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ENHANCING GRID RELIABILITY USING ENERGY STORAGE SYSTEMS

Latest models and updates to the ProGRESS tool

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Sandia National Laboratories

DOE OE Energy Storage Peer Review & Annual Meeting, 2026

U.S. DEPARTMENT of ENERGY

NNSA National Nuclear Security Administration

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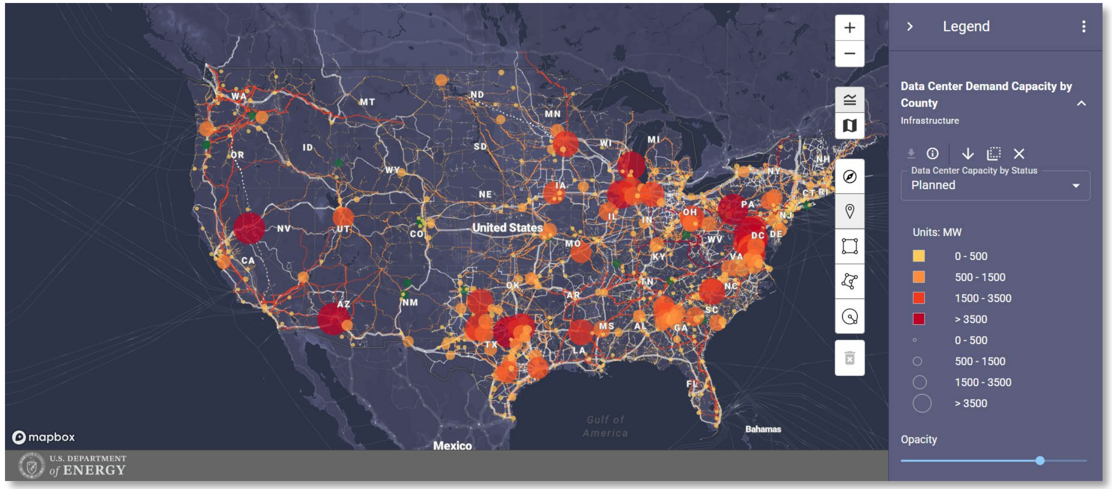
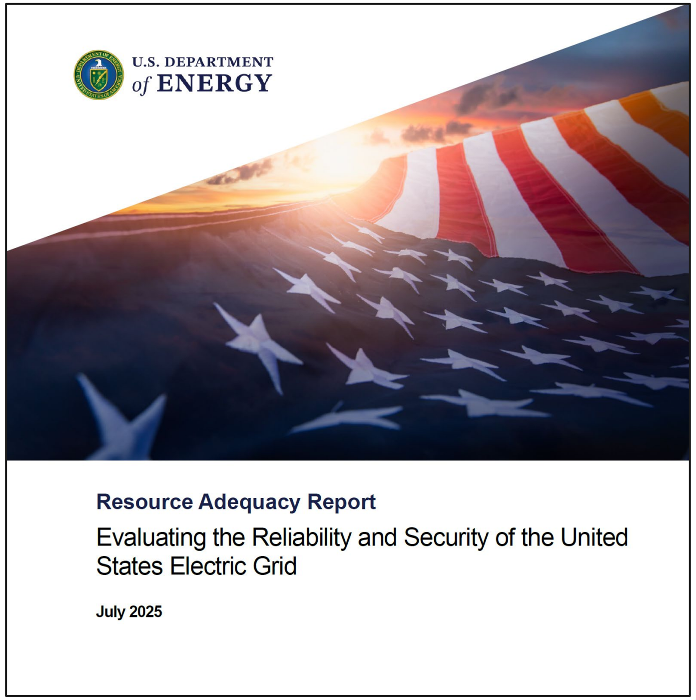
PROJECT OVERVIEW

- **Goal:** Develop models and frameworks for accurately representing and capturing the value of energy storage systems in grid reliability and planning studies.
- **Current Practice:** Existing grid reliability evaluation frameworks and tools do not accurately capture ESS operational and failure characteristics. They are not well coordinated with expansion planning and production cost modeling tools.
- **Why Sandia:** Cross-cutting research at Sandia—expertise in power systems, ESS safety and reliability, demonstrations projects.
- **Innovation:** Developing and integrating state-of-the-art ESS models that reflect their real-world operation and failure characteristics into reliability and planning studies.
- **Duration:** FY24—FY26
- **Impact:** The grid reliability and planning frameworks and open-source tools developed in this project benefit stakeholders including system planners, utilities, researchers, and regulators to accurately capture the contribution of ESS toward enhancing grid reliability.
- **Vertical/Investment Area:**
  - Analytics
- **Alignment/Supports strategic pathway:** Optimize the grid planning process to enhance reliability, increase operational efficiency, and make electricity more affordable.

MOTIVATION

- The U.S. power grid is facing increased reliability challenges.
- Rapid **load growth**, particularly from **data centers**, is a primary contributing factor.
- Other factors include **retirements** of firm capacity and *increased reliance on non-dispatchable resources*.
- **Energy storage systems (ESS)** offer solutions to mitigate these challenges.
- However, traditional reliability frameworks lack advanced models for ESS and large loads.
- **Goal:** Develop an *open-source reliability assessment framework* that explicitly captures the **contribution of ESS toward enhancing system reliability**.





Report on Evaluating U.S. Grid Reliability and Security

- **Old Tools Won't Solve New Problems.** Antiquated approaches to evaluating resource adequacy do not sufficiently account for the realities of planning and operating modern power grids. At a minimum, modern methods of evaluating resource adequacy need to incorporate frequency, magnitude, and duration of power outages; move beyond exclusively analyzing peak load time periods; and develop integrated models to enable proper analysis of increasing reliance on neighboring grids.

NERC

Final

Risk Mitigation for Emerging Large Loads

Large Loads Working Group Reliability Guideline

May 2026

GRID RELIABILITY OVERVIEW

Definition

- Reliability of a power system pertains to its ability to satisfy load demand under specified operating conditions and policies

Quantification

- *Probability* and *frequency* of encountering failure states and the period of time system spends in failure states

Measure

- *Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE)* in days/year, *Loss of Load Frequency (LOLF)* in failures/year, *Expected Unserved Energy (EUE)* in MWh/year

Power Systems Reliability Analysis

Multi-Node Systems

Single-Node Systems

Composite System Reliability Analysis

- Conducts detailed examination of system.
- Focuses on evaluating overall capability of generation & transmission systems to provide adequate electrical energy to major load centers.
- AC/DC OPF models used.

Multi-Area Reliability Analysis

- Typically involves large network of interconnected utilities or control areas.
- DC-OPF or transportation models used for network representation.

Generation Adequacy Analysis

- Evaluate ability of generation resources to meet total system load.
- Assumes transmission system to be capable of transporting generation to load centers without fail.
- Transmission network is not modeled.

Contingency ranking

Stochastic/probabilistic load flow

State space decomposition

Monte Carlo Simulation

Hybrid methods

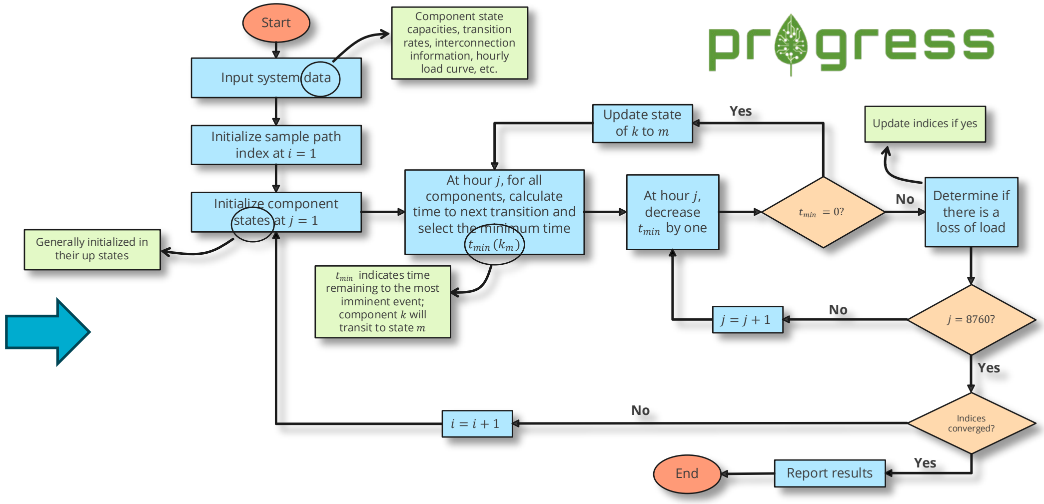
PROGRESS OVERVIEW

Input Data

- System topology
- Energy storage
- Thermal generators
- Weather
- Load profiles

Sequential time-series model allows smooth integration of ESS

Stochastic Monte Carlo Simulation Engine



- Generate samples (each 8760 hours long) with diverse weather conditions and component failures
- Optimize grid operation with energy storage every hour
- Calculate reliability indices characterizing the frequency, duration, and magnitude of outages

In-depth Outage Analysis

```
=== TOTAL OUTAGE MAGNITUDE (MW) ===
Rank  Bus    Magnitude
1     Baker  1970.1928
2     Alger  1107.3469
3     Alder  942.9062
4     Carew  937.0735
5     Bach   847.2246
6     Abel   666.4205
7     Bayle  441.1124
8     Adams  300.6656
9     Bacon  103.2004
10    Clay   44.1628
11    Cabell 22.0749
12    Camus  13.9273
```

```
=== TOTAL OUTAGE HOURS ===
Rank  Bus    Hours
1     Baker  20.0
2     Alger  12.0
3     Carew  9.0
4     Alder  8.0
5     Bayle  7.0
6     Adams  6.0
7     Bach   6.0
8     Abel   4.0
9     Bacon  2.0
10    Cabell 1.0
11    Camus  1.0
12    Clay   1.0
```

	Aug 11 17:00	Aug 11 18:00
A1	-100	-100
A2	22.06623951	18.85933401
A3	28.7475392	44.45873049
A4	-56.44622207	-51.67801868
A5	-100	-100
A6	-100	-100
A7	100	100
A8	-13.03492007	-6.525458082
A9	75.80442405	89.3450138
A10	-9.862868455	-14.02064041
A11	-100	-100
AB1	-20.0105146	-23.83199618
A12-1	100	100
A13-2	-86.66581254	-91.89359934
A14	100	100
A15	-54.95921772	-54.45198557

	Aug 11 17:00	Aug 11 18:00
101_CT_1	0	0
101_CT_2	20	20
101_STEAM_3	76	76
101_STEAM_4	76	76
102_CT_1	20	20
102_CT_2	20	20
102_STEAM_3	76	76
102_STEAM_4	76	76
107_CC_1	355	355
113_CT_1	55	55
113_CT_2	55	55
113_CT_3	55	55
113_CT_4	55	55
115_STEAM_1	12	12
115_STEAM_2	12	12
115_STEAM_3	155	155
116_STEAM_1	155	155

Key Outputs

Index	Description
LOLP	Loss of Load Probability
LOLE	Loss of Load Expectation
MDT	Mean Down Time
nEUE	normalized Expected Unserved Energy
EPNS	Expected Power Not Served
LOLF	Loss of Load Frequency

Quantify System Reliability

BATTERY DEGRADATION MODELS

- Stress-factor-based degradation models developed in [1] and deployed within ProGRESS
- Users can provide following additional BESS configuration parameters:
  - Battery cell chemistry (LMO, LFP, NMC, NCA)
  - Option to evaluate capacity degradation and the frequency at which it is evaluated
  - Option to perform thermal simulation using PyBaMM [2]
- ProGRESS coordinates between the degradation and sub-unit failure models to obtain usable capacity

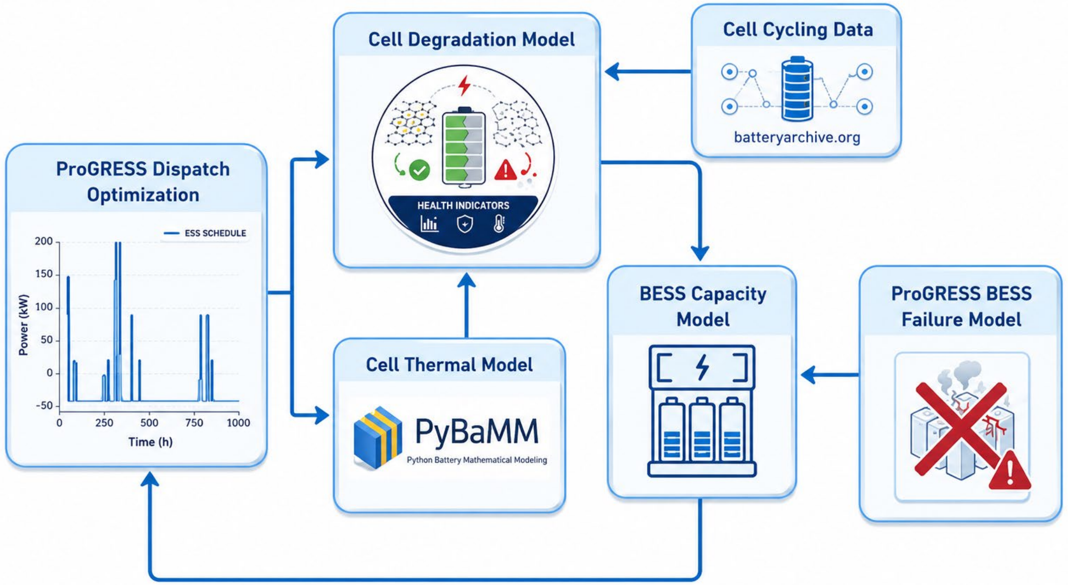


Fig. 1: Degradation Model Details

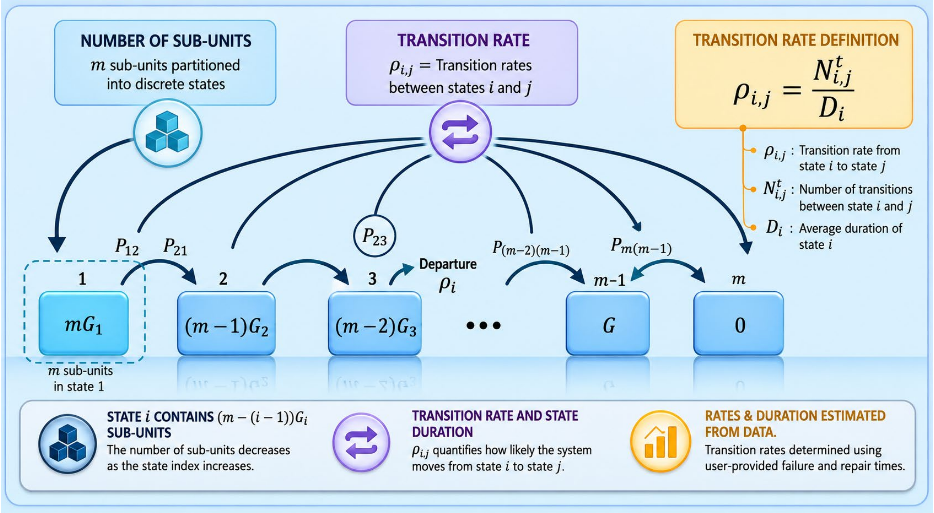


Fig. 2: BESS failure model in ProGRESS

[1] Pandit, Dilip, et al. "Impact of Cell Chemistry on the Degradation and Revenue Potential of Energy Storage Systems." *2026 IEEE Electrical Energy Storage Applications and Technologies Conference (EESAT)*. IEEE, 2026.

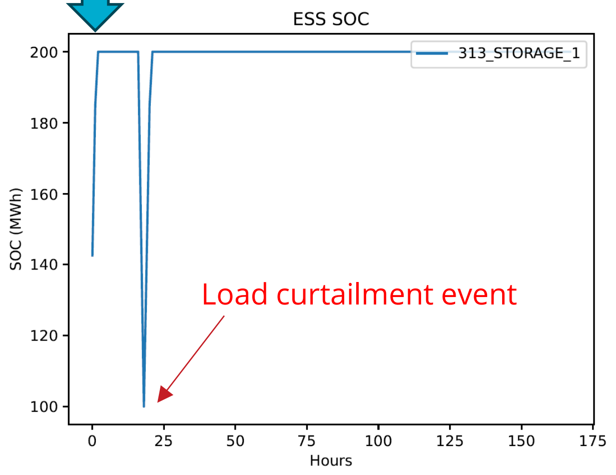
[2] Sulzer, Valentin, et al. "Python battery mathematical modelling (PyBaMM)." Journal of Open Research Software 9.1 (2021).

ESS OPERATION MODELS

- ProGRESS now supports multiple ESS operation modes

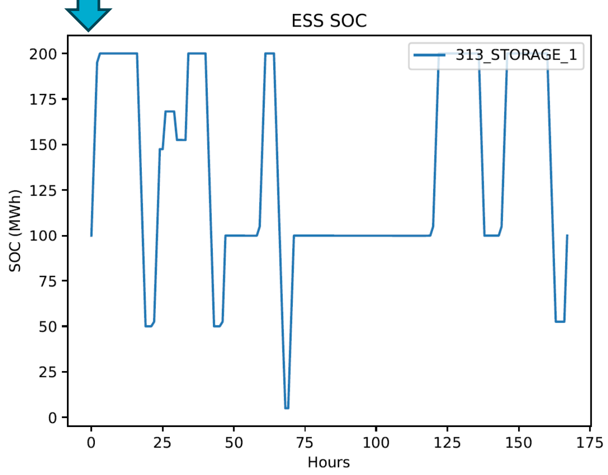
Reliability Mode

- **Objective:** Use ESS only during load curtailment events; maintain full SoC otherwise.
- **Implementation:** Configure ProGRESS in single-period optimization mode
- **Advantages/Limitations:**
  - ✓ Simple operational representation
  - ✓ Strategy useful for critical loads and systems with low overall reliability
  - ✗ Slower overall execution due to repeated model construction
  - ✗ Underutilization of ESS asset



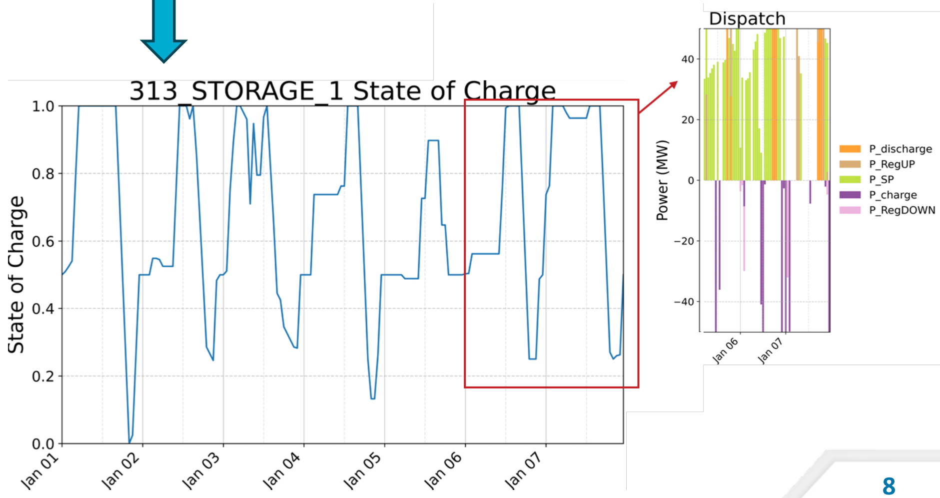
Cost-Based Dispatch Mode

- **Objective:** Operate ESS to minimize total system operating cost across the optimization horizon.
- **Implementation:** Configure ProGRESS in multi-period optimization mode
- **Advantages/Limitations:**
  - ✓ Faster execution than single-period simulations for small/medium systems
  - ✓ Captures intertemporal ESS decisions
  - ✓ Prioritizes mitigating load curtailment while providing better overall ESS utilization
  - ✗ Higher modeling complexity
  - ✗ Model execution can be slow for bigger systems



Service Stacking Mode

- **Objective:** Enable ESS participation across energy and ancillary service markets.
- **Implementation:** Coordinate QuESt PCM with ProGRESS
- **Advantages/Limitations:**
  - ✓ Highest operational fidelity and most accurate operational model
  - ✓ Captures market co-optimization and unit commitment effects
  - ✗ High data requirements
  - ✗ High computation burden due to unit commitment formulation



AI DATA CENTER LOAD MODEL

- Stochastic data-center reliability model developed using semi-Markov process
- Proposed model:
  - Overall load for data-center i is:

$$P_i(t) = P_i^{base}(h) + P_i^{IT}(t)$$

  - **Base Load** = HVAC + Chiller + Auxiliaries (Driven by ambient Temperature)

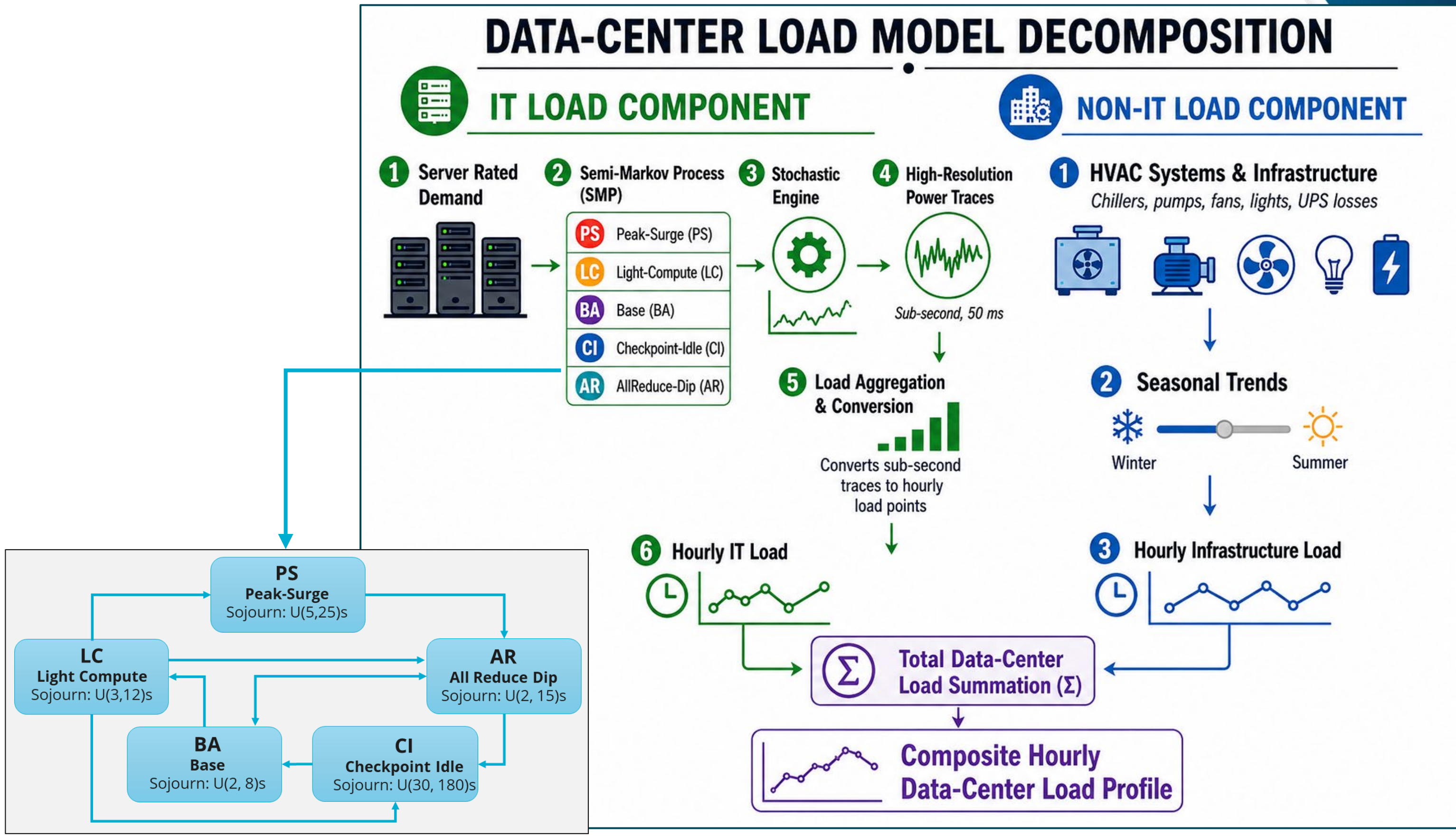
$$P_i^{base}(h) = [\alpha_{cl}(T_{amb}(h) + \alpha_{aux})]P_i^{rated}$$

  - **IT Load** = Fast Stochastic AI Workload *(5 State Semi-Markov Model)* Shaped by diurnal envelope of AI usage, Potential correlation between facilities
    - Nominal hourly IT load is:

$$\overline{P_i^{IT}}(h) = \alpha_{IT} P_i^{rated} \mu_D(h)$$

    - IT load after semi-Markov process is:

$$P_i^{IT}(t) = \overline{P_i^{IT}}(h)(1 \pm \delta_{state} + \sigma_{state})$$



Five State Semi Markov IT Load Model

Peak Surge: $\delta_{PS} \sim U(0.25, 0.40)$
- High power surge, Peak tensor-compute burst
- +25 to +40% above nominal load

Light Compute: $\delta_{PS} \sim U(0.25, 0.40)$
- Moderate compute
- +5 to +15% above nominal IT load

Base: $\delta_{BA} = 0$
- Short inter-iteration baseline gap
- Nominal Load

Checkpoint Idle: $\delta_{PS} \sim U(0.15, 0.25)$
- Low Power Idle point
- -15% to -25% of Nominal Load

AllReduce Dip: $\delta_{PS} \sim U(0.35, 0.50)$
- Communication synchronization dip
- -35% to -50% of Nominal Load

Indices:

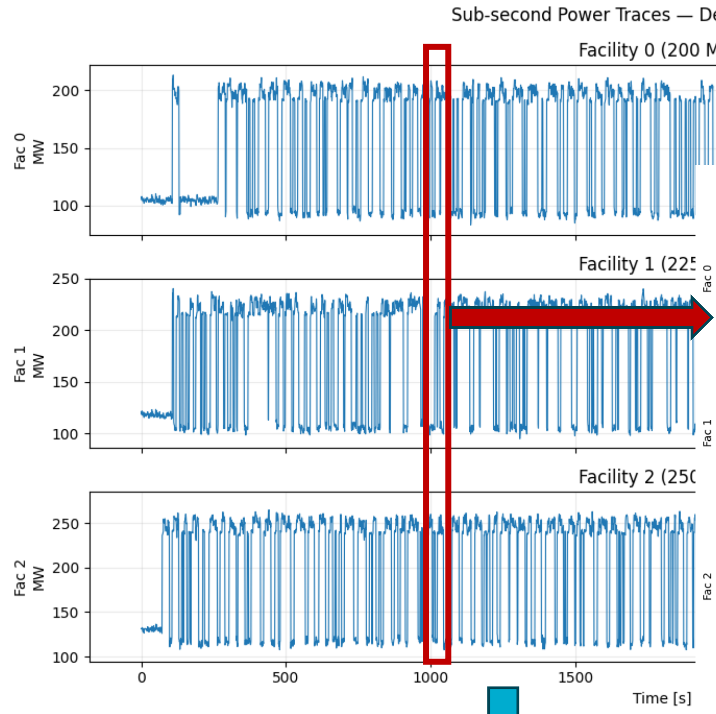
α_{cl} = Cooling fraction
T_{amb} = Ambient temperature
α_{aux} = Auxiliary fraction
P_i^{rated} = Rated data-center power
α_{IT} = IT load fraction
$\mu_D(h)$ = Diurnal utilization envelope
δ_{state} = Power fraction from Markov state
σ_{state} = Noise corresponding to the state

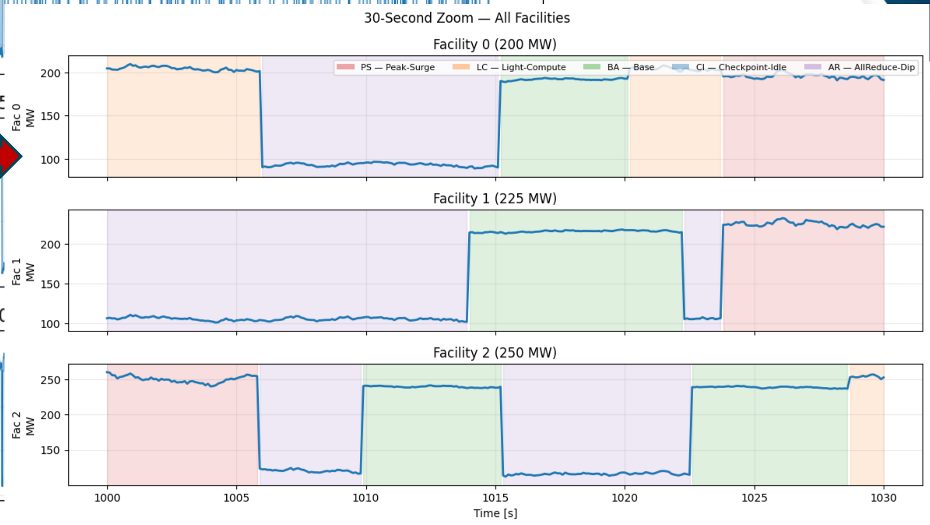
AI DATA CENTER LOAD MODEL

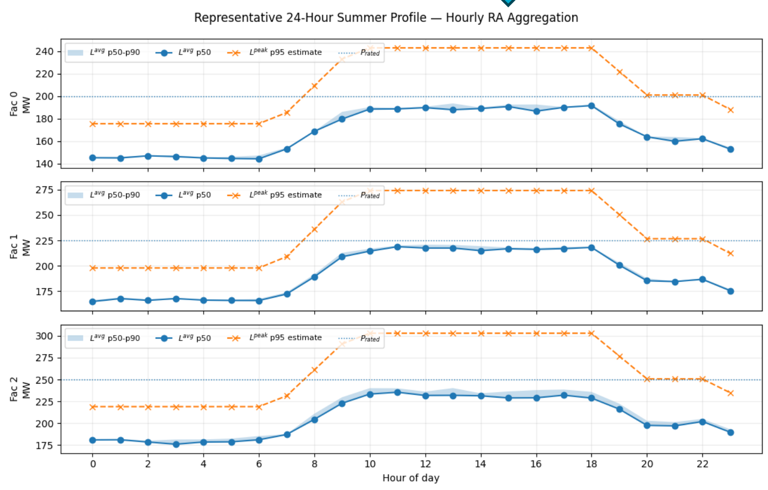
- IT load obtained using $P_i^{IT}(t)$ generates sub-second power traces
- Converted to hourly demand for reliability assessment using the peak state encountered during that hour:

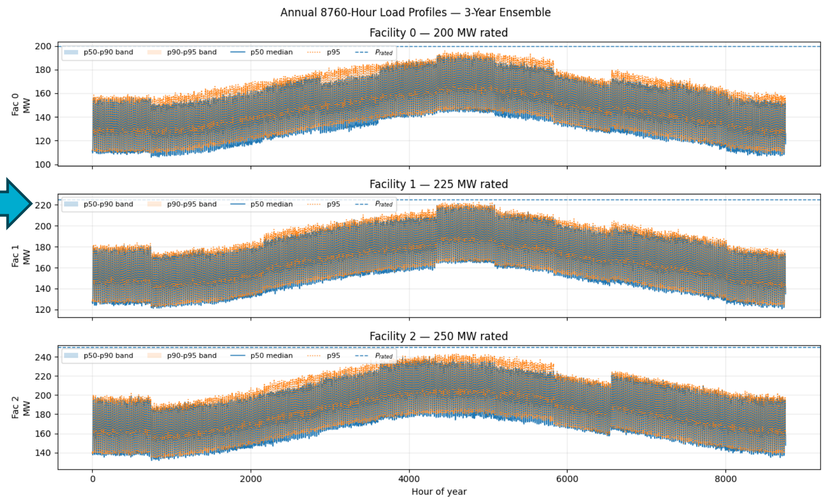
$$P_i^{IT,peak}(h) = \max_{state} P_i^{IT}(t) \quad \forall t \in h$$

- Correlation among data center facilities:
  - ○ Shared orchestration or synchronized AI jobs
  - ○ Same-region operational similarity and common environment drivers
- Modeling correlation:
  - ✓ Modeled as a likelihood of two or more facilities operating in same state
  - ✓ Embedded via workload synchronization (hourly states)









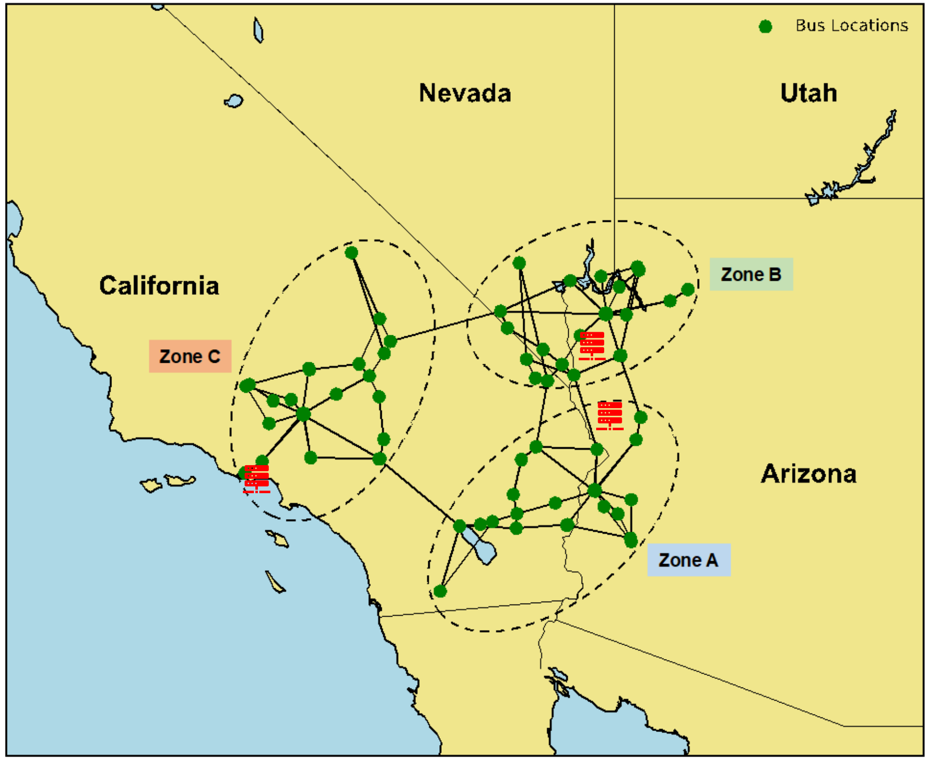
RELIABILITY-BASED SIZING OF ESS TO SUPPORT AI DATA CENTERS

- Case studies performed on the RTS-GMLC test system
- 3 data-center facilities added based on headroom and bus connectivity; peak estimate used for hourly data center load from sub-second power traces

No.	Size (MW)	Location (Bus, Zone)
1	200	Anna (11), A
2	230	Bardeen (35), B
3	250	Cary (59), C

- Composite model reliability analysis with detailed *Nodal* network model performed to evaluate system reliability
- ESS sized and sited based on reliability performance of system and nodes

RTS GMLC Test System




```
=== TOTAL OUTAGE HOURS =
Rank      Bus       Hours
1         Baker     4003.0
2         Carew     2758.0
3         Adams     1335.0

=== AVERAGE OUTAGE MAGNITUDE
Rank     Bus       Average
1        Baker     112.7704
3        Carew     107.8146
18       Adams      52.2001
```

Table. *Bus statistics w. DC load*

Capacity (MW)	Duration (hr.)	Location (Bus)
60	4, 8	Adams (2)
115	4, 8	Baker (31)
110	4, 8	Carew (55)

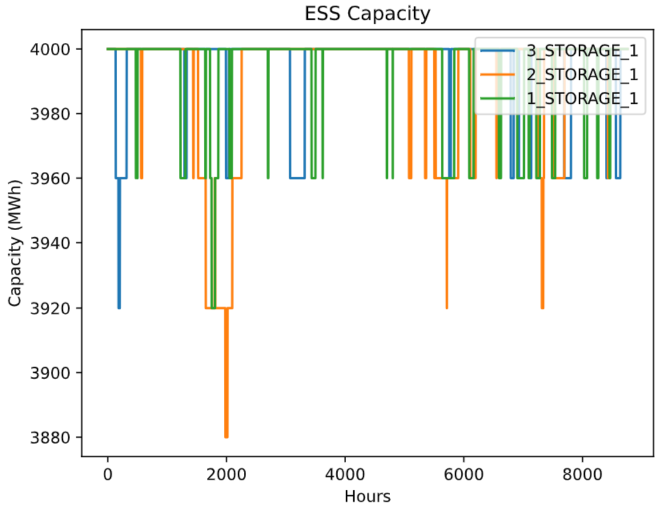
Table. *ESS added to the most-affected buses after adding data center load*

Case	LOLE (days/year)	MDT (hours)	EUE (MWh/yr)
Base	0.26	0.87	38.37
DC w/o ESS	2.55	2.78	1839.93
DC w. ESS 4-hr	0.73	1.54	699.01
DC w. ESS 8-hr	0.70	1.25	424.64

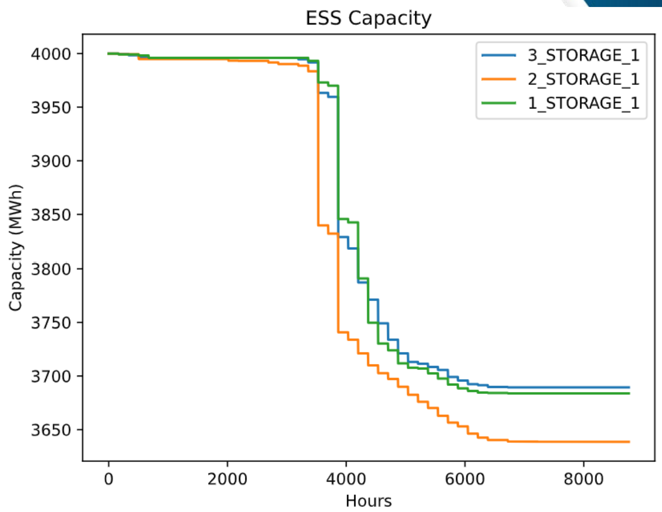
Table. *System reliability metrics (detailed nodal network model) with DC load and ESS addition*

IMPACTS OF INTEGRATING BATTERY DEGRADATION MODELS

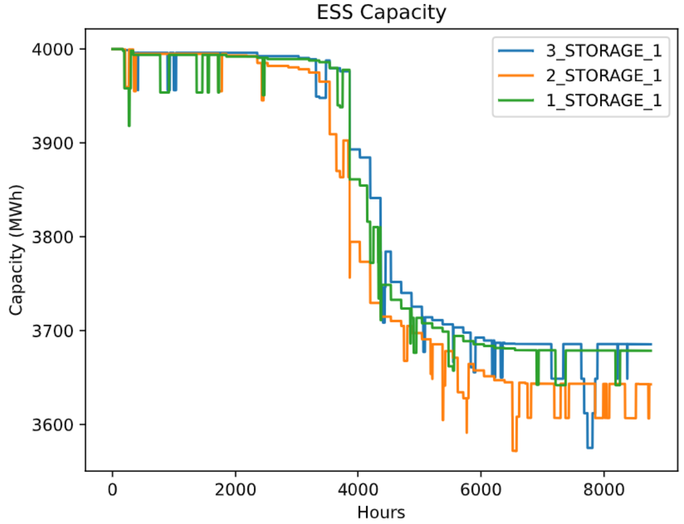
- Case studies performed to assess impacts of BESS degradation on system reliability
- Simulation parameters:
  - Spatial fidelity: zonal
  - 1000 MW, 4-hr BESS in each zone
  - Each ESS has 100 sub-units, each with MTTF of 500 hrs. and MTTR of 48 hrs.
  - Load factor = 1.5
  - Samples: 20,000
  - ESS mode: cost-based dispatch mode



Capacity loss due to sub-unit failures



Capacity loss due to degradation

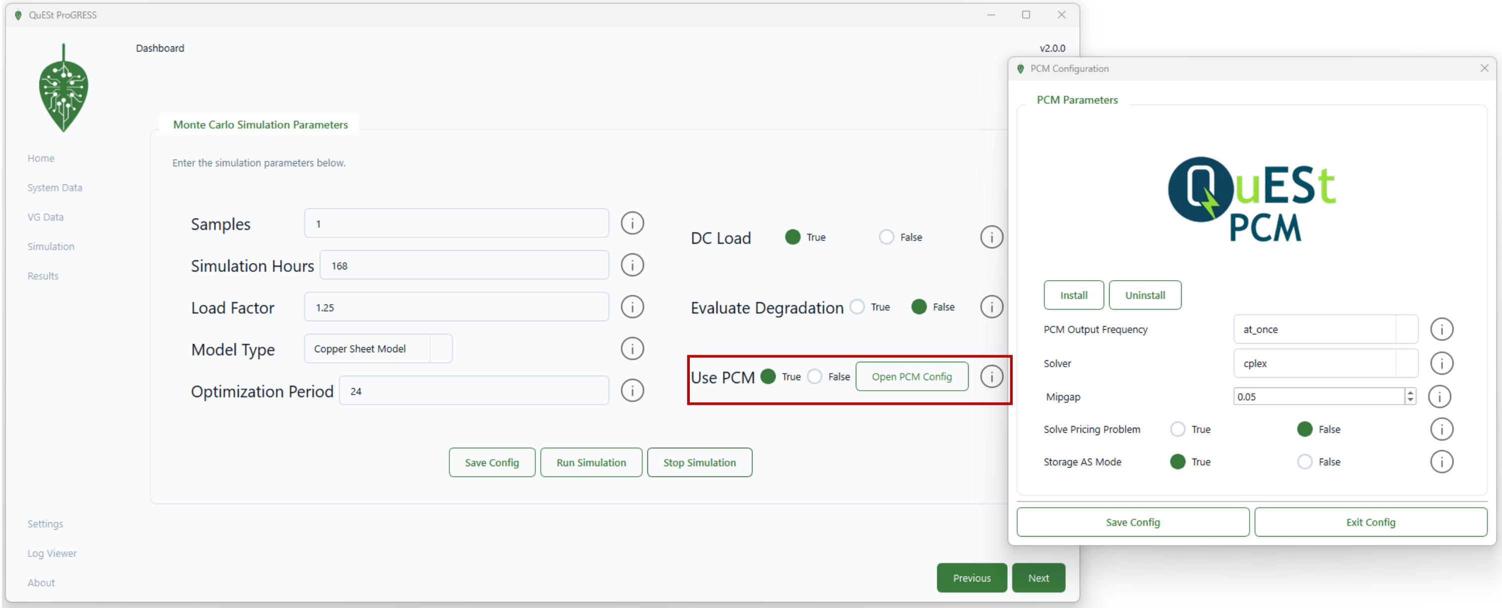


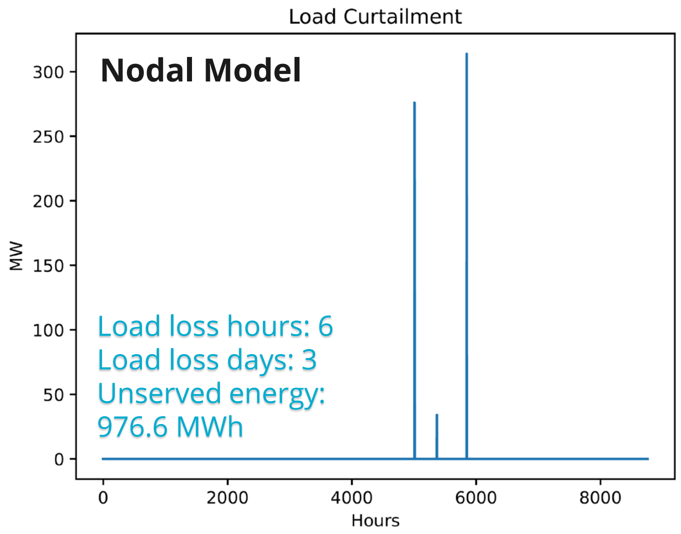
Combined capacity loss

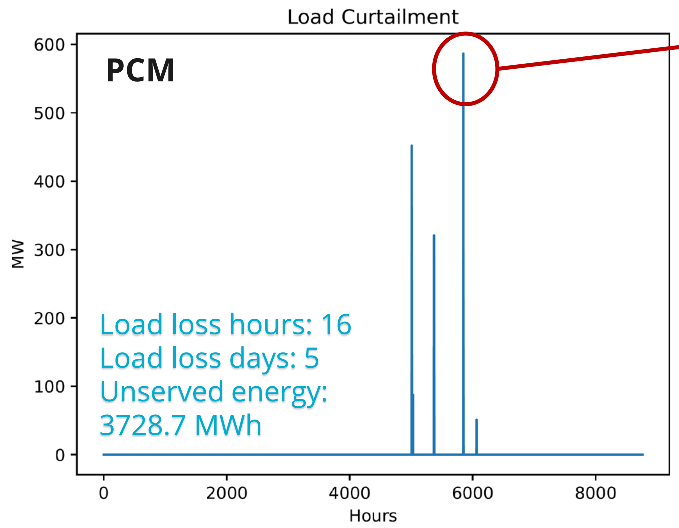
Case	LOLE (days/year)	MDT (hours)	EUE (MWh/yr)
No degradation no failure	1.218	2.12	3884
No degradation only failure	1.232	2.15	3912
Degradation only: LFP	1.237	2.14	3913
Degradation only: NMC	1.566	2.45	4857
NMC degradation + failures	1.583	2.45	4877

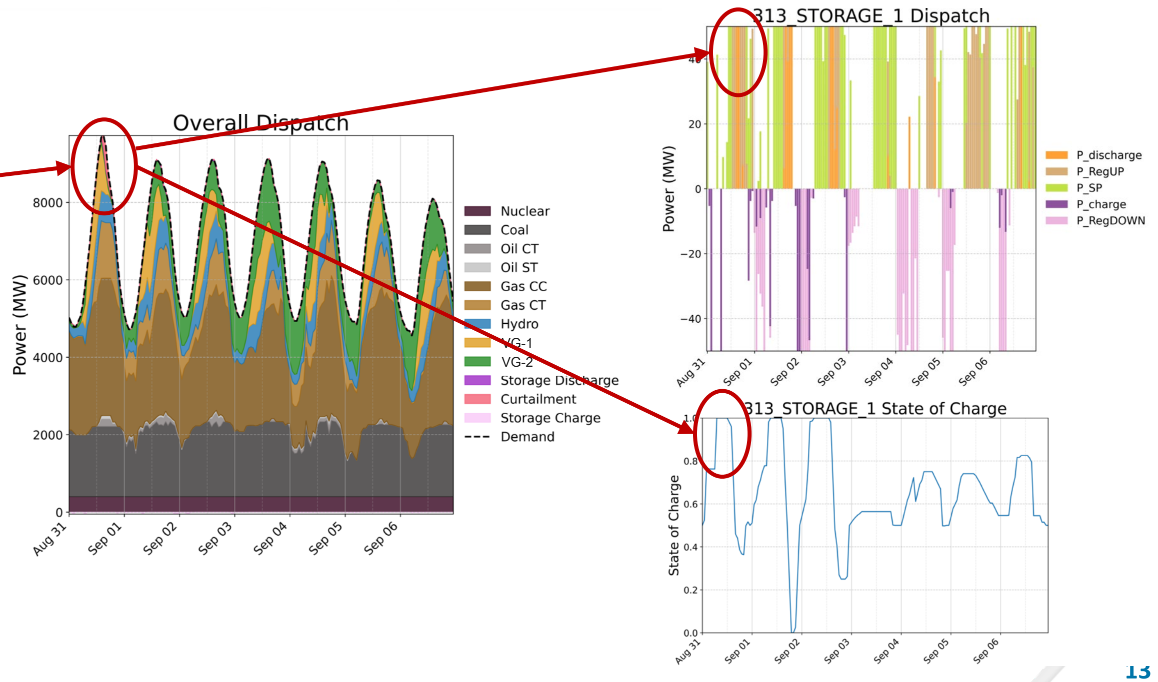
IMPACTS OF MODELING FIDELITY

- Tested reliability impacts of different optimization complexity
- Two modes:
  - ✓ Nodal simulation with LP optimization
  - ✓ Nodal simulation with PCM
- Same stochastic conditions for all tests



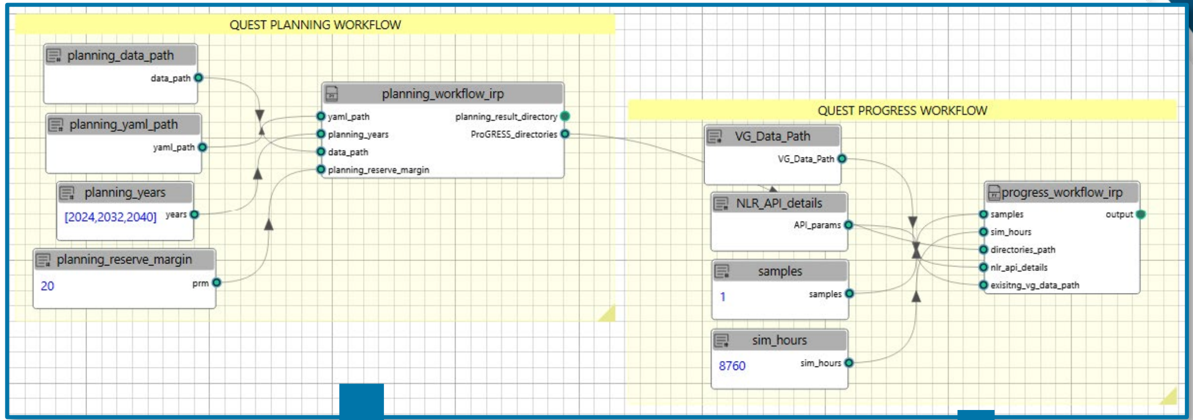


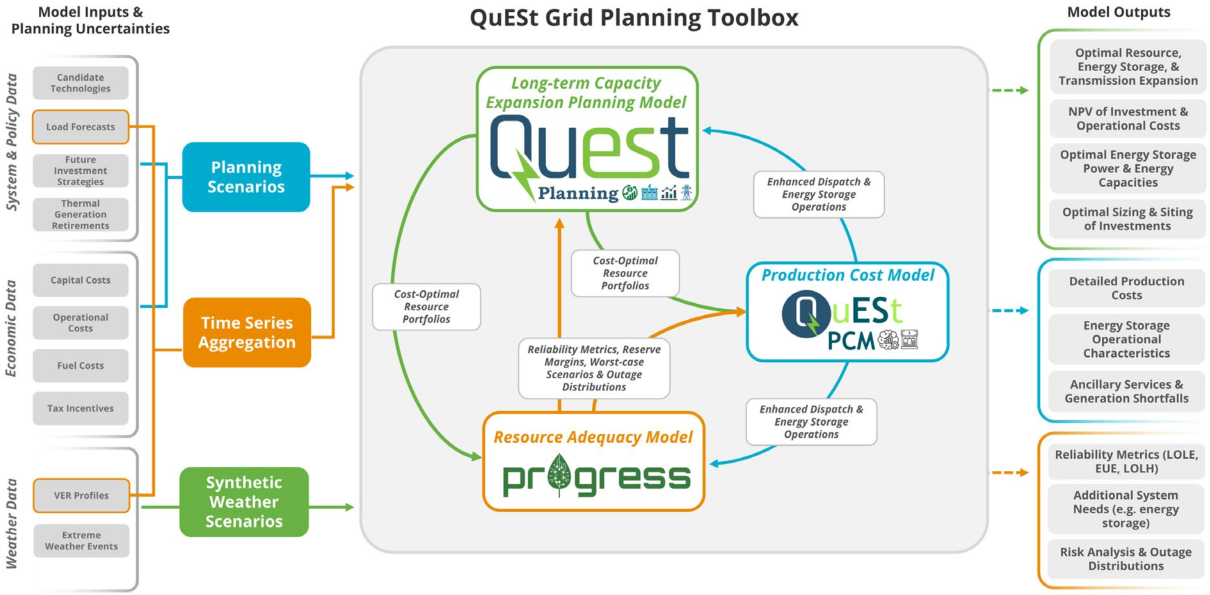


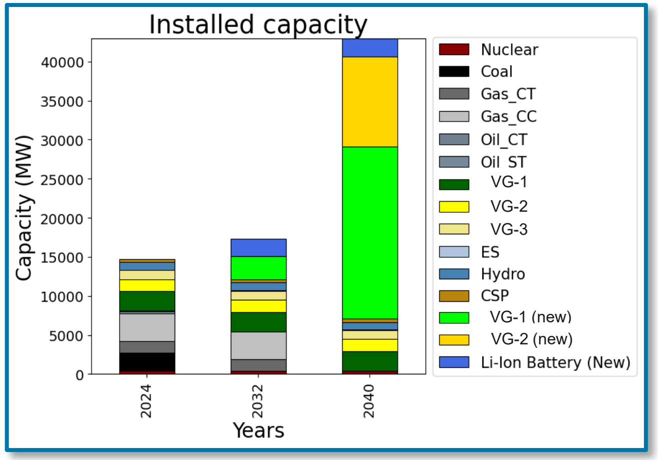


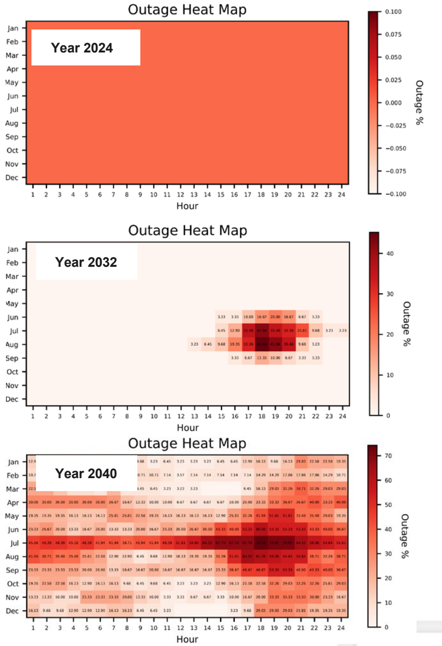
TOOL INTEGRATION USING QUEST WORKSPACE

- **Motivation:** Accurate grid planning requires systematic coordination among planning tools
- Leverage the QuESt 2.1 workspace to integrate grid planning tools
- Why QuESt Workspace:
  - ✓ Integration of different Python environments
  - ✓ Visual representation of modules, processes
  - ✓ Enhanced workflow development, runtime debugging, and result interpretation using QuESt AI agent









AI-POWERED WORKFLOW IN QUEST WORKSPACE

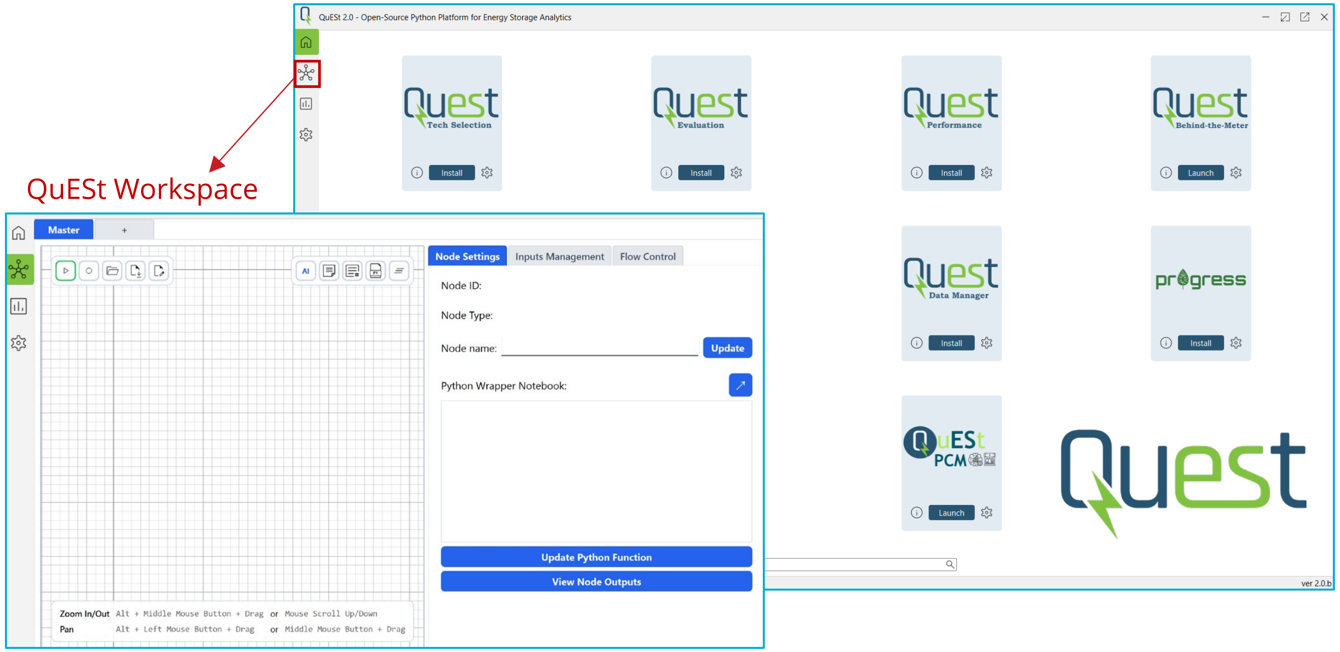
Users interact with the QuESt AI Agent using natural language prompts

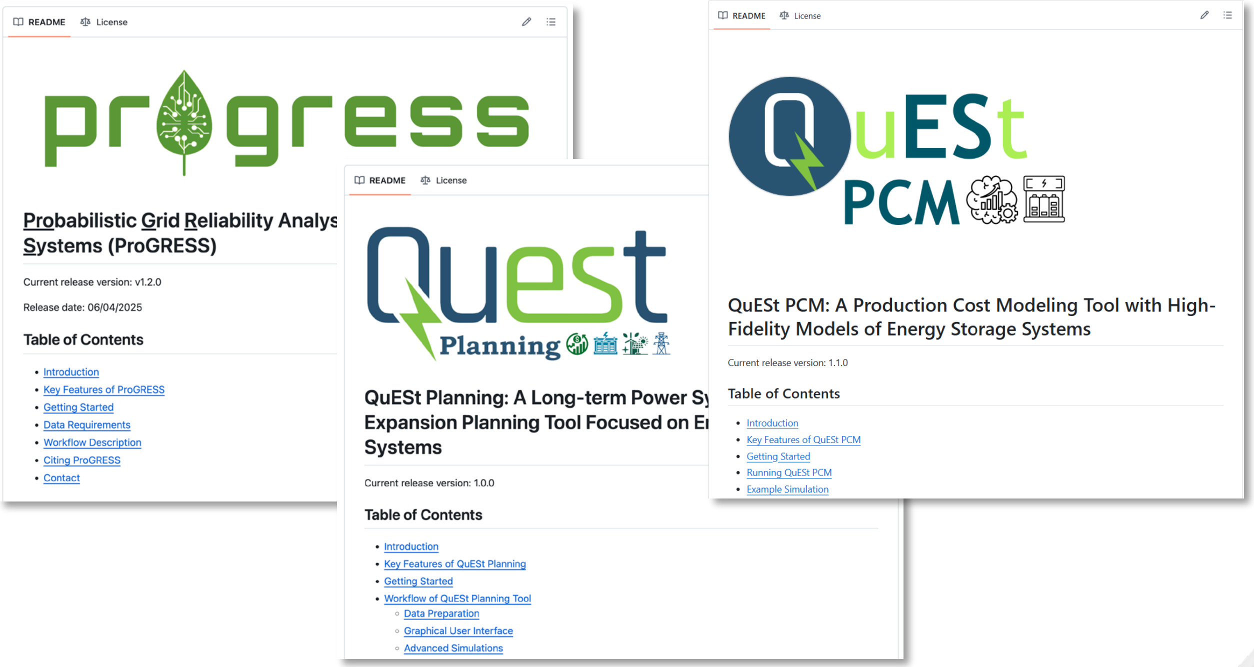
The QuESt Agent selects and executes the most relevant saved skills to generate optimized workflows

Users can customize workflow modules, debug execution in real time, and analyze results through the agent

DISTRIBUTION

- Available on GitHub
  - PROGRESS
  - QuESt Planning
  - QuESt PCM
- Available via QuESt 2.0 platform
- Available on pypi, can be pip installed
- Executable version (.exe file) available for Windows users
- Documentation available on GitHub, in-app, and GitHub Pages





SUMMARY & IMPACT

- **Project contributions in FY26:**
  - ✓ Several *new capabilities* added to ProGRESS: modeling features, more in-depth analysis, usability improvements, and bug fixes
  - ✓ New **battery degradation and failure models** allow estimating true capacity availability for BESS
  - ✓ **Multiple operation modes** (reliability, economic dispatch, market participation) provide users with flexibility of evaluating storage contribution under a wide range of operating conditions
  - ✓ **Detailed AI data center load model** allows accurate sizing of storage required for maintaining desired reliability level with high penetration of large loads
- **Accomplishments & Impact:**
  - ✓ New version of tool, **ProGRESS 2.0,** released
  - ✓ Paper on battery degradation model presented at *IEEE EESAT 2026*
  - ✓ **Downloaded 3.3k+** times from GitHub and pypi repositories
  - ✓ New ProGRESS allows stakeholders including *utilities, system planners, operators, regulators, and researchers* to plan for an **affordable** and **reliable** power grid with **state-of-the-art energy storage models**
  - ✓ **Integration with other grid planning tools** like *QuESt Planning* and *QuESt PCM* using *QuESt Workspace* allows users comprehensive grid planning options

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THANK YOU!

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