IDAES Framework for Grid Expansion Planning Models

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Advanced PSE+ Stakeholder Summit

09/18/2024

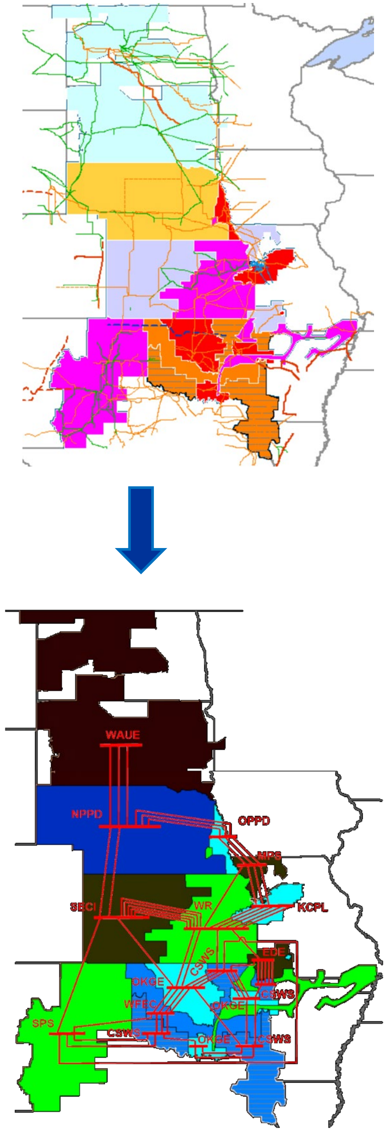
Expansion Planning and Why it is Hard

- **What is a capacity expansion model?** – Determining lease cost deployment of technologies to meet future load demand **over multi-decade horizons in a region** (state, ISO/RTO, nationwide)
  - What technologies/ designs **deployed, when and where?**
  - What generators will be **retired, renewed** and what technologies are **phased out**?

- At the core, an expansion planning model considers
  - Systems with **>10^2** generators, **>10^3** transmission lines,
  - Balancing loads over each of **10^6 time periods**,
  - With numerous opportunities to install, extend, and retire assets,
  - And significant uncertainty in all parameters (generator costs, available technology, load growth and patterns, renewable resources),

- **Too large to "directly solve"**

- Numerous **simplifications and approximations to develop "tractable" models** which **will impact accuracy**
  - ACOPF → DCOPF → Transshipment
  - Full network → "skeletonized" network → "copper plate"
  - Individual generators → generator clusters
  - Full time horizon → representative days → representative loads
  - Discrete decisions → continuous relaxations



Why is IDAES Developing Expansion Planning Models?

- Integrated Energy Systems must be designed for the *system*
  - Designing in isolation (e.g., “max efficiency”) does not guarantee participation / revenue from the market

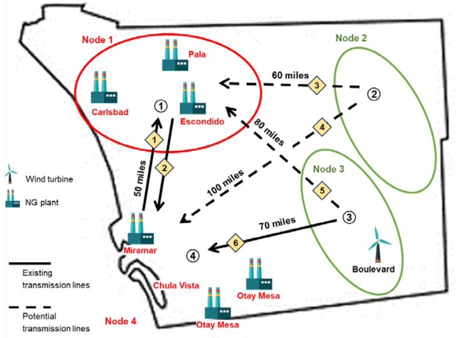
- Existing expansion planning models focus primarily on *capacity*
  - Operability (e.g., the role of **dynamics, flexibility, and uncertainty**) is not explicitly included, leading to results that overvalue LCOE and undervalue dispatchability and flexibility
  - New and diverse set of technologies **needed to reach decarbonization goals**
  - **Advanced algorithms required** to solve new, challenging problems

- Extending expansion planning models is more than just adding features
  - Scaling up the model requires exploring new algorithmic approaches to solving the model. **Model is open, allowing for customization for the problem you are interested in addressing**

Solving Problems that Represent Today’s Challenges

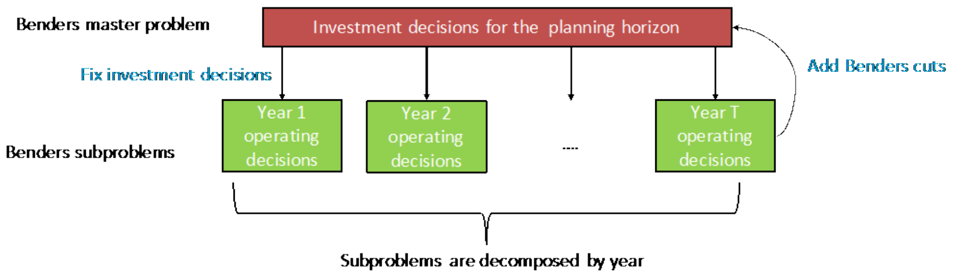
Improved capabilities in models (e.g. reliability)

San Diego County Case Study



Begin with smaller, **less complex models** (smaller regions/ time-scales)

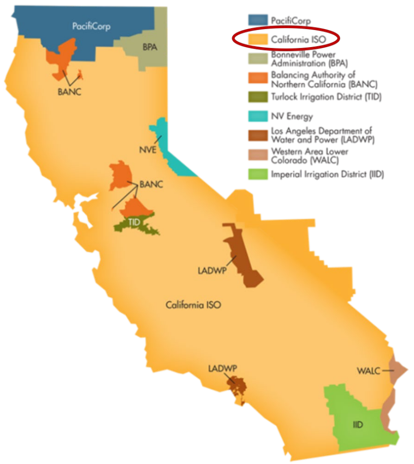
Advanced Algorithms



Higher Complexity

Improve/ develop new algorithms to address convergence challenges

ISO/RTO Scale Problem



Improved capability to address challenging problems on complex models

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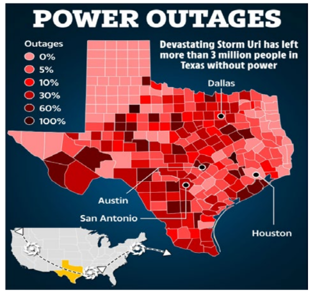
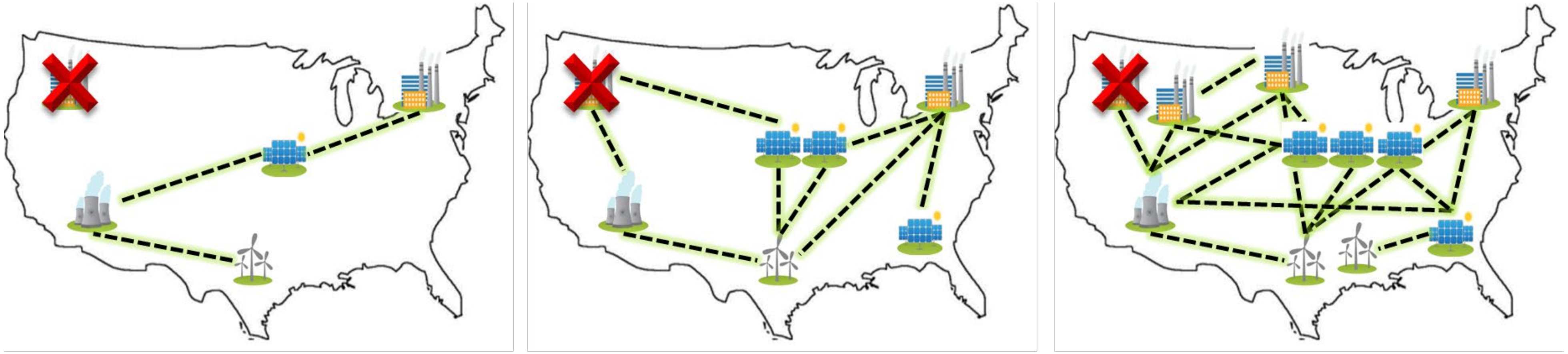
Reliability motivation

- ***Reliability*** An ability of power systems to supply uninterrupted electricity to satisfy the demand.
- *Why is it important?*

→ Failure of components in power systems leads to major disruptions (e.g., 2021 Texas Outage)



- Adding extra generators, batteries, and transmission lines can improve the reliability of power systems.
- In case some generators fail, other connected generators can replace the workload of failed ones to minimize power loss.
- **Issue:** optimize where, when, and what type and size of *generators and transmission lines* should be added to satisfy the load demand while improving reliability at a minimum cost.



Reliability ↑

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[1] Ben Hill, Niamh Cavanagh, Sarah Grealish, "POWER OUT Texas outage map: When will power be back on?", THE U.S. Sun, February 18, 2021

Reliability definition

Design reliability (Resource adequacy)[2]

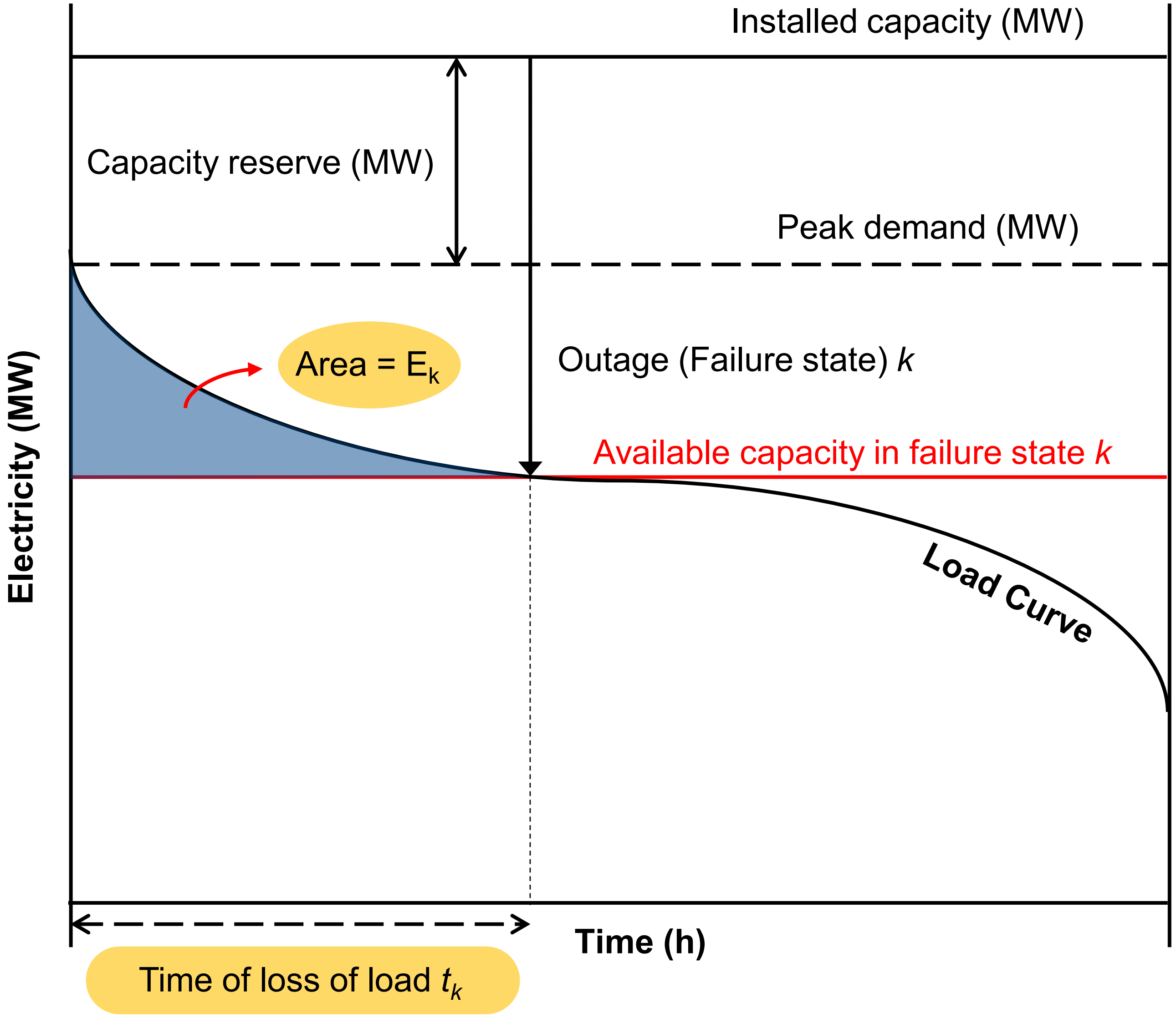
- The ability to supply enough electricity
- Focus on ensuring sufficient capacity.
- Measured by the probability of failure (inherent properties of generators and lines)
- Renewable generators are known to have lower probability of failures than dispatchable generators[4].
- Evaluated by two factors: loss of load expectation (LOLE) and expected energy not served (EENS)

Operational reliability (or flexibility)[3]

- The ability to balance supply and demand and rapidly respond to unexpected events.
- Focus on optimizing operation strategies
- Dispatchable generators are known to be more flexible than renewable generators.
- Evaluated by load shedding (unmet demand)

[2] NREL, Resource Adequacy, https://www.nrel.gov/research/resource-adequacy.html
[3] NREL, Operational Reliability, https://www.nrel.gov/research/operational-reliability.html
[4] Generating Unit Statistical Brochure (2020), https://www.nrc.gov/reading-rm/basic-ref/glossary/outage.html

Reliability evaluation



1) **LOLE** (Loss of Load Expectation, unit: ***hours***): **the time** of not satisfying the load demand.

$$LOLE = \sum_{k=1}^{n} p_k t_k$$

p_k: Probability of capacity failure state k
t_k: Outage time of capacity failure state k

2) **EENS** (Expected Energy Not Served, unit: ***MWh***): **the amount of demand** that is not satisfied.

$$EENS = \sum_{k=1}^{n} p_k E_k$$

E_k: Unserved energy in capacity failure state k

LOLE & EENS ↓

→ Power System Reliability ↑

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[4] Generating Unit Statistical Brochure (2020), https://www.nrc.gov/reading-rm/basic-ref/glossary/outage.html

Model 1 : Expansion planning model without reliability

Generalized Disjunctive Programming (GDP) model[5,6]

Min Cost = CAPEX + OPEX + Curtailment penalty

Python 3.10.12
Pyomo 6.6.2

s.t.

Investment constraints

- Installation/lifetime extension/early retirement of dispatchable generators
- Installation of renewable generators and battery & transmission lines

Operation & reliability constraints

- Power balance and unit commitment for dispatchable generators
- State of charge/discharge of battery (storage systems)
- Power flow of transmission line (simple network and DC power flow)
- CO_2 emission estimation & minimum share of renewable generation

[5] I. E. Grossmann et al., "Systematic Modeling of Discrete-Continuous Optimization Models through Generalized Disjunctive Programming", AIChE Journal, 2013
[6] F. Trespalacios et al., "Review of Mixed-Integer Nonlinear and Generalized Disjunctive Programming Method", Chemie Ingenieur Technik 86, 2014

Model 2 : Reliability-constrained planning model

Generalized Disjunctive Programming (GDP) model[5,6]

Min Cost = CAPEX + OPEX + Curtailment penalty
+ Design reliability penalty (LOLE and EENS penalties)

s.t.

Investment constraints

- Installation/lifetime extension/early retirement of dispatchable generators
- Installation of renewable generators and battery & transmission lines

Operation & reliability constraints

- Power balance and unit commitment for dispatchable generators
- State of charge/discharge of battery (storage systems)
- Power flow of transmission line (simple network and DC power flow)
- CO_2 emission estimation & minimum share of renewable generation
- Probability of each failure state using a forced outage rate of generators and/or transmission lines
- Estimation of power production under each failure state
- **Simplified** LOLE (loss of load expectation) and EENS (expected energy not served) estimation

PYOMO GDP

Python 3.10.12
Pyomo 6.6.2

Rigorous LOLE and EENS analysis requires the enumeration of all capacity failure states of all facilities. However, this work only considers the failures of some critical nodes and facilities.

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[5] I. E. Grossmann et al., "Systematic Modeling of Discrete-Continuous Optimization Models through Generalized Disjunctive Programming", AIChE Journal, 2013
[6] F. Trespalacios et al., "Review of Mixed-Integer Nonlinear and Generalized Disjunctive Programming Method", Chemie Ingenieur Technik 86, 2014

Algorithm for reliable expansion planning

Model 1. Expansion planning model **w/o reliability**

Min Cost = CAPEX + OPEX + Curtailment penalty

s.t.
- Installation of **generators and battery & transmission lines**
- **Unit commitment, stage of charge/discharge, DC power flows**
- **Fuel consumption and CO_2 emission estimation**

Using the optimal results of Model 1,

✓ Identify ***N*** numbers of critical **nodes** where the power loss is expected to be significant in the event of a failure.

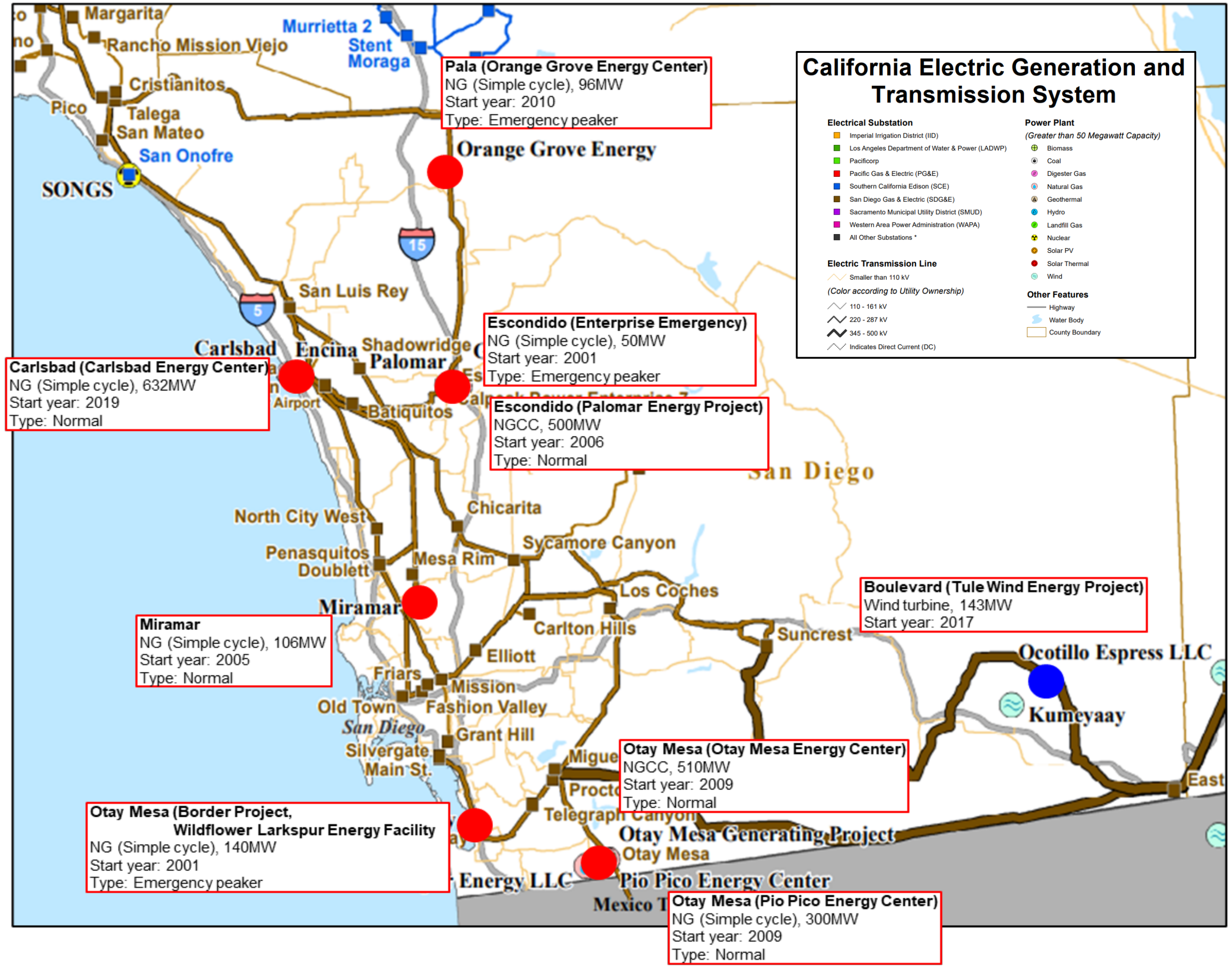
✓ Select ***N*** numbers of critical **generators** that largely account for demand satisfaction.

Model 2. Reliability-constrained planning model

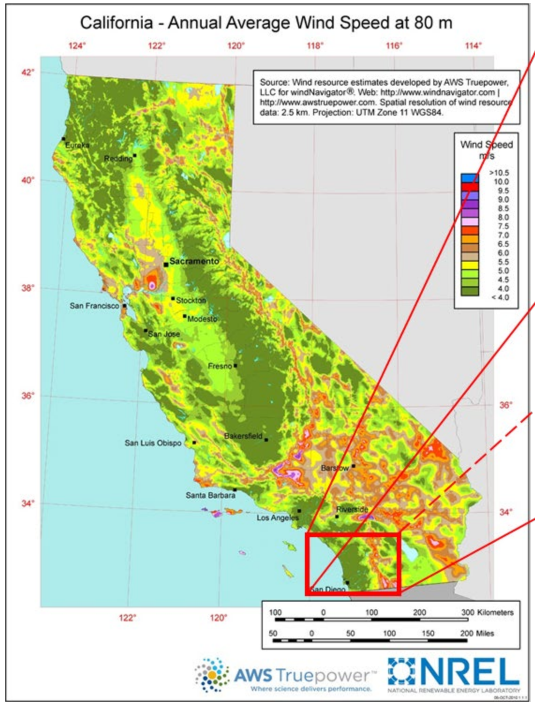
Min Cost = CAPEX + OPEX + Curtailment penalty
+ Design reliability penalties (i.e. LOLE and EENS penalties)

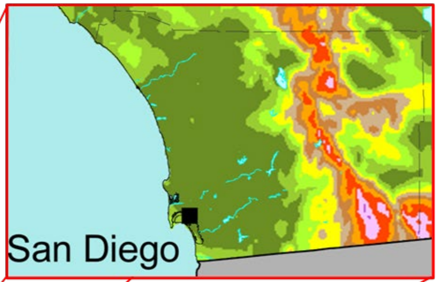
s.t.
- Installation of **generators and battery & transmission lines**
- **Unit commitment, stage of charge/discharge, DC power flows**
- **Fuel consumption and CO_2 emission estimation**
- **Enumeration of capacity failure state and probability of state**
- **LOLE and EENS estimation**

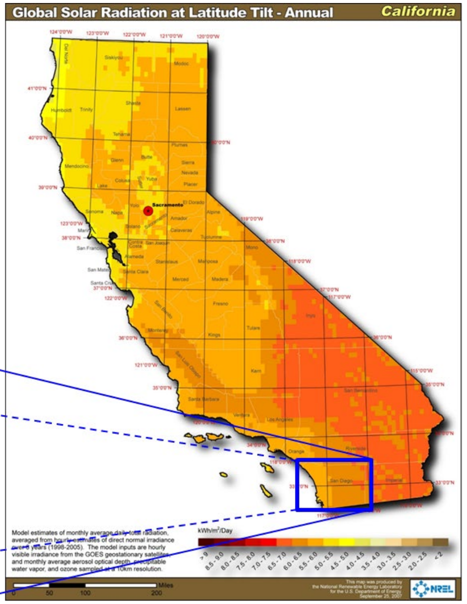
Case Study: Resource & Technology Status of San Diego County in 2021

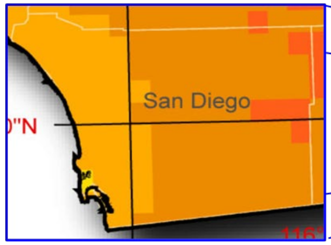


< Generation and transmission network in 2021 >









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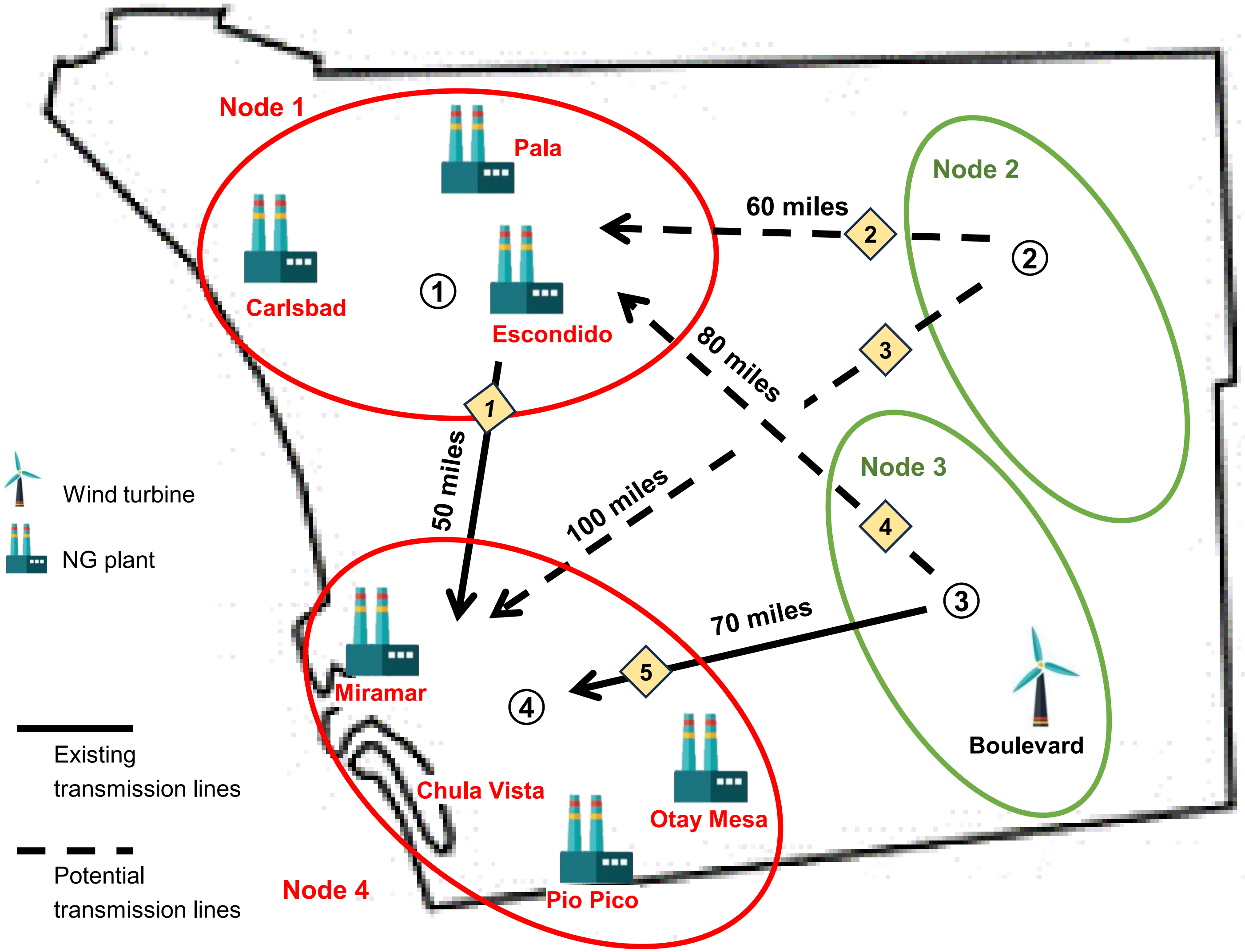
[7] Figure: https://cecgis-caenergy.opendata.arcgis.com/documents/CAEnergy::california-electric-generation-and-transmission-system-part-2-of-2, modified 2021-12-14

Case Study: Representation of San Diego County



Latitude/Longitude
① 32.210880 / -117.190754 ② 33.232716 / -116.320088
③ 32.702726 / -116.270649 ④ 32.590562 / -116.802113

- ✓ Horizon: **10-year planning (planning interval: 2 years, a total of 5 planning periods)**
- ✓ 5 representative days and 24 hours for each day (operation interval: 2 hours, a total of 12 operation periods)
- ✓ Size: **4 nodes**
  - ◯ Demand and supply nodes
  - ◯ Supply-only nodes

Assumptions

- ✓ Generator types: NG (Simple cycle), NGCC (w/o CCS), NGCC (w/ CCS), Wind turbine, PV, and Li-ion battery.
- ✓ **Supply-only nodes (green circle)** can only install **renewable generator** and **batteries.**
- ✓ **Dispatchable generators in demand and supply nodes (red circle)** can be extended, dispatchable generators (w/ and w/o CCS) can be installed, and renewable generators can be installed.
- ✓ Distance between nodes is estimated by measuring the distance between centers of each node.

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Case Study: Scenario generation

California Policy and Regulatory Environment[8]

	Case 1		Case 2		Case 3	
	Solution A	Solution B	Solution A	Solution B	Solution A	Solution B
The power load should always be satisfied (Loadshedding is not allowed) → Operation reliability should always be maximized						
Design reliability penalties (LOLE, EENS penalties)	x	√	x	√	x	√
CO_2 emission limits (**30%** reduction by 2030)[1]	x	x	√	√	√	√
Renewable generation share (**60%** of the total generation by 2030)[2]	x	x	x	x	√	√

[1] It is assumed that CO_2 emissions should gradually decrease over the planning horizon and reach a 30% reduction by 2030.

[2] 60% of the power demand should be satisfied by renewable generations and storage by 2030. It is also assumed to increase gradually.

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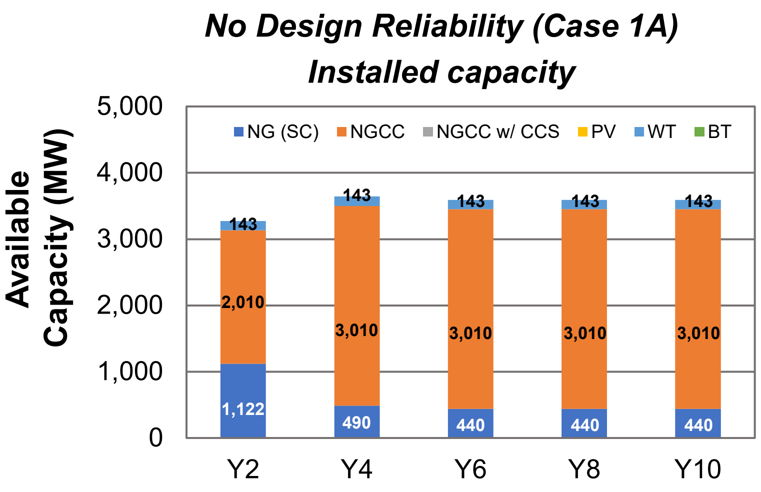
[8] California Peaker Power Plants: Energy Storage Replacement Opportunities, PSE Healthy Energy, 2020

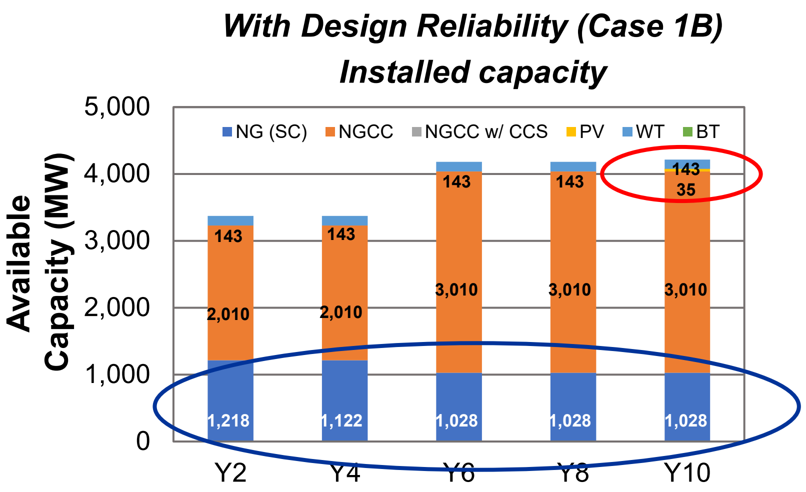
Case 1 Study Results

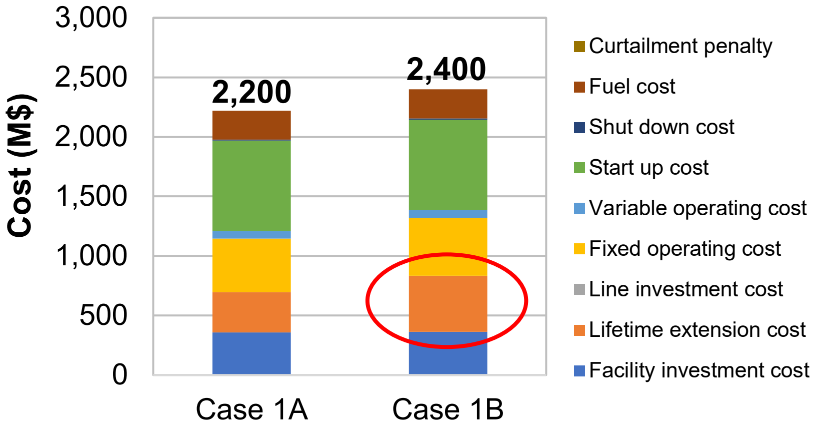
Python 3.10.12, Pyomo 6.6.2

Case 1 – No regulation on CO_2 emission & renewable generation

- 5 representative days (4 representative days + 1 day with the highest demand and lowest capacity factor)







- Total available capacity in Y10: **Case 1A – 3,593MW, Case 1B – 4,216MW (15% ↑)**
- Reliability is largely provided by extended life of simple cycle gas turbines.
- Some solar panels are installed as the probability of failure of solar panels is lower, but limited due to operational reliability (flexibility).
- Renewables, in general, are limited due to transmission and relatively higher costs.
- Increased cost largely due to lifetime extension.

[1] Generation only includes the amount of electricity used to meet the demand. Curtailment, the amount of electricity used to charge the battery, is not included. The generation from the battery indicates the amount of electricity discharged.

- The total cost is calculated after multiplying the weighting factor.

	# Binary	# Continuous	# Constraint	CPU (sec)	Gap (%)
Case 1A	39,767	80,585	271,353	88.5	0.9779
Case 1B	58,987	102,346	379,579	13.3	0.4119

Gurobi 10.0.2

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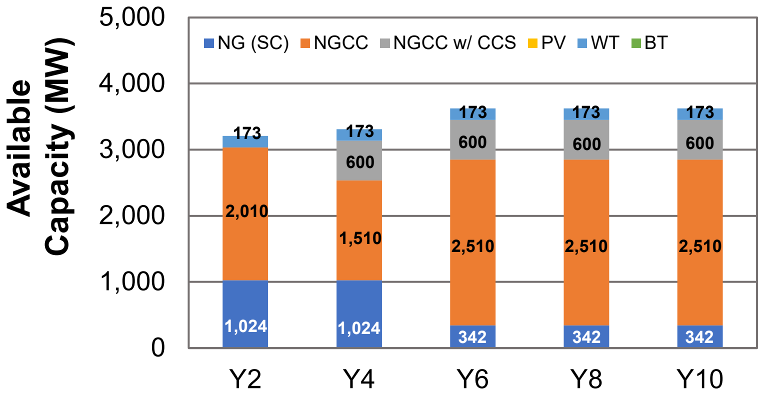
Case 2 study results

Python 3.10.12, Pyomo 6.6.2

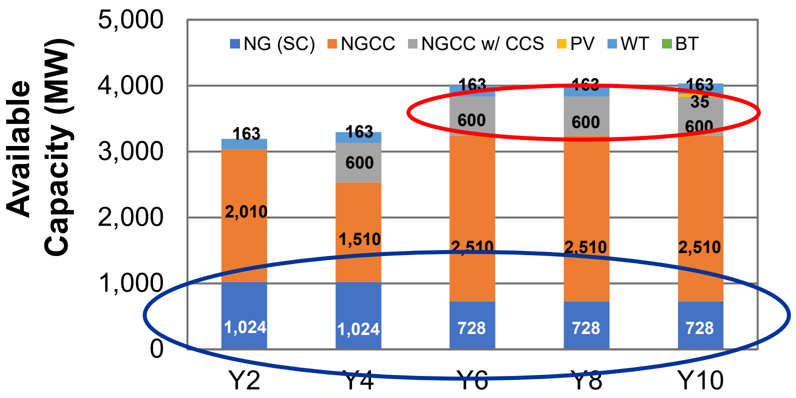
Case 2 – Only regulation on CO_2 emission (-30%)

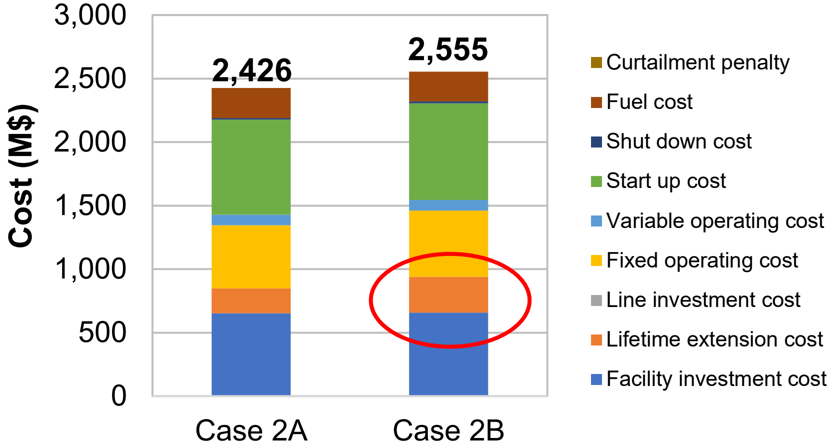
- 5 representative days (4 representative days + 1 day with the highest demand and lowest capacity factor)

No Design Reliability (Case 2A)
Installed capacity



With Design Reliability (Case 2B)
Installed capacity





- Total available capacity in Y10: **Case 2A – 3,625MW, Case 2B – 4,036MW (10% ↑)**
- Reliability still largely provided by lifetime extensions of simple turbines.
- CO_2 emission cuts largely provided by NGCC with CCS.
- Increase in cost in Case 2B largely driven by lifetime extension costs.

[1] Generation only includes the amount of electricity used to meet the demand. Curtailment, the amount of electricity used to charge the battery, is not included. The generation from the battery indicates the amount of electricity discharged.

- The total cost is calculated after multiplying the weighting factor.

	# Binary	# Continuous	# Constraint	CPU (sec)	Gap (%)
Case 2A	39,767	80,585	271,358	6,825	0.9959
Case 2B	58,967	102,346	379,549	40.4	0.9294

Gurobi 10.0.2

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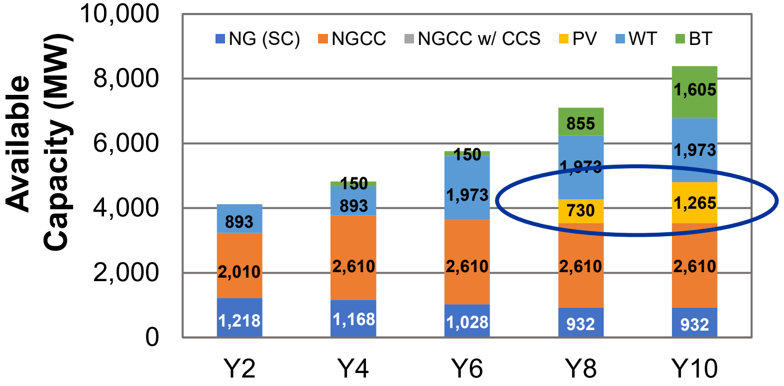
Case 3 study results

Python 3.10.12, Pyomo 6.6.2

Case 3 – CO_2 emission (-30%) & renewable generation (min 60%)

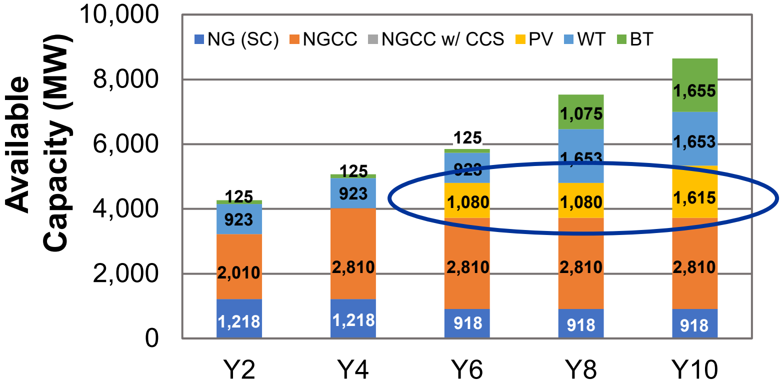
- 5 representative days (4 representative days + 1 day with the highest demand and lowest capacity factor)

No Design Reliability (Case 3A)
Installed capacity

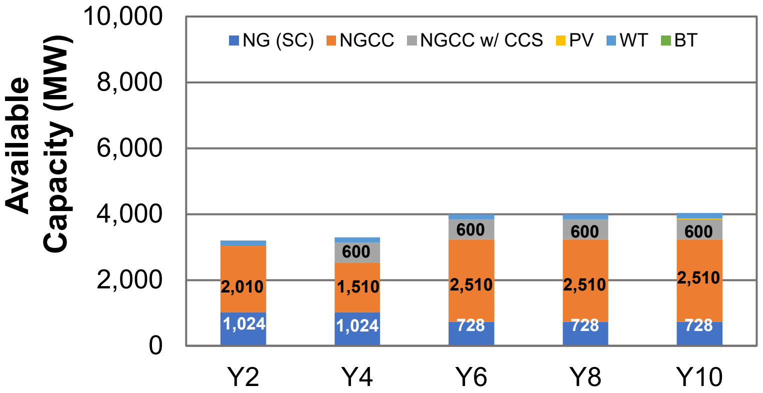


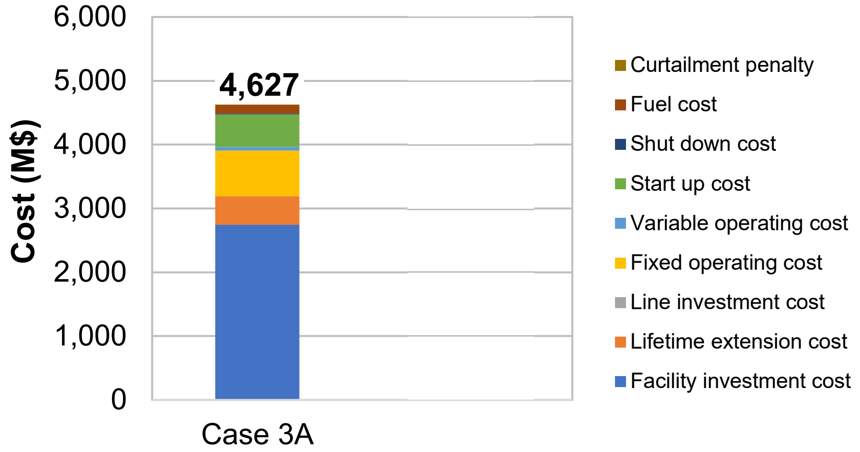
- Total available capacity in Y10:
  Case 3A – 8,385MW, Case 3B – 8,651MW (3%)
- Solar penetration higher because of higher reliability of solar generators.
- No CCS installed (emission cuts achieved through renewables).
- Min 60% renewable case results in drastically increased capacity requirements. Dispatchable power required effectively equivalent.
  Case 3B disp. – 3,728MW, Case 2B disp.– 3,838MW

With Design Reliability (Case 3B)
Installed capacity



With Design Reliability (Case 2B)
Installed capacity





[1] Generation only includes the amount of electricity used to meet the demand. Curtailment, the amount of electricity used to charge the battery, is not included. The generation from the battery indicates the amount of electricity discharged.

- The total cost is calculated after multiplying the weighting factor.

	# Binary	# Continuous	# Constraint	CPU (sec)	Gap (%)
Case 3A	39,767	80,585	271,363	25,200	8.4181
Case 3B	58,967	102,346	379,564	233.2	8.1096

Gurobi 10.0.2

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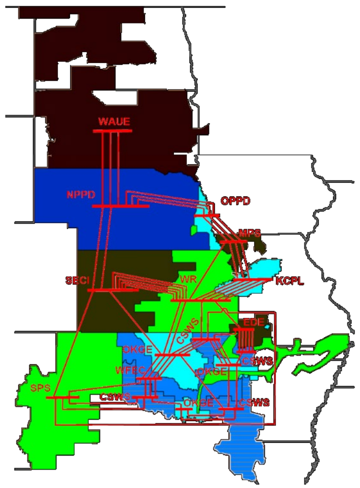
Accounting for Intermittency and Volatility

- “Non-representative” capacity and ramp scenarios critical in understanding dispatchable unit requirements

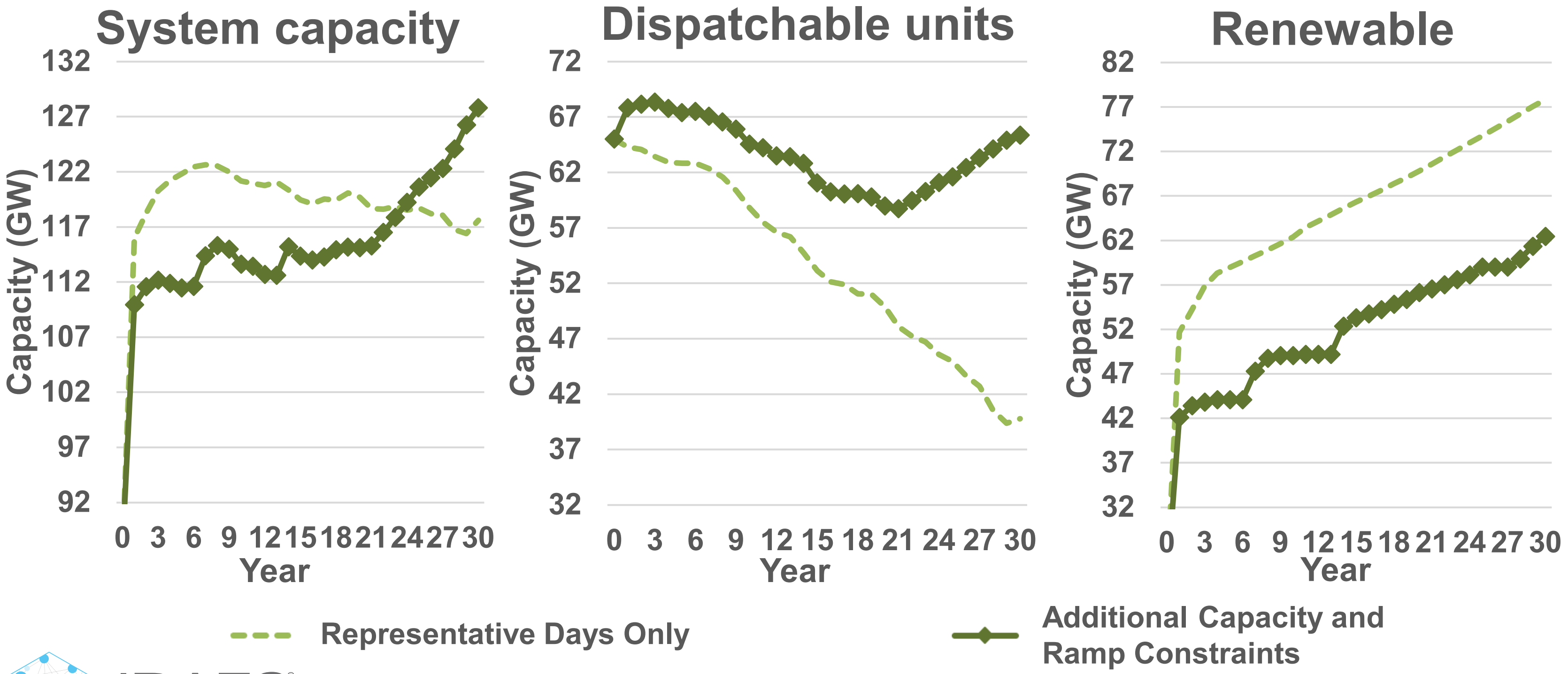
- Modified algorithm provides insights into low renewable capacity and/or rapid dispatchable ramp scenarios
  - Lazy capacity constraints
  - Extreme ramp events

SPP Case Study



- “Representative Days Only” underestimates total required capacity

- More dispatchable capacity required with inclusion with extreme scenarios



* SPP scenarios under high carbon tax

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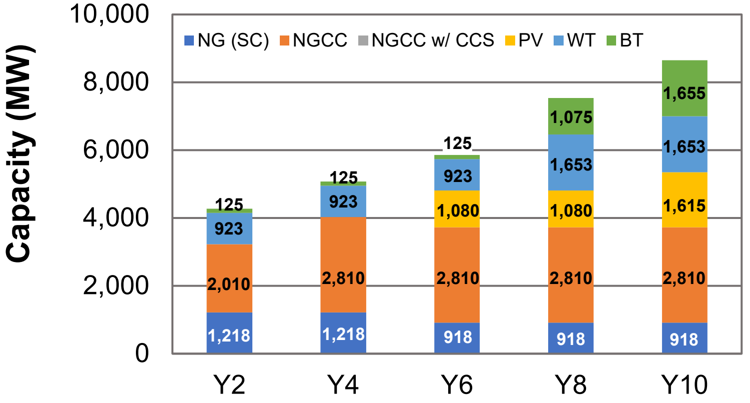
Impact of extreme day on the optimal design

Python 3.10.12, Pyomo 6.6.2

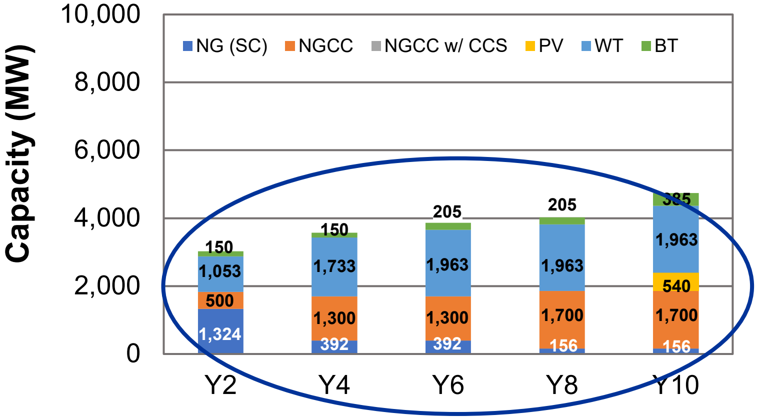
Revisit Case 3 (30% CO_2 emission cut and 60% renewable generation)

- ***original case*** : 5 representative days (4 avg. days + **1 extreme day** with the highest demand and lowest capacity factor)
- ***w/o op. reliability*** : 4 representative days (**w/o extreme day**)

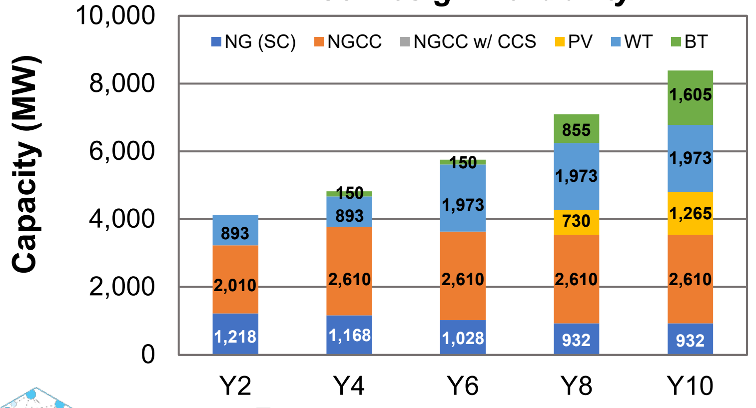
Case 2B (5 Rep. days) – Installed capacity
With Design Reliability



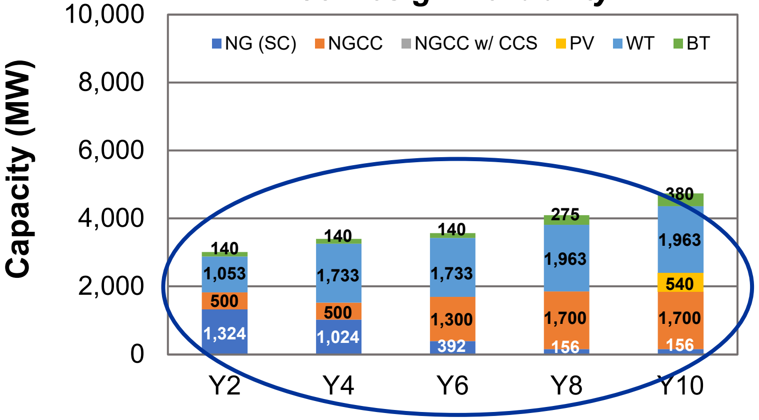
Case 2B (4 Rep. days) – Installed capacity
With Design Reliability



Case 2A (5 Rep. days)
w/o Design Reliability



Case 2A (4 Rep. days)
w/o Design Reliability

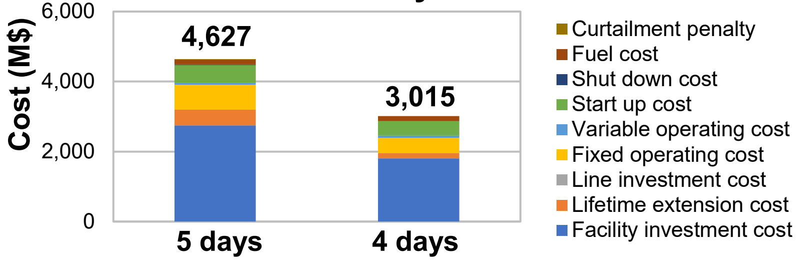


- When extreme day with the lowest capacity factor for wind and solar is excluded, the capacity required is significantly reduced.

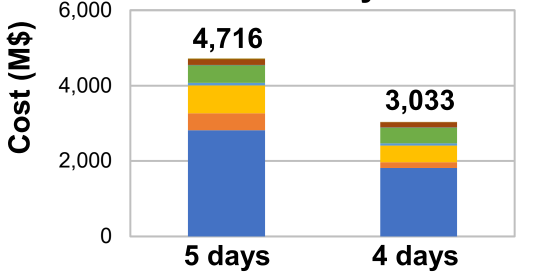
w/ Reliability – **"5 days": 8,651MW, "4 days": 4,744MW**
w/o Reliability – **"5 days": 8,385MW, "4 days": 4,739MW**

- Design reliability does not significantly affect the results of "4 days" method, because renewable generators themselves can increase design reliability.

Without Reliability



With Reliability



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- The total cost is calculated after multiplying the weighting factor.

Conclusions

- Inclusion of reliability in GTEP models is difficult and requires new solution algorithms

- Reliability impacts the solution, and other tools don’t consider it

- GTEP models are difficult to solve in general, with simplifying assumptions required for tractability. The IDAES GTEP model is open and flexible to tailor the problem and solution to a specific problem that may be of interest.

- End goal: ISO scale GTEP models that return an optimal and operationally feasible solution that can be verified and validated seamlessly with tools such as PRESCIENT

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Sandia National Laboratories: John Siirola, Bethany Nicholson, Michael Bynum, Jordan Jalving, Emma Johnson, Katherine Klise, Shawn Martin, Miranda Mundt, Edna Soraya Rawlings, Kyle Skolfield

Lawrence Berkeley National Laboratory: Deb Agarwal, Dan Gunter, Keith Beattie, John Shinn, Hamdy Elgammal, Joshua Boverhof, Karen Whitenack, Oluwamayowa Amusat, Sarah Poon

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