Automation Applications in the Energy Industry:

Derivation of the Multi-Dimensional ELCC Surface and its Endogenous Modeling in Capacity Expansion

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Reliability Studies in Modern Power Systems

What is Resource Adequacy?

Resource adequacy is the ability of a power system to supply enough electricity to always meet demand. It is measured probabilistically using LOLE and LOLP, with the industry-standard target of no more than 0.1 days of lost load per year.

Why Reliability Studies Are Becoming More Critical

- **Variable generation:** Solar and wind cannot be dispatched on demand — output depends on weather, creating supply gaps during peak hours.

- **Retirement of thermal capacity:** As coal and gas plants retire, firm dispatchable capacity shrinks, leaving grids more exposed during extreme weather events.

- **Correlated generation patterns:** Solar drops simultaneously across entire regions at sunset; wind farms in the same zone go quiet together, compounding reliability risk.

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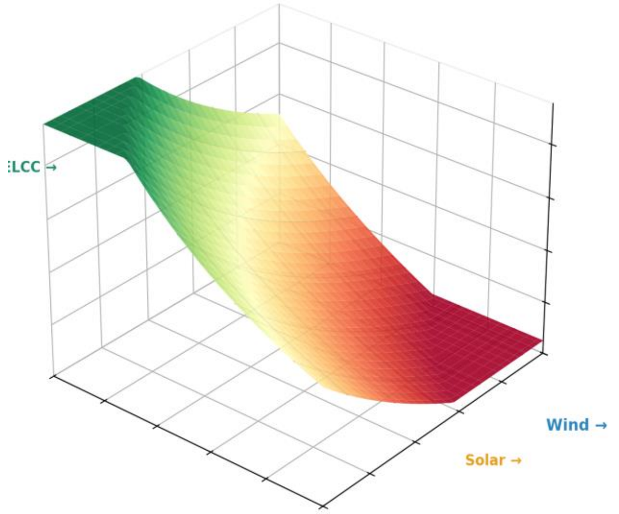
What Is ELCC?

Definition: Effective Load Carrying Capability (ELCC) is a reliability-based measure of how much additional load a power system can serve after adding a resource (or portfolio of resources) while maintaining the same reliability level (e.g., the same LOLE or LOLP).



Multi-Dimensional ELCC Surfaces

Beyond Single-Resource ELCC

- **ELCC is not additive:** Adding more solar reduces the marginal reliability value of additional solar (diminishing returns).

- **Technology interactions matter:** The ELCC of solar depends on the penetration level of wind and storage in the portfolio, and vice versa.

- **A multi-dimensional surface captures all interaction effects:** Each axis represents the installed capacity of one technology. The surface encodes the ELCC value realized at every combination of technology penetration levels.

- **The surface is not flat —** it curves due to diminishing marginal reliability contributions as the installed capacity of any single technology keeps increasing beyond the point where it meaningfully reduces loss-of-load events.

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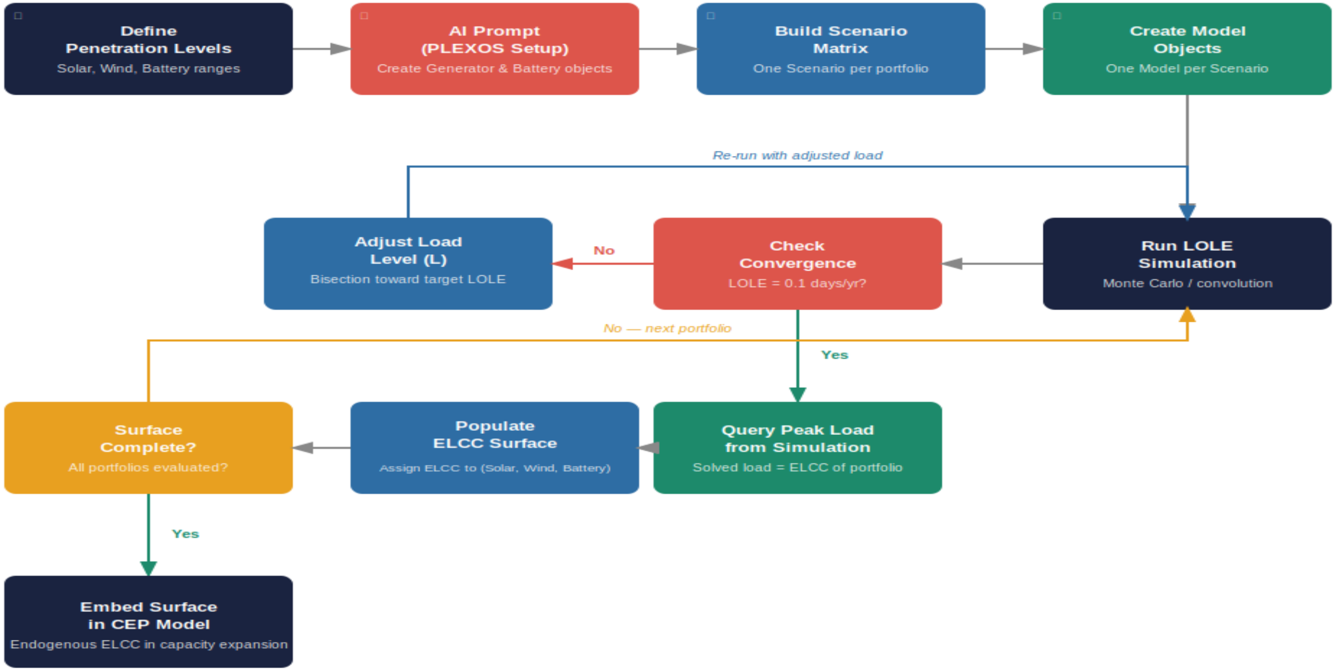
End-to-End Workflow



Building the LOLE Simulation Grid

AI-Assisted Scenario Generation

A PLEXOS-aware AI prompt drives the full scenario matrix build directly within the tool's data model:

Example prompt: *"I have Solar generators with possible penetrations of 1, 5, 10, 15 GW and Wind generators with the same levels. Batteries have penetrations of 1, 3, 5 GW. In PLEXOS, create Generator class objects for each Solar and Wind unit and Battery class objects for each battery unit. For each combination of penetration levels, create a Scenario object and tag the Max Capacity property of the corresponding Generator and Battery objects to that scenario. Finally, create a Model object for each scenario so that each portfolio can be simulated and evaluated independently."*

Output: A fully built PLEXOS dataset with Generator and Battery objects, one Scenario per portfolio combination, and one Model per scenario — ready for parallel dispatch to the LOLE simulation engine.

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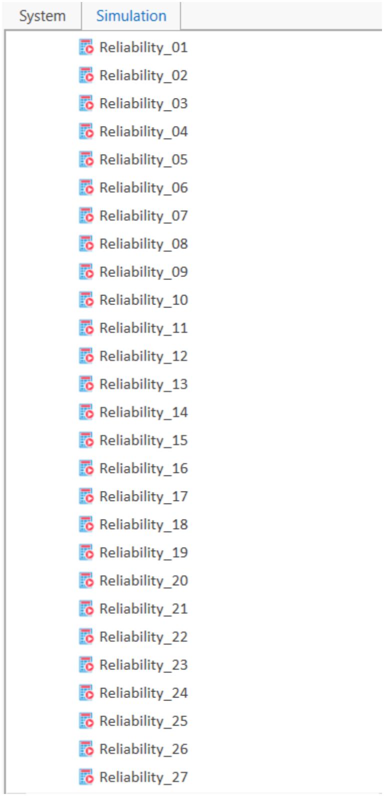
Building the LOLE Simulation Grid

Portfolio	Coal (GW)	Solar (GW)	Wind (GW)	Battery (GW)	ELCC (MW)
1	10	1	1	1	10640.62
2	10	1	1	3	13804.69
3	10	1	1	5	15937.5
4	10	1	5	1	12070.31
5	10	1	5	3	14203.12
6	10	1	5	5	16359.38
7	10	1	15	1	12539.06
8	10	1	15	3	14695.31
9	10	1	15	5	16898.44
10	10	5	1	1	11953.12
11	10	5	1	3	14062.5
12	10	5	1	5	16218.75
13	10	5	5	1	12281.25
14	10	5	5	3	14437.5
15	10	5	5	5	16593.75
16	10	5	15	1	12843.75
17	10	5	15	3	14976.56
18	10	5	15	5	17132.81
19	10	15	1	1	12445.31
20	10	15	1	3	14507.81
21	10	15	1	5	16757.81
22	10	15	5	1	12726.56
23	10	15	5	3	14906.25
24	10	15	5	5	16968.75
25	10	15	15	1	13382.81
26	10	15	15	3	15539.06
27	10	15	15	5	17648.44



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Iterative Convergence: LOLE = 0.1 days/yr

The Bisection Algorithm — Each LOLE run outputs an ELCC value by solving for the load that achieves exactly 0.1 days/yr of lost load:

1. **Initialize:** Start with a base load level L_0 for the given technology portfolio (e.g. current peak demand).
2. **Run LOLE Simulation:** Compute LOLE via Monte Carlo sampling or analytical convolution over the generation fleet and load uncertainty.
3. **Check Target:** Is $|LOLE - 0.1| < \varepsilon$ (convergence tolerance)? If yes → record and exit. If no → continue.
4. **Adjust Load:** If LOLE > 0.1, decrease load L (system is under-reliable). If LOLE < 0.1, increase load L (system has excess reliability). Load is adjusted using a bisection search until convergence.
5. **Record ELCC:** The converged peak load L^* is the ELCC of the activated portfolio. Typical convergence: 5–15 iterations per scenario, $\varepsilon = 0.02$ days/yr.

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Endogenous ELCC in Capacity Expansion

The realized ELCC surface is embedded as a **set of big-M constraints with binary decision variables** inside the Capacity Expansion Planning (CE) LP/MILP model. The optimizer selects the least-cost portfolio that satisfies minimum reserve margin — using the endogenous ELCC of all chosen technologies.

Objective Function: Minimize Σ (Capital Cost × Capacity + Fixed O&M + Variable O&M + Fuel Cost + Carbon Cost) across the planning horizon.

Reserve Margin Constraint: $\Sigma\ [\mathrm{ELCC}(x_s, x_v, x^b) \times \mathrm{Capacity}_i] \geq (1 + \mathrm{RM\%}) \times \mathrm{Peak\ Load}$, where Binary variables select the active simplex (pseudo-triangle in 3D, pseudo-rectangle in 4D). Big-M constraints enforce L2-norm interpolation within it to evaluate ELCC — not a static assumption.

Integrated Workflow: Build ELCC Surface → Break surface into simplices → Plug into the CE model → Run the optimizer → Get the least-cost portfolio. No fixed capacity credit assumptions needed.

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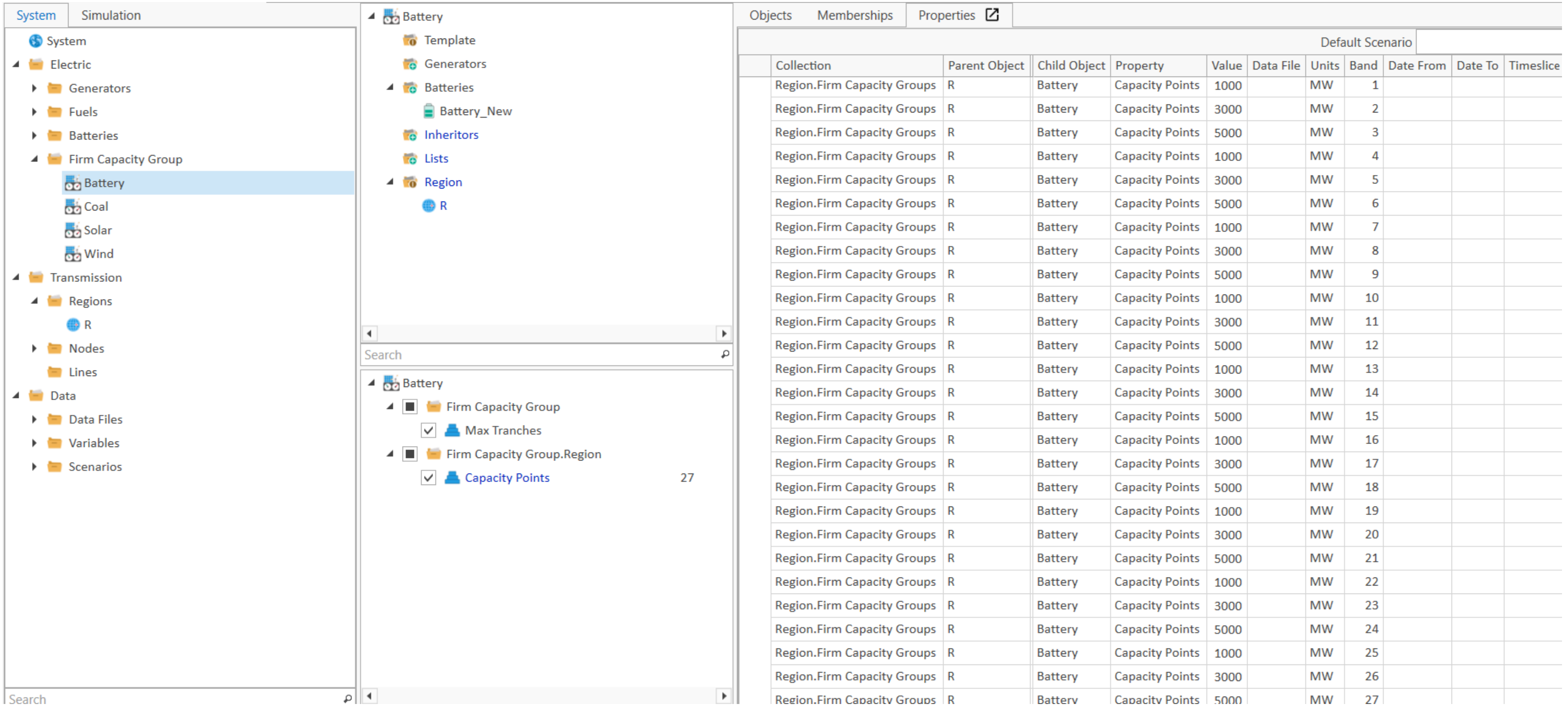
Endogenous ELCC in Capacity Expansion



Collection	Parent Object	Child Object	Property	Value	Data File	Units	Band	Date From	Date To	Timeslice
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	1			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	2			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	3			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	4			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	5			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	6			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	7			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	8			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	9			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	10			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	11			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	12			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	13			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	14			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	15			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	16			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	17			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	18			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	19			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	20			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	21			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	22			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	23			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	24			
Region.Firm Capacity Groups	R	Battery	Capacity Points	1000		MW	25			
Region.Firm Capacity Groups	R	Battery	Capacity Points	3000		MW	26			
Region.Firm Capacity Groups	R	Battery	Capacity Points	5000		MW	27			

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Conclusions & Future Work

What We Have Demonstrated

1. **ELCC is portfolio-dependent:** The capacity value of any renewable resource cannot be evaluated in isolation from the rest of the mix.
2. **Multi-dimensional surfaces work:** LOLE simulation grids over all technology combinations precisely capture cross-technology interaction effects.
3. **AI accelerates scenario setup and code generation:** AI agents drive PLEXOS API calls, auto-generate Python scripts, and build the full scenario matrix — turning a multi-day manual task into a prompt.

Tools Used in This Workflow: PLEXOS Model AI Agent (model & scenario creation) • PLEXOS APIs (model execution) • AI code generation agents (Python scripting & scenario automation) • Python (data processing, bisection algorithm, surface construction)

Enhancements: Consistent ∂ELCC/∂penetration implies a constant credit for that technology, reducing surface dimensions. • Lazy constraint + neural network: predict ELCC from capacity builds; if reserve margin is violated, add a cut and re-solve until convergence.

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