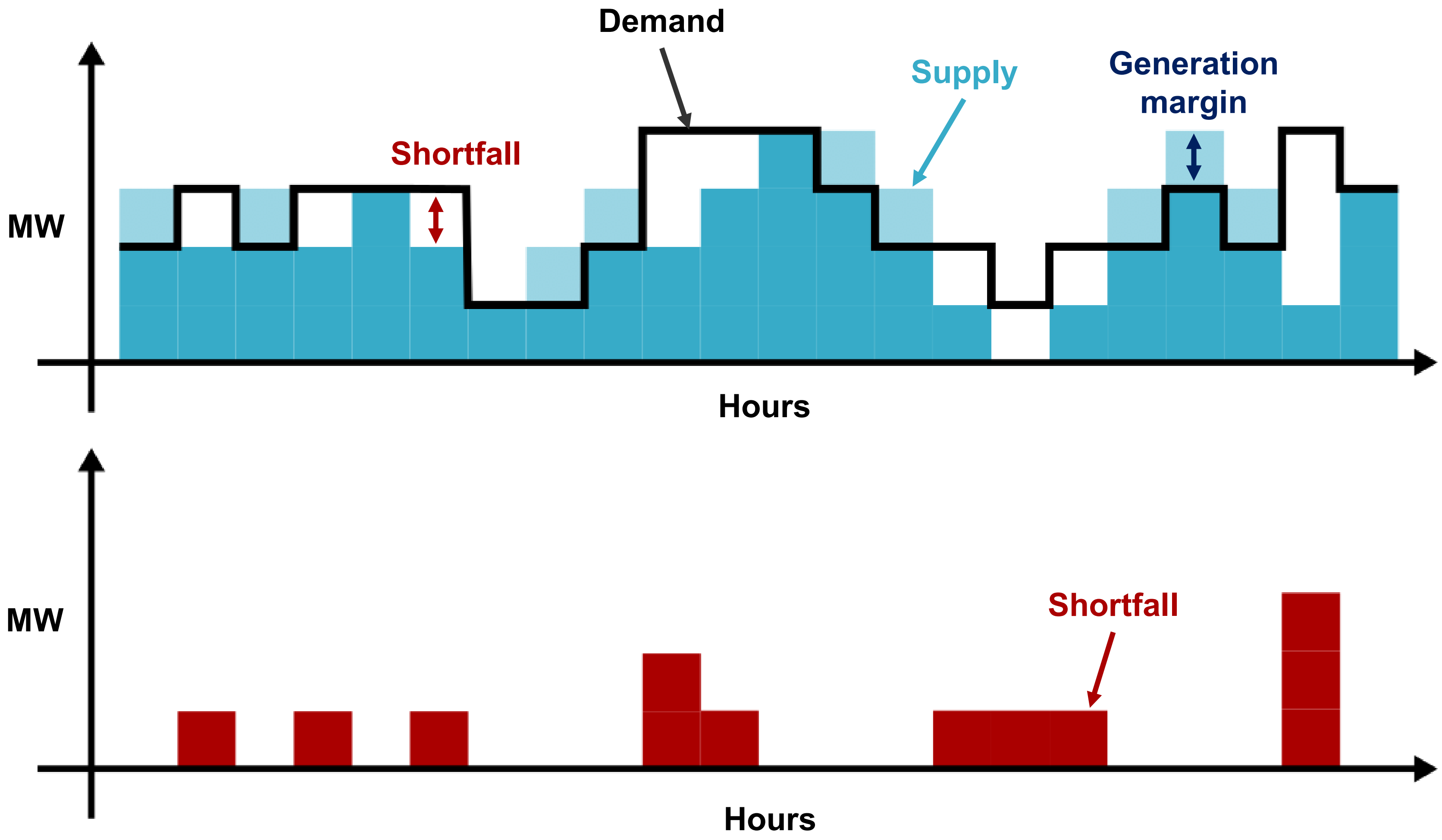
Spatial Coupling

Leveraging wide-area resource diversity requires understanding interregional transmission

Temporal Coupling

Storage and demand response allow shifting electrical energy between time periods

Key Question: Can We Balance Supply and Demand?



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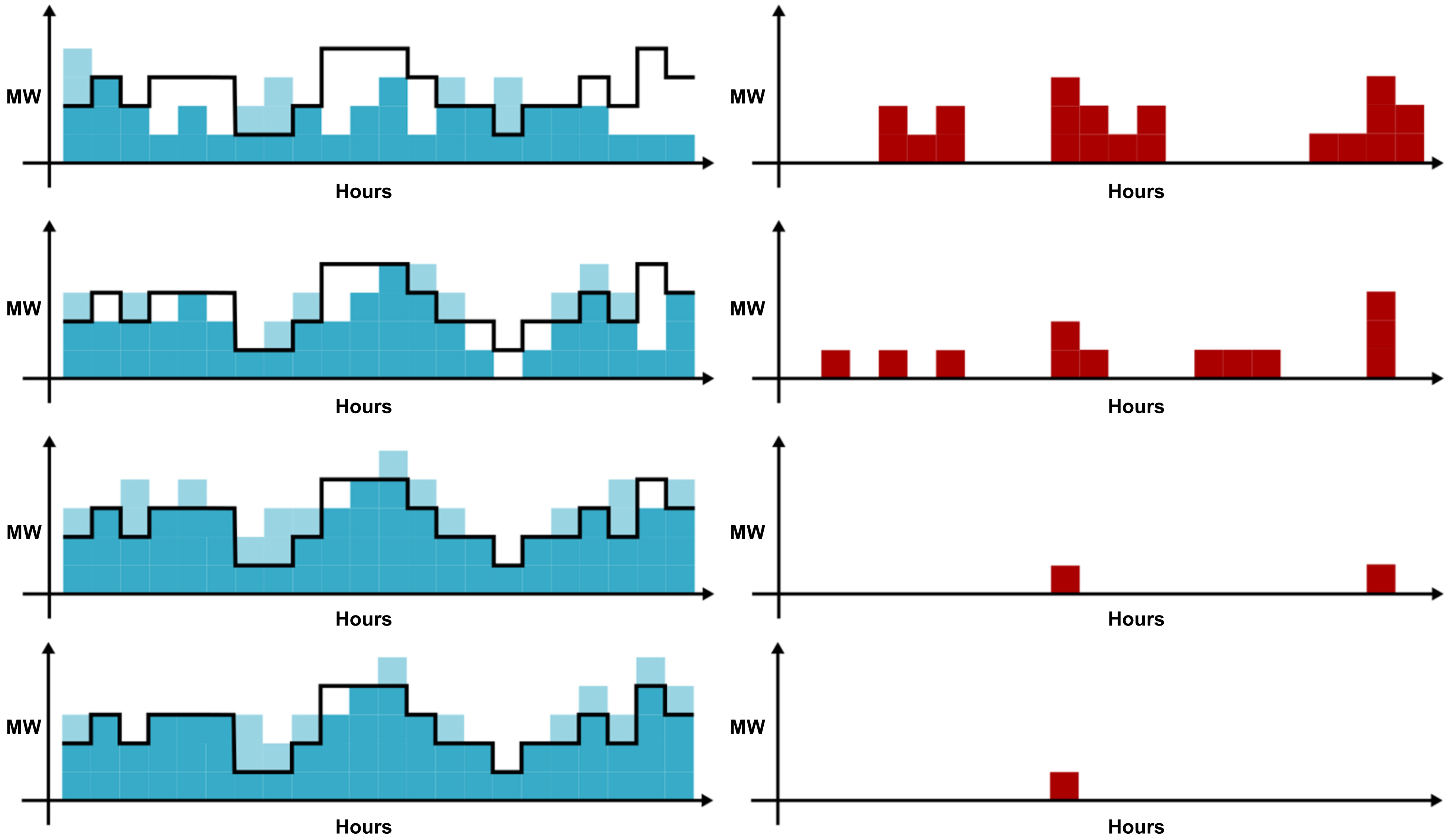
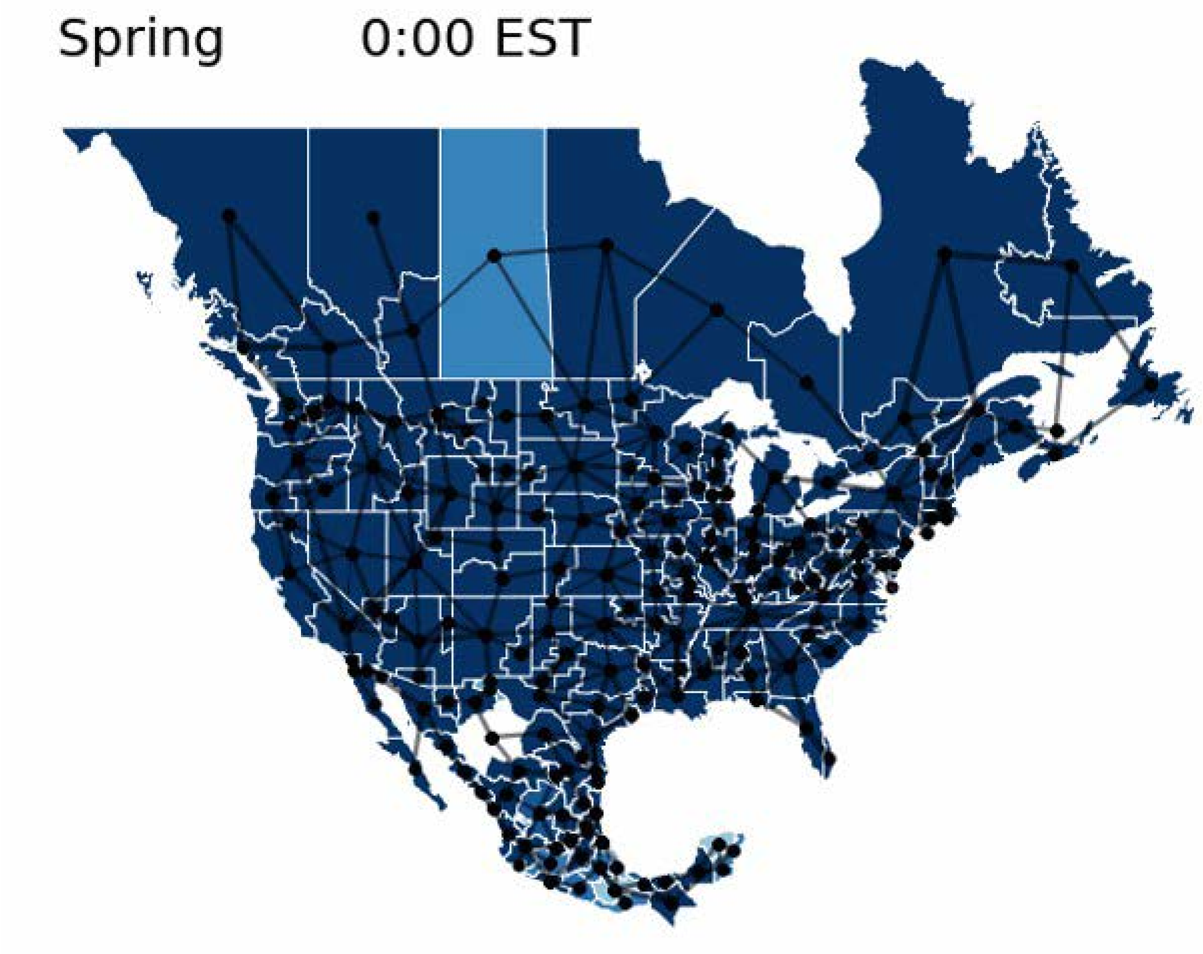


Combine different possible outcomes into statistical risk metrics

Probabilistic Resource Adequacy Suite (PRAS)

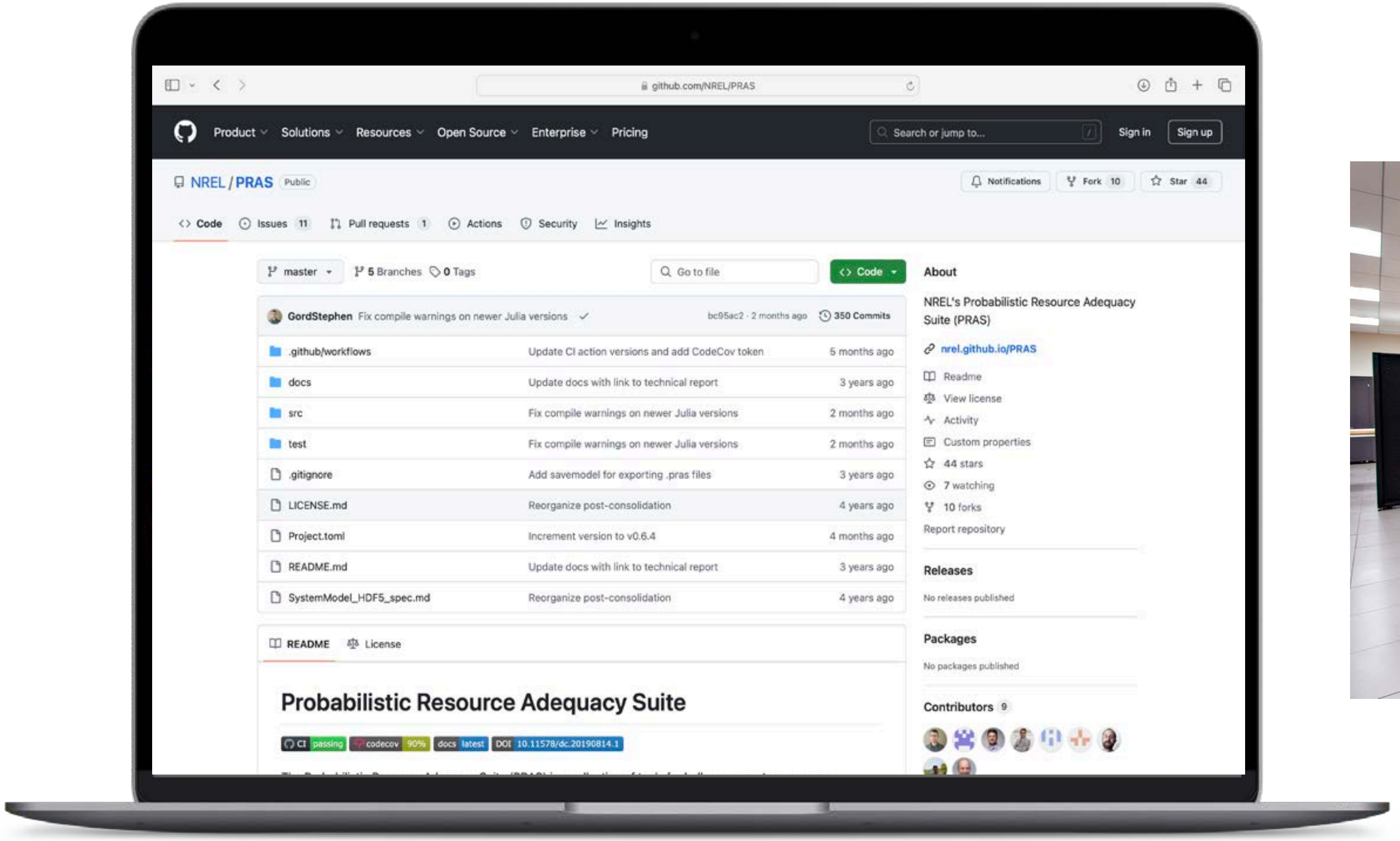
Efficient, open-source simulation engine for conducting wide-area probabilistic resource adequacy assessments



Fast operations simulations capture:

- Resource and load diversity
- Regional transmission constraints
- Full chronological storage dynamics
- Weather-dependent outages.

What Is PRAS?



https://github.com/NREL/PRAS

What Is PRAS?

Power system representation → **Probabilistic simulations** → Probabilistic outcomes

Regional load, generator ratings, reliability statistics, interregional transfer limits, and so on

Randomly drawn operating conditions + grid operations simulation under those conditions

Spatially and temporally resolved Expected Unserved Energy (EUE), Loss of Load Expectation (LOLE), Loss of Load Probability (LOLP), and so on

Power System Representation

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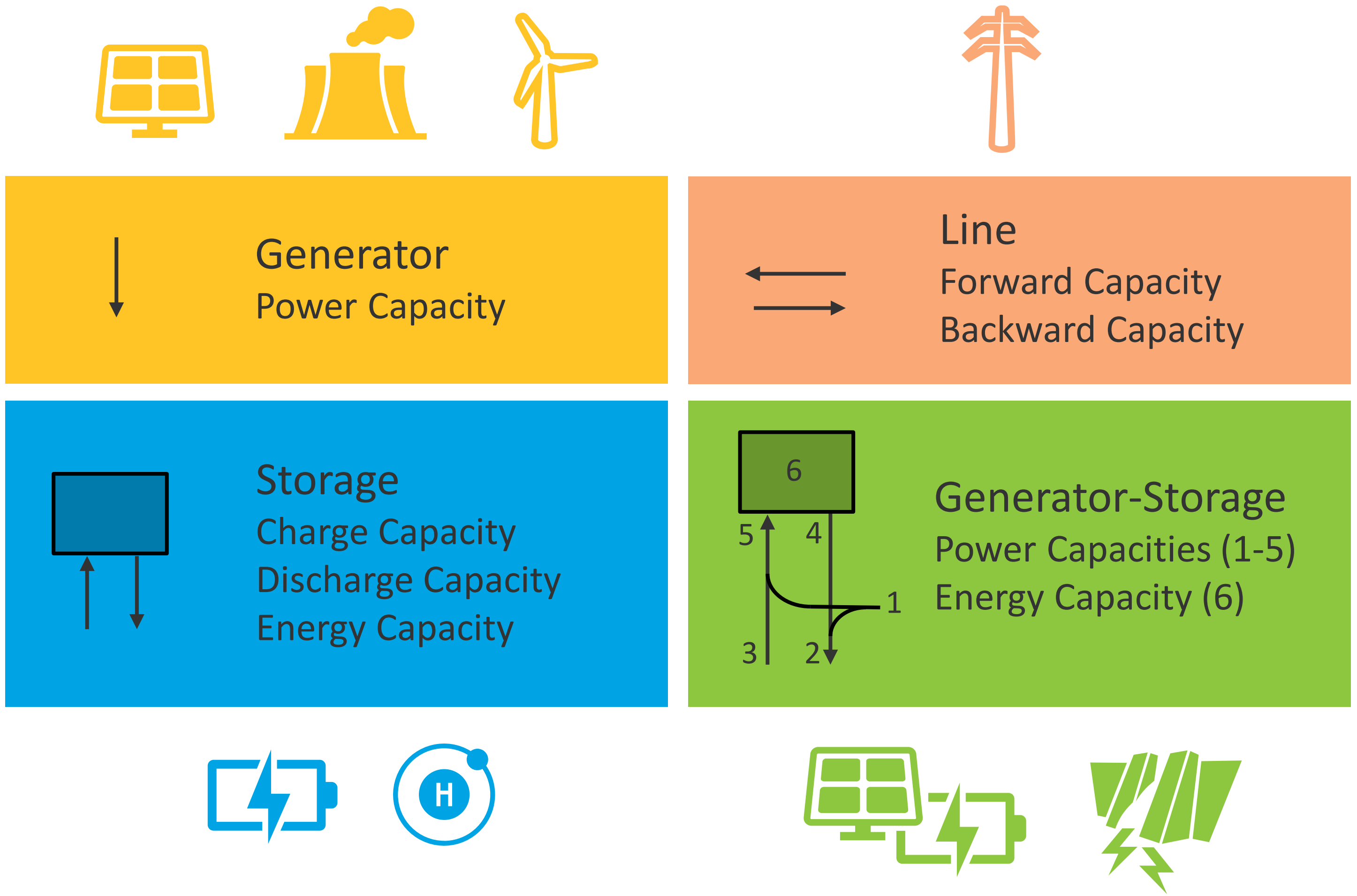
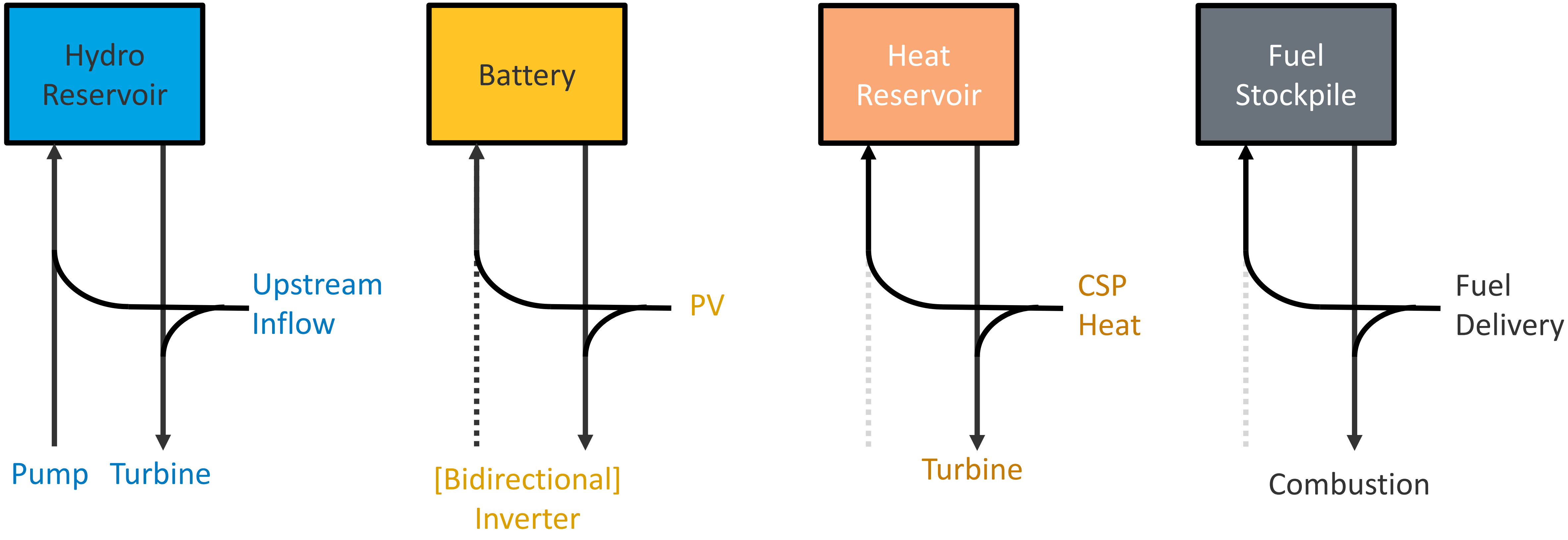
PRAS System Components



All components support reliability statistical data
(forced outage rate, mean time to repair)

Example Generator-Storage Applications



Probabilistic Simulations

Power system representation

Probabilistic simulations

Probabilistic outcomes

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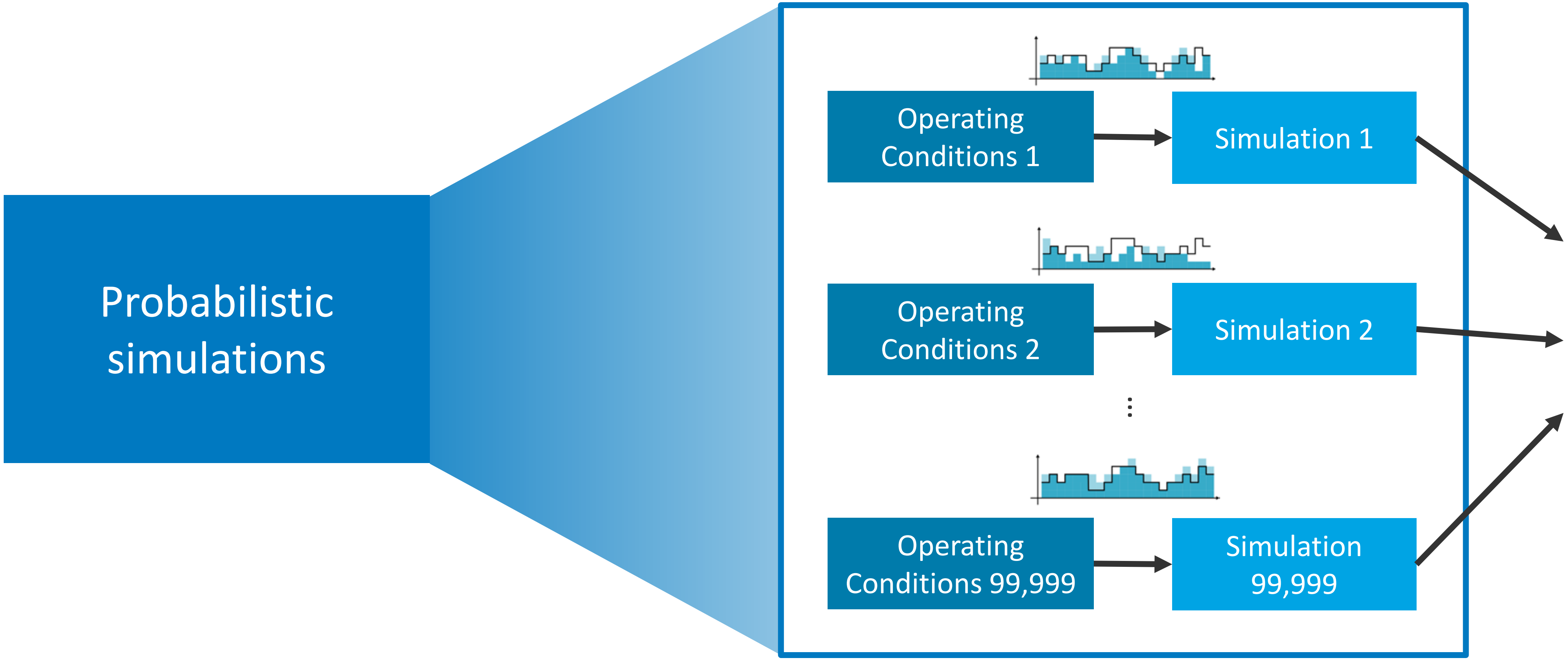
Probabilistic Simulations



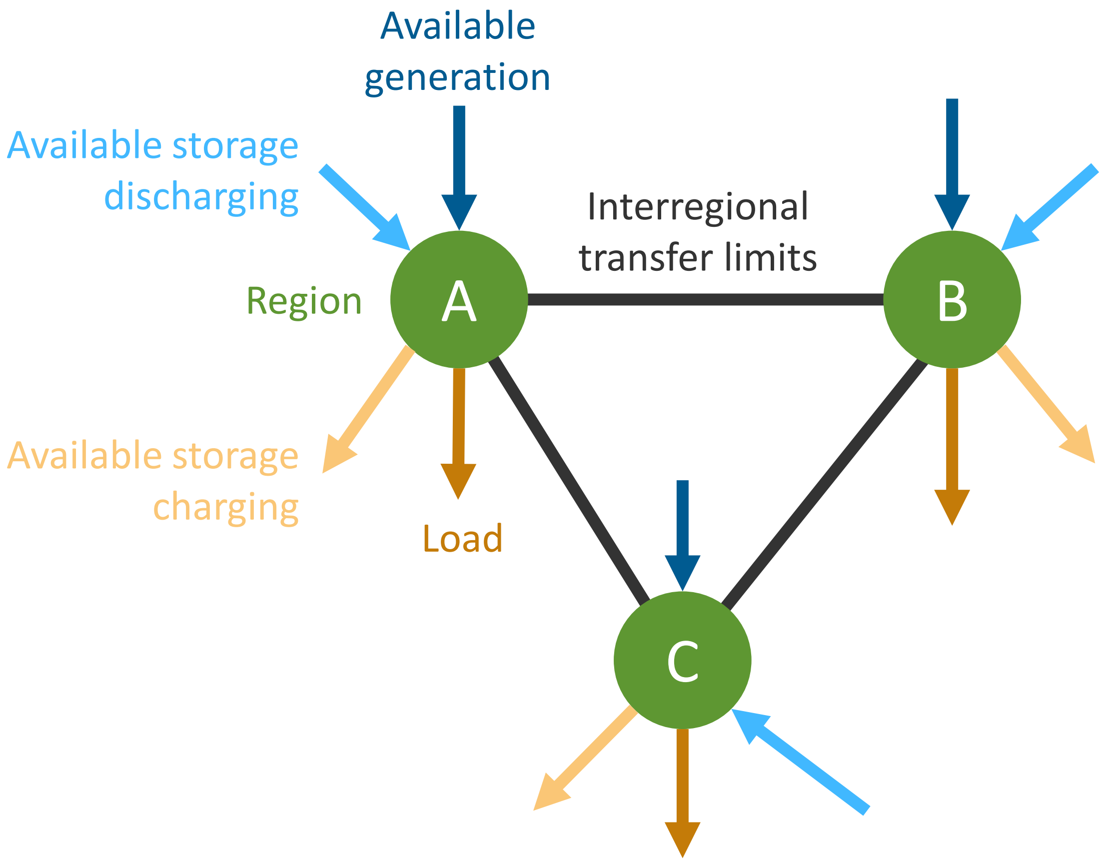
Operations Problem Formulation

Considers:

- Renewable profiles and dispatchable generator ratings
- Generator availability (outage rates)
- Storage power and energy ratings
- Load profiles
- Interregional transmission constraints ("pipe-and-bubble").

Does not consider:

- Costs and prices
- Unit commitment or economic dispatch
- AC or linearized nodal power flow.



PRAS Outputs

Power system representation

Probabilistic simulations

Probabilistic outcomes

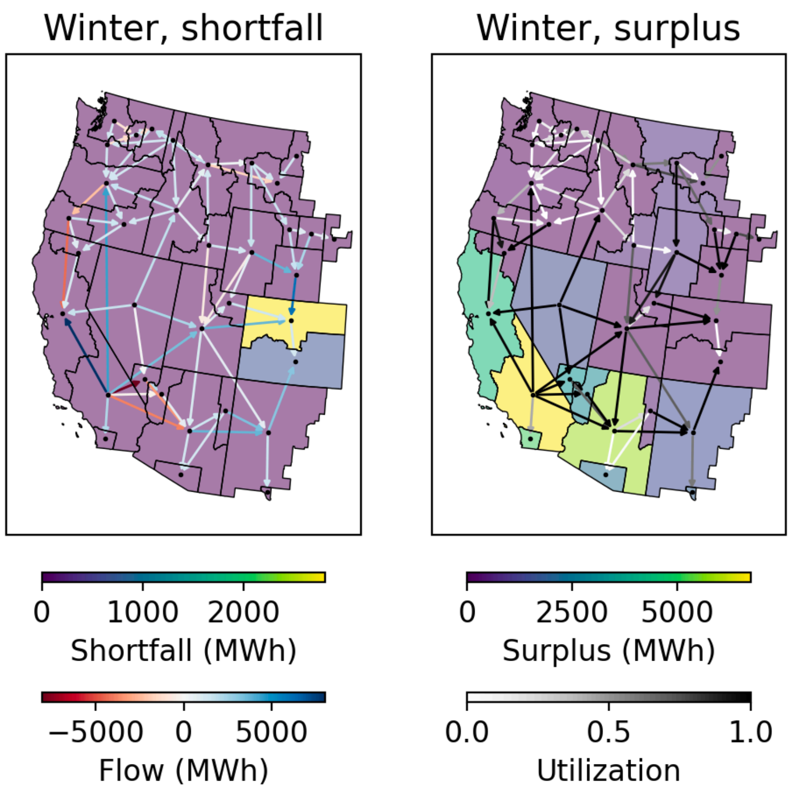
Regional load, generator ratings, reliability statistics, interregional transfer limits, etc

Randomly-drawn operating conditions + grid operations simulation under those conditions

Spatially and temporally resolved Expected Unserved Energy (EUE), Loss of Load Expectation (LOLE), Loss of Load Probability (LOLP), and so on

PRAS Outputs

Entity Type	Metric
Regions	**Shortfall** (EUE and LOLE)
	Surplus (megawatt-hour, MWh)
Interfaces	**Flow** (MW)
	Utilization (%)
Storages/Generator-Storages	**State-of-Charge** (MWh)
All Resources	**Availability Status**

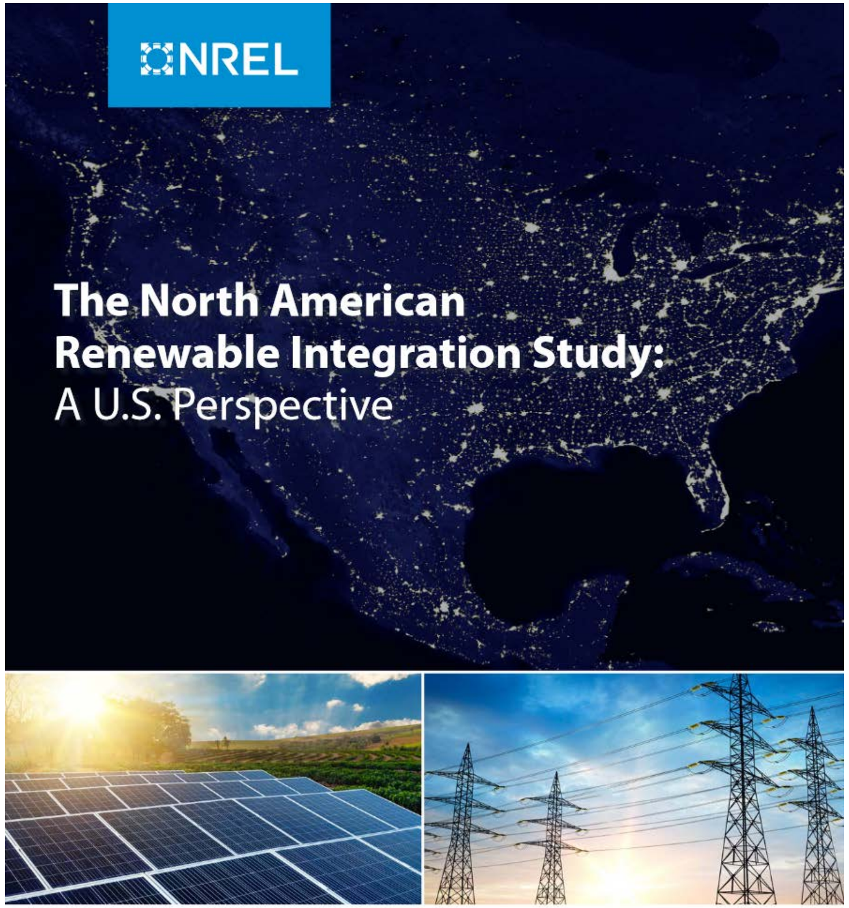


Most properties available as either sample-level outcomes or sample mean + standard deviation
Additional custom outputs available via user extensions

Use Cases

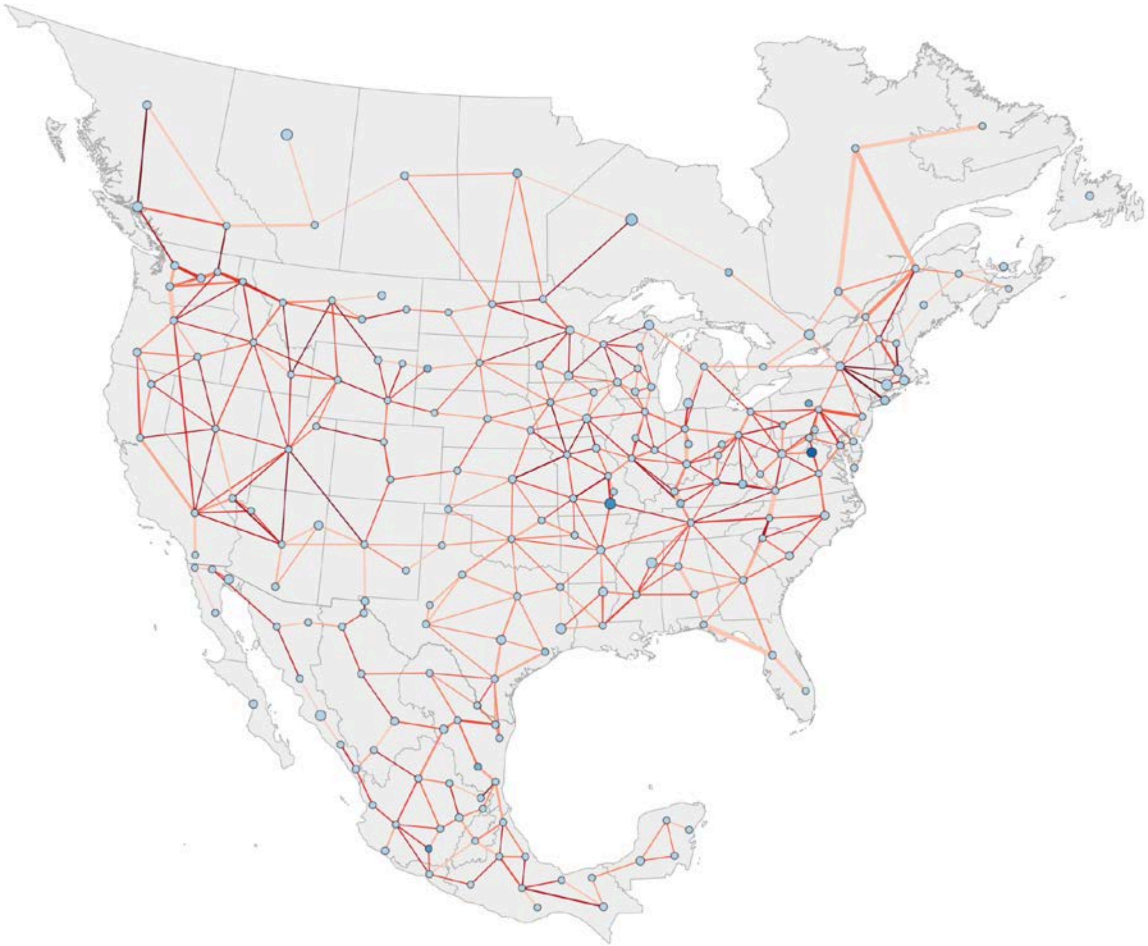
Photo by Werner Slocum, NREL 65316

Studying Large Systems…

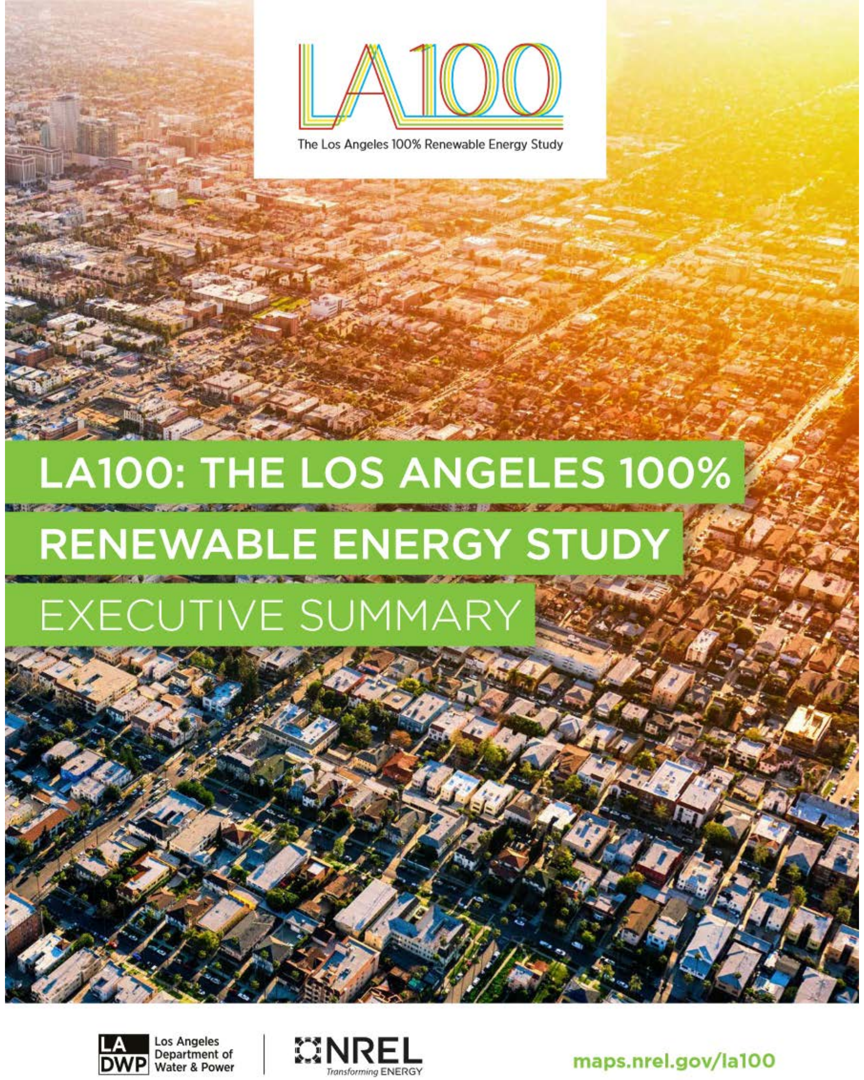


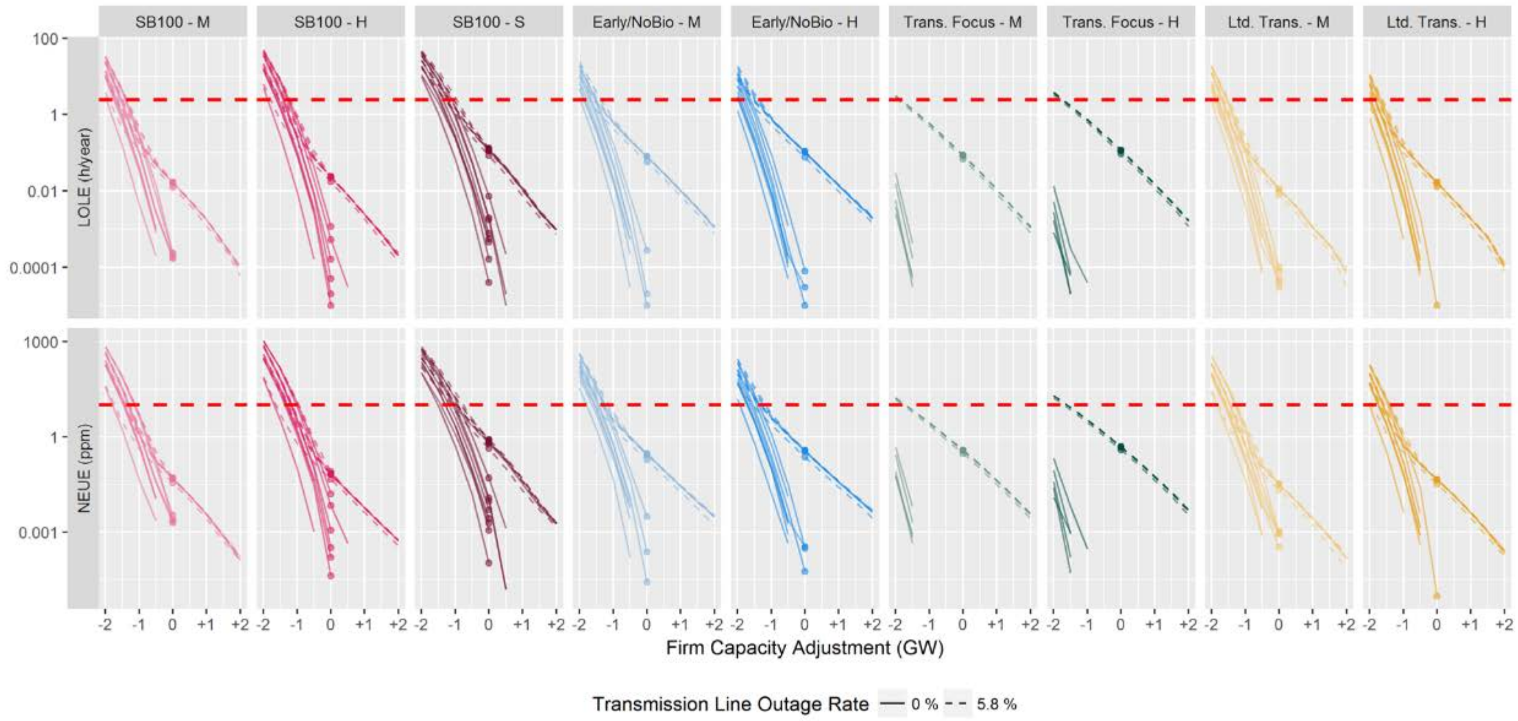
Gregory Brinkman,[1] Dominique Bain,[1] Grant Buster,[1] Caroline Draxl,[1] Paritosh Das,[1] Jonathan Ho,[1] Eduardo Ibanez,[2] Ryan Jones,[3] Sam Koebrich,[1] Sinnott Murphy,[1] Vinayak Narwade,[1] Joshua Novacheck,[1] Avi Purkayastha,[1] Michael Rossol,[1] Ben Sigrin,[1] Gord Stephen,[1] and Jiazi Zhang[1]

[1] National Renewable Energy Laboratory
[2] GE Energy
[3] Evolved Energy Research

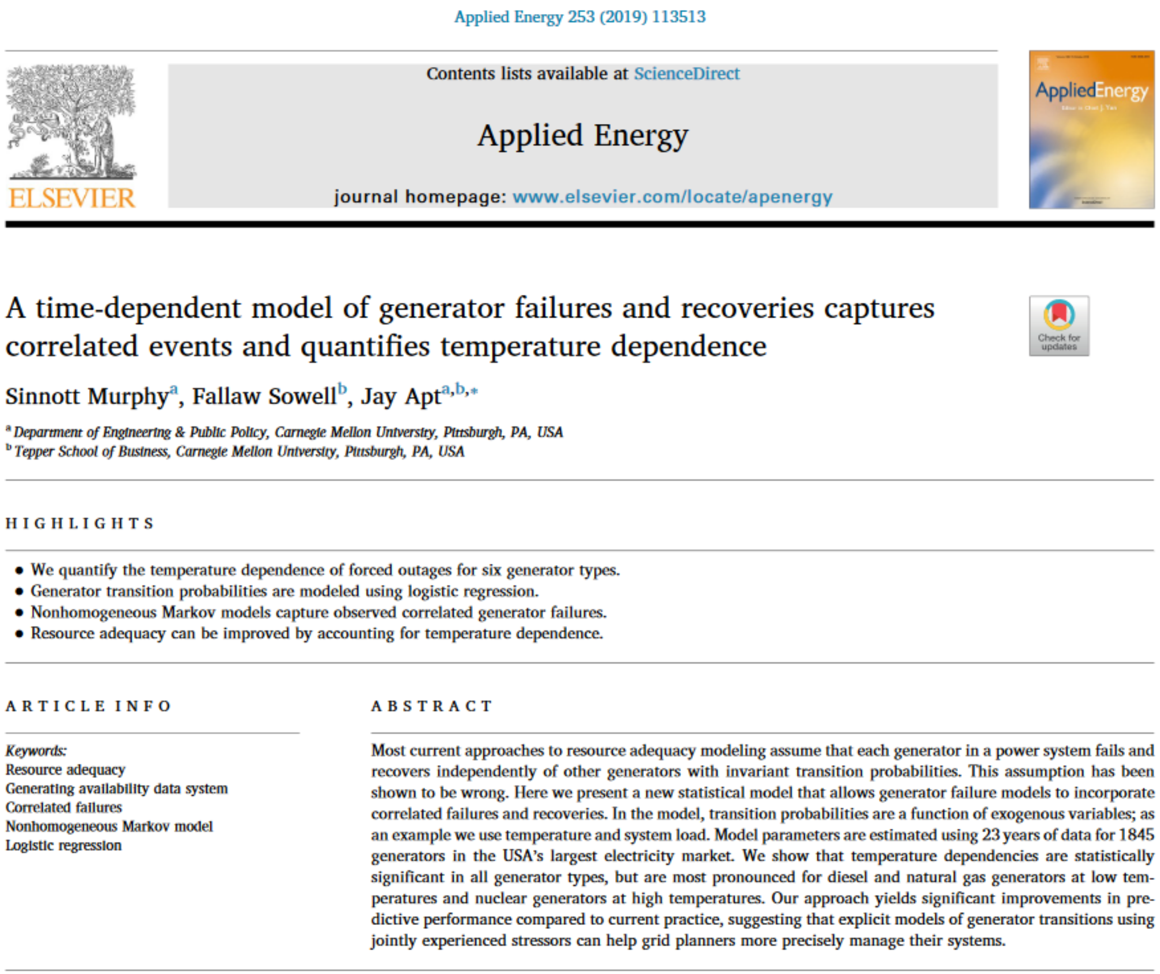


… and Large Scenario Spaces





Capturing Weather-Dependent Outages


Applied Energy 253 (2019) 113513

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence

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HIGHLIGHTS

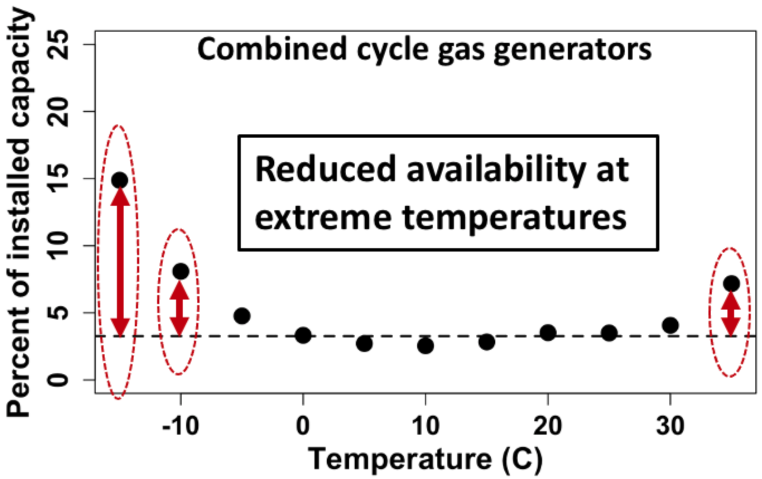
- We quantify the temperature dependence of forced outages for six generator types.
- Generator transition probabilities are modeled using logistic regression.
- Nonhomogeneous Markov models capture observed correlated generator failures.
- Resource adequacy can be improved by accounting for temperature dependence.

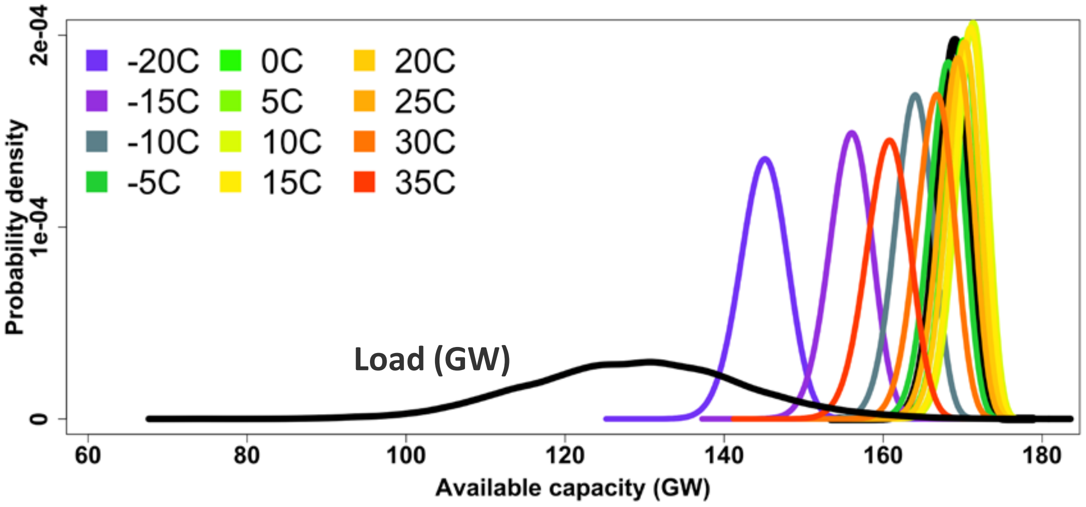
ARTICLE INFO

Keywords:
Resource adequacy
Generating availability data system
Correlated failures
Nonhomogeneous Markov model
Logistic regression

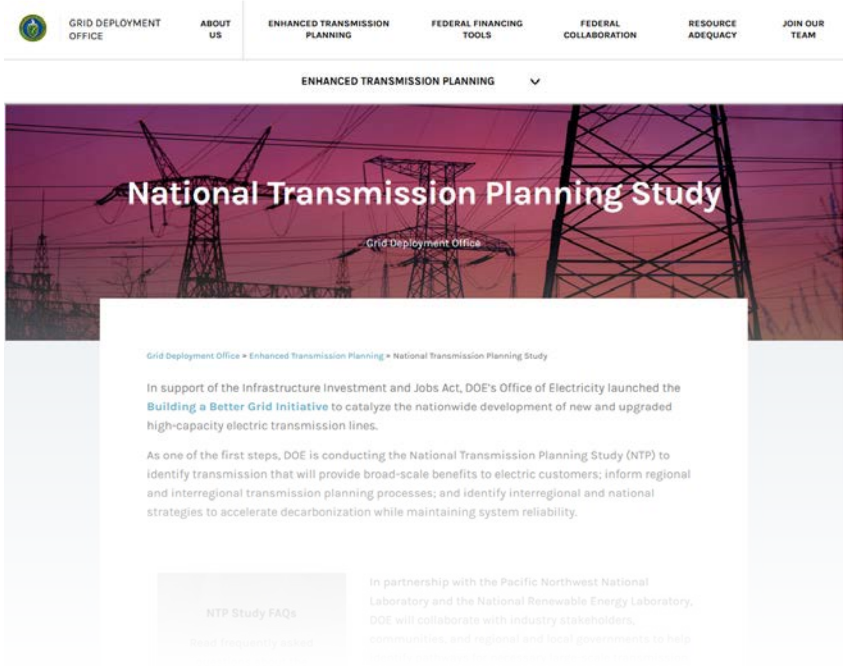
ABSTRACT

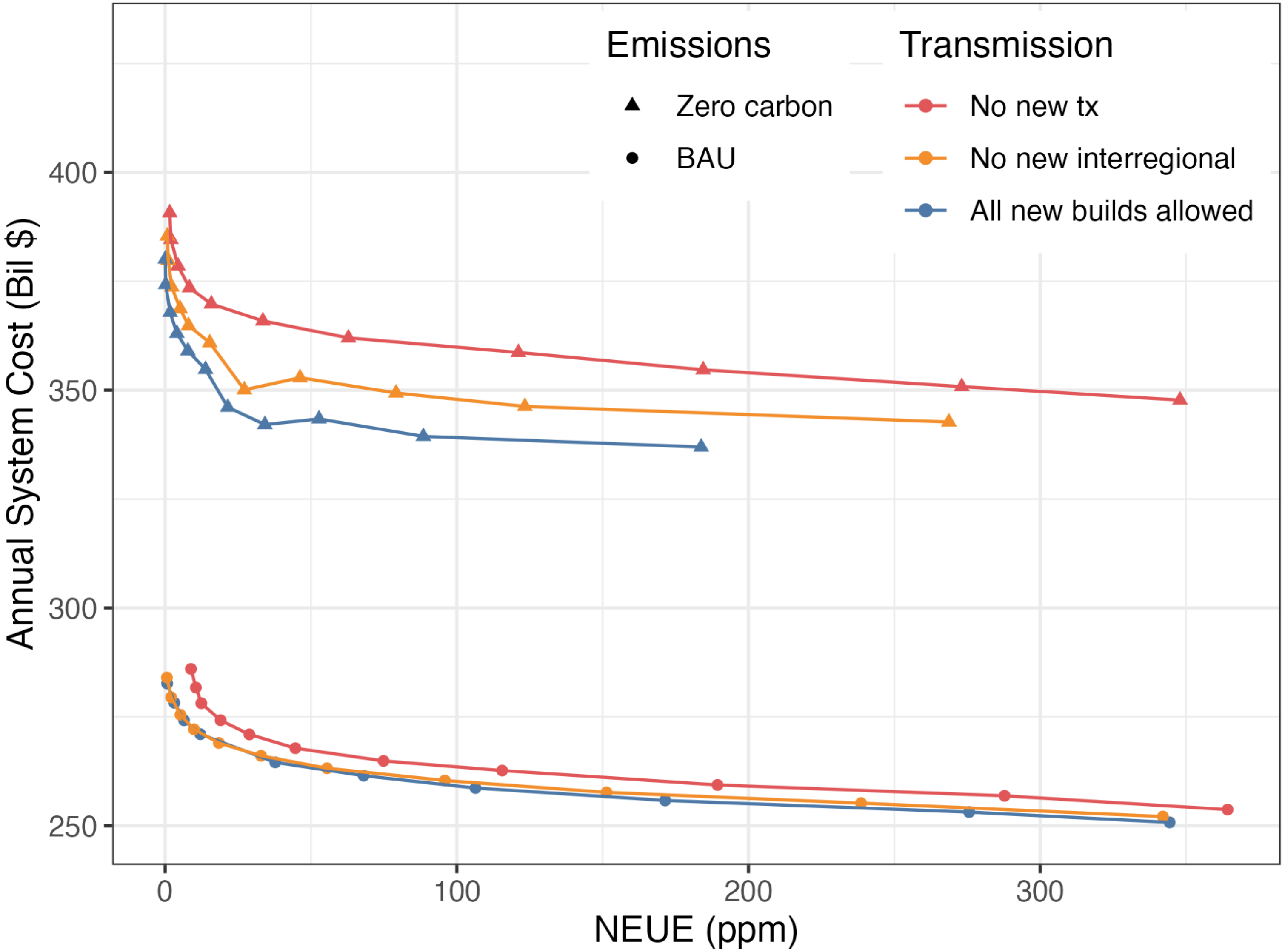
Most current approaches to resource adequacy modeling assume that each generator in a power system fails and recovers independently of other generators with invariant transition probabilities. This assumption has been shown to be wrong. Here we present a new statistical model that allows generator failure models to incorporate correlated failures and recoveries. In the model, transition probabilities are a function of exogenous variables; as an example we use temperature and system load. Model parameters are estimated using 23 years of data for 1845 generators in the USA's largest electricity market. We show that temperature dependencies are statistically significant in all generator types, but are most pronounced for diesel and natural gas generators at low temperatures and nuclear generators at high temperatures. Our approach yields significant improvements in predictive performance compared to current practice, suggesting that explicit models of generator transitions using jointly experienced stressors can help grid planners more precisely manage their systems.





Understanding Economic Trade-Offs





Complementing More Detailed Grid Simulations

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Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Insights into methodologies and operational details of resource adequacy assessment: A case study with application to a broader flexibility framework

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[b] Environmental Health and Engineering Department, Johns Hopkins University, Baltimore, MD, USA

HIGHLIGHTS

- We evaluate the impact of operational modeling details on resource adequacy results.
- Multi-stage probabilistic assessments may better capture operational details.
- Thermal generator outages may impact results more than solar forecast errors.
- Flexibility provided by hybrids can reduce the number of load-shedding events.
- Results are more sensitive to hybrid inverter sizing than other hybrid features.

ARTICLE INFO

Keywords:
Probabilistic resource adequacy modeling
Monte Carlo
Production cost modeling
Hybrid resources
ERCOT

ABSTRACT

Assessing and maintaining resource adequacy (RA) is a core pillar of power systems. However, recent changes in the physical makeup of these systems and the conditions under which these systems must operate have yielded a renewed interest in the methods, metrics, and assumptions that underpin RA assessments. In this paper, we systematically explore a wide range of RA modeling dimensions, including: the objective function and level of operational detail in the underlying model formulation; the quantity (look-ahead) and quality (accuracy) of data that is available for making operational decisions within those models; and the physical configuration of solar photovoltaics (PV) with battery storage hybrid resources. We apply a set of probabilistic RA tools and production cost modeling tools to a realistic test system based loosely on a future Electric Reliability Council of Texas power system dominated by solar PV resources. Under the assumptions of our system and models, we find that multi-stage probabilistic assessments may provide a more robust evaluation of RA by capturing a wider range of operational and system interactions, but this comes at a computational cost of 1–2 orders of magnitude longer run time depending on the specific configuration. In addition, the information on thermal generator availability impacts RA performance by an order of magnitude more than solar resource forecasts, which is driven by the comparatively larger magnitude of thermal outages than solar forecast errors within our test system. Lastly, the flexibility provided by hybrid and other resources can help reduce system load-shedding event frequencies and enable the system to be more robust to inaccurate forecast information, and alternative hybrid inverter sizes can impact RA levels by 1–2 orders of magnitude. Our results point to the importance of a broader flexibility framework to describe the interaction between (1) flexibility "supply" from both physical resource capabilities and operational constraints considered in the modeling, and (2) flexibility "demand" from forecast errors, thermal generator outages, and other sources of uncertainty, as well as their RA impacts. Results are likely sensitive to the system buildout explored; future work could consider additional system configurations and conditions.

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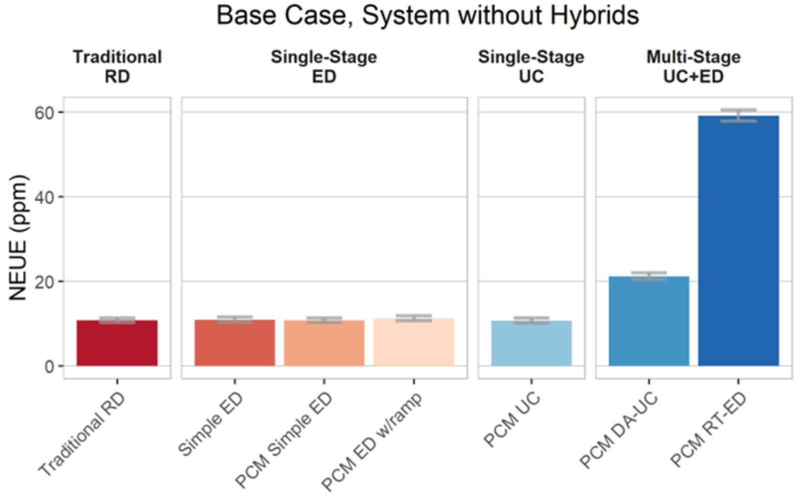
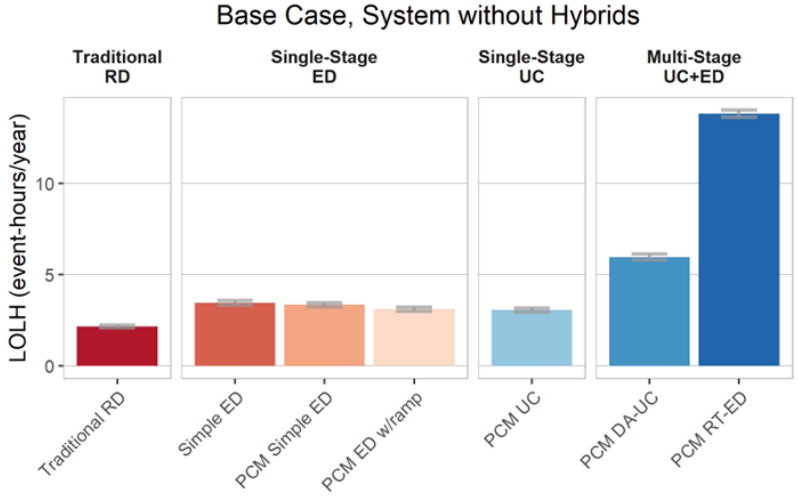
E-mail address: Yinong.Sun@nrel.gov (Y. Sun).





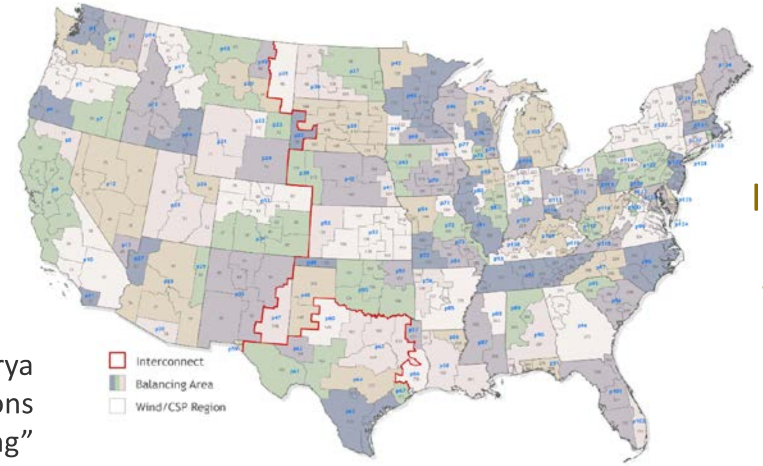
Coupling Capacity Expansion and Resource Adequacy

Beyond Capacity Credits: Adaptive Stress Period Planning for Evolving Power Systems

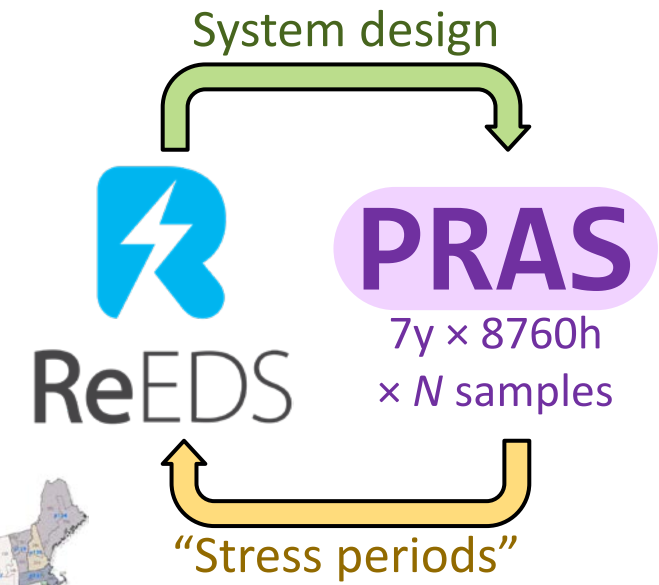
Jess Kuna, Gord Stephen, and Trieu Mai

National Renewable Energy Laboratory

Forthcoming: Trieu Mai, Patrick R. Brown, Luke Lavin, Surya Dhulipala, and Jess Kuna, “Incorporating Stressful Grid Conditions for Reliable and Cost-Effective Electricity System Planning”



Disaggregate MW capacity into individual **units**
Apply hourly failure and recovery **probabilities**



Identify days with highest risk of **unserved energy** and include them in the Regional Energy Deployment System (ReEDS)

Interested in Using PRAS for Yourself?

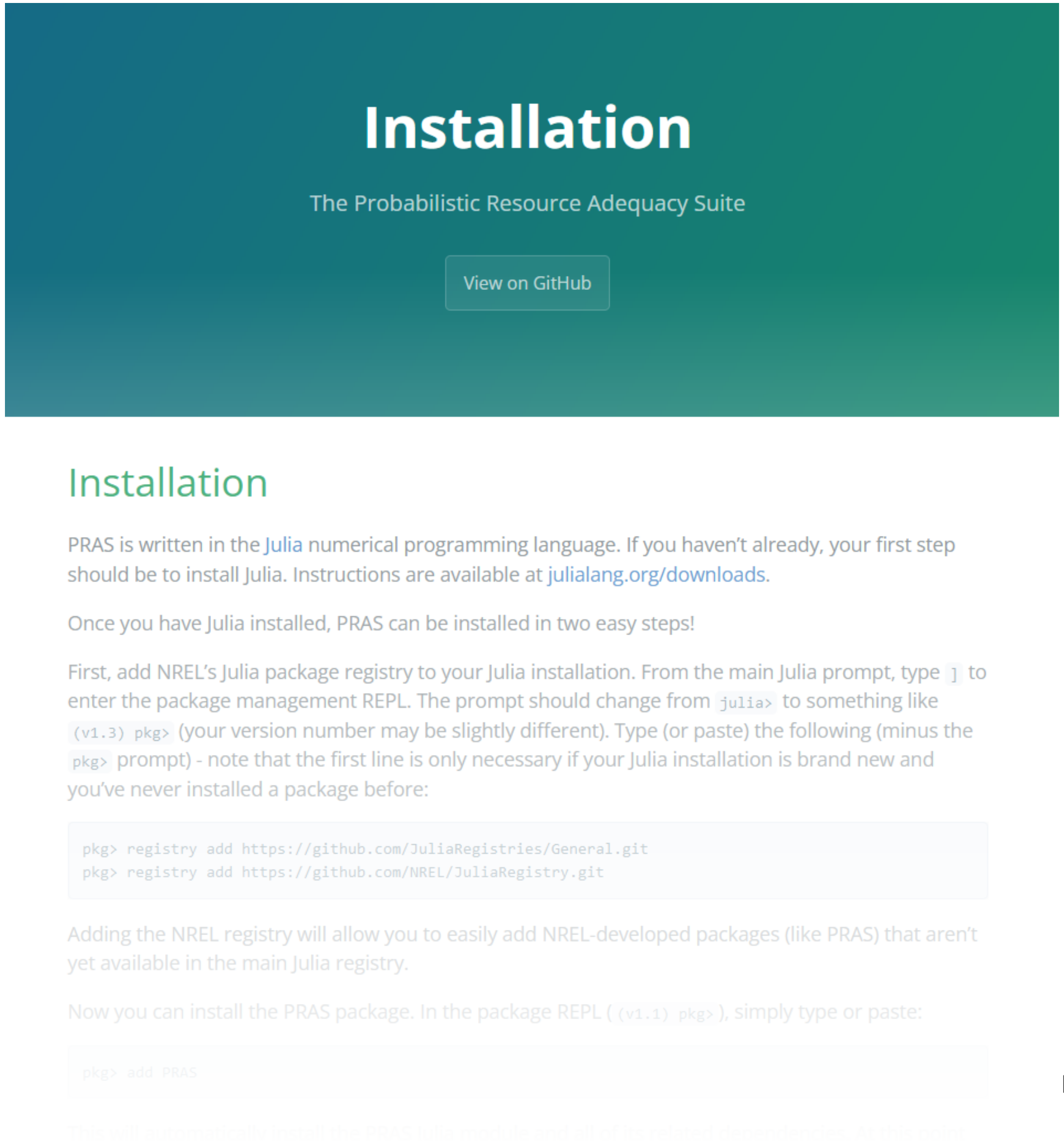
Julia

```
               _
   _       _ _(_)_     |  Documentation: https://docs.julialang.org
  (_)     | (_) (_)    |
   _ _   _| |_  __ _   |  Type "?" for help, "]?" for Pkg help.
  | | | | | | |/ _` |  |
  | | |_| | | | (_| |  |  Version 1.9.3 (2023-08-24)
 _/ |\__'_|_|_|\__'_|  |  Official https://julialang.org/ release
|__/                   |

julia> using PRAS

julia> sys = SystemModel("rts.pras");

julia> length(sys.generators)
153

julia> shortfall, storage_soc = assess(sys, SequentialMonteCarlo(samples
=40000), Shortfall(), StorageEnergy());

julia> eue = EUE(shortfall)
EUE = 0.07±0.03 MWh/8784h

julia> lole = LOLE(shortfall)
LOLE = 0.0006±0.0002 event-h/8784h

julia> _
```

Accessing PRAS

PRAS is free and open-source software—try it today!

Installation and Getting Started instructions are available at nrel.github.io/PRAS



Installation

The Probabilistic Resource Adequacy Suite

View on GitHub

Installation

PRAS is written in the Julia numerical programming language. If you haven't already, your first step should be to install Julia. Instructions are available at julialang.org/downloads.

Once you have Julia installed, PRAS can be installed in two easy steps!

First, add NREL's Julia package registry to your Julia installation. From the main Julia prompt, type `]` to enter the package management REPL. The prompt should change from `julia>` to something like `(v1.3) pkg>` (your version number may be slightly different). Type (or paste) the following (minus the `pkg>` prompt) - note that the first line is only necessary if your Julia installation is brand new and you've never installed a package before:

```
pkg> registry add https://github.com/JuliaRegistries/General.git
pkg> registry add https://github.com/NREL/JuliaRegistry.git
```

Adding the NREL registry will allow you to easily add NREL-developed packages (like PRAS) that aren't yet available in the main Julia registry.

Now you can install the PRAS package. In the package REPL (`(v1.1) pkg>`), simply type or paste:

```
pkg> add PRAS
```

Looking Ahead

Planned enhancements for 2025:

- Better economics (merit order dispatch, price-sensitive demand)
- Optional friction/suboptimalities in interregional resource sharing
- C and Python interfaces

Photo from iStock-627281636

Questions?

www.nrel.gov NREL/PR-6A40-91234

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