Long-Term Load and DER Forecasting

An ESIG Task Force report briefing — forecasting practices for a grid reshaped by electrification, large loads, and DERs

Prepared for the Indiana Utility Regulatory Commission's 2026 IRP Technical Conference

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Agenda

Nine sections, organized around building, reconciling, and applying long-term forecasts

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Why This Report, Why Now

Report pages 1–4

Why This Report, Why Now

Annual energy and peak demand were enough for a centralized grid. They no longer are.

2.8% → 8.2%

five-year national electricity demand growth forecast

128 GW

anticipated increase in U.S. peak demand by 2029

65–90 GW

of new data center load by 2029 — the single largest component of forecast growth

Three changes challenging the paradigm

- Variable, weather-dependent, less-centralized renewable generation — demanding temporally precise forecasts
- Unprecedented load growth from building and transportation electrification, plus new large loads
- Rising customer-sited DERs — solar PV, battery energy storage, and electric vehicles

What this forces on planners

- Hourly (8,760) profiles rather than two annual metrics
- Finer geographic resolution to find load pockets
- Reconciled projections across entities and use cases

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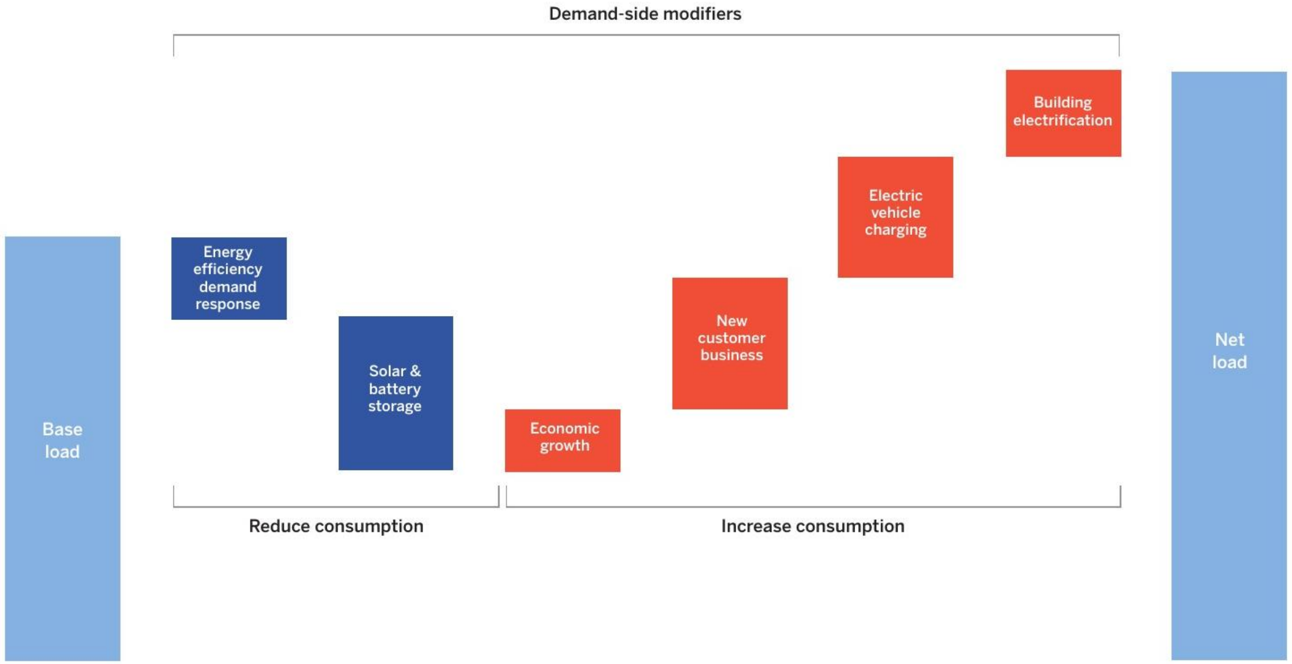
Source: ESIG (2025), Introduction and p. 29; Wilson, Zimmerman, and Gramlich (2024)

From Base Load to Net Load

Forecasting now requires explicit modeling of demand-side modifiers (Figure 1)

FIGURE 1

Demand-Side Modifier Adjustments to the Base Peak Load to Produce a Net-Peak Load Forecast



The figure represents the transition from base load toward expected net load as the forecasts incorporate more elements that reduce, increase, or change the patterns of demand.

What changed

- Historically forecasts focused primarily on economic growth and new load additions — the orange boxes
- Today efficiency, demand response, solar and storage pull load down, while large loads, EV charging and building electrification push it up
- The same logic applies to 8,760 profiles, total energy, or peak demand

The recurring trap

- Double-counting, when a technology is already embedded in the historical data used to forecast base load

Source: ESIG (2025), Figure 1

Stakeholders, Use Cases and Coordination

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Who Forecasts, and For What

Actors, use cases, horizons, and spatial granularity (Table 1)

Actors	Use Cases	Time Horizon	Spatial Granularity
States and regional planning entities (ISOs / RTOs)	Resource planning / IRP; market design	10–30 yr annual energy and peak, with weather variants	Load zone and ISO-system level
	Transmission planning	10–30 yr annual peak, with weather variants	Load zone allocated to transmission node
Utilities	Resource planning / IRP; financial planning and rate design; customer programs	10–30 yr annual energy and peak, with weather variants	Service territory by customer or revenue class
	Transmission planning	10–30 yr peak, including peak and low-load conditions	Transmission node, or substation aggregated up
	Distribution planning	5–10 yr annual peak; 1-in-10 or 90th percentile common	Distribution substation or feeder

Even inside a single utility, more than one long-term forecast usually exists — built by different business units, for different requirements.

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Source: ESIG (2025), Table 1

Coordination: Where Alignment Breaks Down

Some coordination already happens — four alignment challenges remain

Current areas of coordination

- ISOs and RTOs use load-serving entity data — efficiency savings, existing distributed solar, new large load requests
- Vertically integrated utilities allocate system forecasts to transmission nodes using distribution-level values
- Distribution planning produces its own local forecasts, which may or may not be coordinated with the system forecast
- States set electrification, PV, and storage policy — and in California, prepare the forecast itself

Challenges that remain

Cross-organization data sharing
Availability and standardization are the binding constraints on customer usage, weather, and DER program data.

Standardized forecasting practices
Common data formats, accuracy benchmarks, and planning horizons across organizations.

Policy and program alignment
Policies set adoption targets but rarely specify the inputs and assumptions forecasters need.

Operational characteristics of technologies
Assumptions on consumer behavior, tariffs, and market participation shape how DERs hit the system.

Multiple forecasts covering overlapping regions on different core assumptions is an inefficient outcome — it breeds confusion and introduces planning error.

Source: ESIG (2025), Figures 2–3, pp. 8–11; key takeaway, p. 46

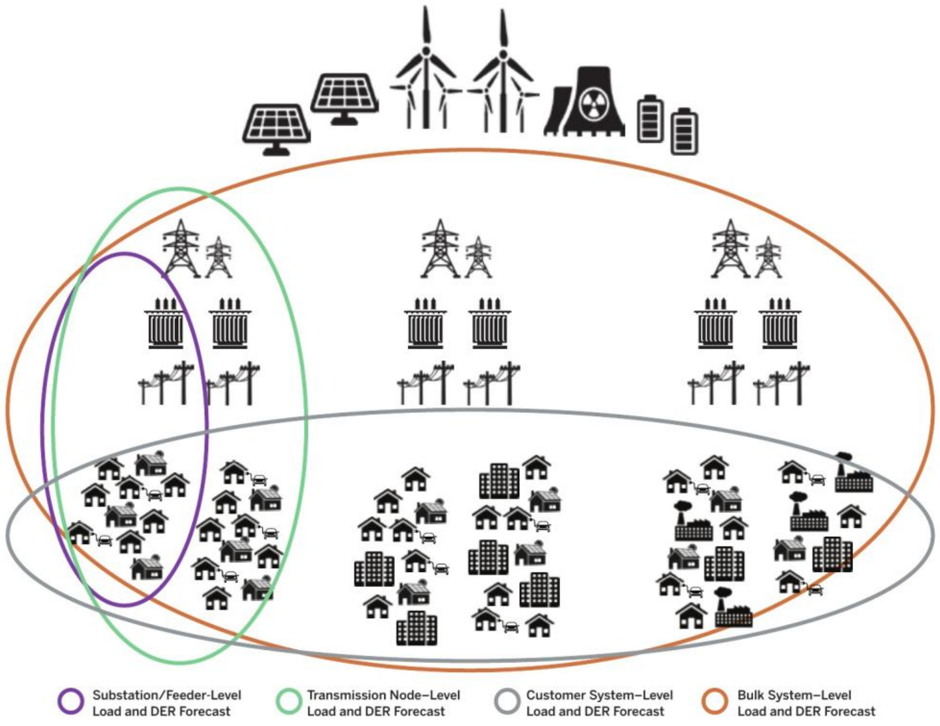
Building the Forecast

Report pages 12–40

Granularity: Match the Forecast to the Decision

Spatial hierarchy (Figure 4) and the temporal resolution trade-off

FIGURE 4
Grid Hierarchy and Use-Case Forecast Resolution



Temporal resolution trade-offs

Hourly (8,760) captures DER behavior, ramping needs, and intra-day variability — resource intensive across many feeders over 20+ years

Daily captures weather and behavioral variation at lower computational cost

Monthly practical for financial planning and regulatory reporting — masks DER-relevant dynamics

Annual simple to fold into investment planning — misses seasonal and temporal trends

Precision is not accuracy

- A parcel-level model is precise, but where adoption rates are low its accuracy at the unit level may be poor — communicate that uncertainty.

Source: ESIG (2025), Figure 4, pp. 12–15; precision vs. accuracy, p. 35

The Forecasting Process

Three steps — and a methodological choice that is distinct from grid resolution (Figure 5)

1

Forecast base load

- Back out weather-dependent distributed energy resources such as solar and demand response to determine gross or native base load
- Extrapolate base load based on historical data and/or weather and economic variables

2

Adjust base load forecast with exogenous forecasts for new loads

- Distribution-level known new customer business growth
- Bulk system–level large loads

3

Adjust base load forecast with exogenous forecasts for new consumer-adopted technologies

- Distributed energy resources such as solar and battery storage
- Building and transportation electrification technologies

Top-down methodology

- Aggregate customer behavior modeled from macro variables — regional GDP, population, demographic trends
- Easier to execute; common for system-level resource, transmission, and financial planning
- Too coarse to apply directly to distribution planning without disaggregation

Bottom-up methodology

- Starts from micro-level inputs — customer-class usage, end-use stock, site-level DER adoption — then aggregates upward
- More data- and labor-intensive, requiring substantial preprocessing and coordination
- Offers real insight into spatial variation in adoption and load growth

Resolution does not necessarily dictate method — a substation-level forecast can be built either way.

Source: ESIG (2025), Figure 5, pp. 16–17

Uncertainty and Scenario Planning

Point estimates are not enough — three sources of uncertainty, four analysis techniques

Three sources of uncertainty

Natural variability
Uncertainty in historical load and weather data, usually characterized statistically

Model structure
Uncertainty in selecting the most accurate model structure for future load

Assumptions
Uncertainty in key inputs such as DER adoption rates and policy changes

Four core techniques

1. **Deterministic** One factor at a time
2. **Deterministic joint** Multiple factors together, to expose interaction effects
3. **Parametric** Input values varied across a range — the most common route to low / medium / high scenarios
4. **Probabilistic** Monte Carlo and related methods; growing where input distributions are trusted

FERC Order 1920 pushes ISOs toward multiple future portfolios · MISO runs three 20-year planning scenarios · Dominion Energy South Carolina, Xcel Upper Midwest, DTE Electric, and National Grid model varying EV, heat pump, and DER levels

Source: ESIG (2025), pp. 18–19

Long-Term Base Load Forecasting

The foundation under every adjustment — historical trends projected forward, before exogenous factors

Three base-load modeling methods

Time-extrapolation
Projects future load from historical growth rates, assuming past patterns persist. Simple, with minimal data and compute — but it accounts for no economic, demographic, policy, or weather drivers.

Econometric and machine learning
Regression relates historical load to weather, economic activity, and population growth. Neural networks and boosting capture non-linear interactions. Requires high-quality data, compute, and skills.

Statistically adjusted end use (SAE)
Econometric models plus an end-use framework — equipment saturation, efficiency, DSM programs, floor area, thermal shell. Best suited to policy and electrification scenarios; needs detailed end-use data and stakeholder engagement.

Historical load data and preprocessing

Where the data comes from
ISO market settlements, SCADA, and AMI smart meters — none of which were built for forecasting. They exist to serve reliability and financial objectives.

Depth versus detail
Longer historical records usually mean older datasets with less temporal and spatial resolution. Available granularity often dictates the level at which base load is modeled.

Data quality is the gating step
Missing or erroneous points, inconsistencies between sources, and aggregation discrepancies across systems. Practice: handle outliers, interpolate gaps, cross-check against validated load, and synthesize representative series to fill records.

Back out embedded solar and demand response first — otherwise they distort the timing of system peaks and the coincidence factors between load zones and get counted twice as DER adjustments later.

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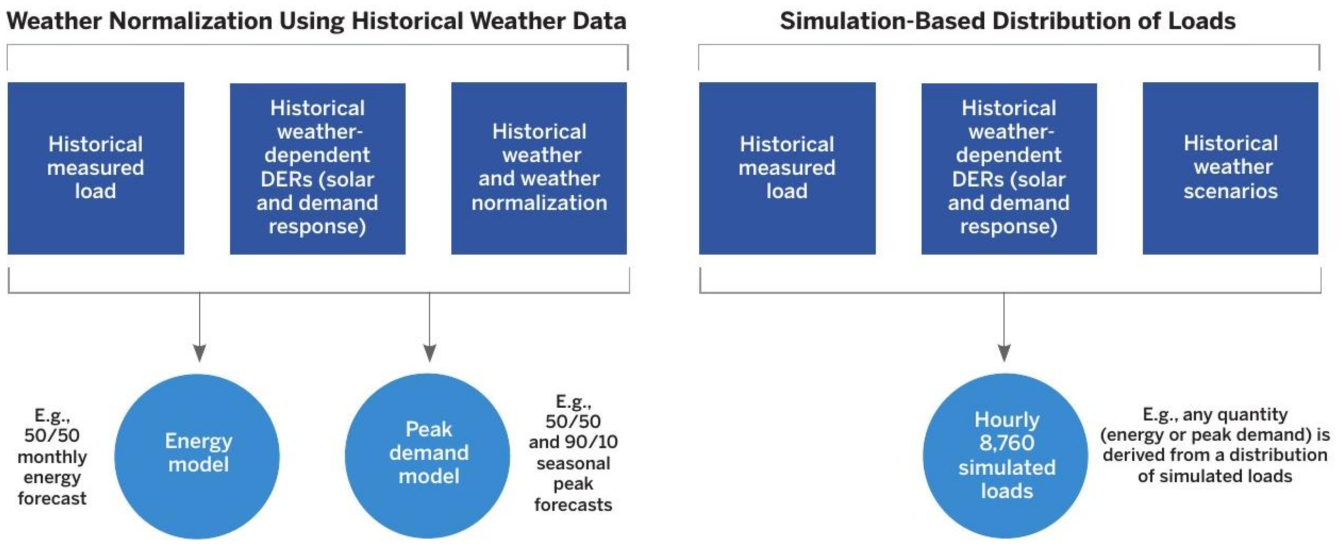
Source: ESIG (2025), pp. 20–21

Weather, Climate and Extreme Events

Normalization versus simulation — and the limits of the historical record (Figure 6)

FIGURE 6

Weather Normalization Using Historical Weather Data Versus Simulation-Based Distribution of Loads



Choosing an approach

Normalization
25–30 years of history define typical (1-in-2) and extreme (1-in-10) conditions. The most common method.

Simulation
Many weather scenarios generate hourly load distributions. Better at capturing volatility and ramp rates.

As the reliance on weather-sensitive energy sources grows, it becomes increasingly important to understand the relationship between historical weather patterns and future climate trends

Climate adjustment

Trend-based CDD/HDD adjustments are simple; GCM methods need dynamical, statistical, or ML downscaling

Model spread

Downscaling-method variance can in some cases exceed variance from emissions or inter-annual weather — use multiple models

Extreme events

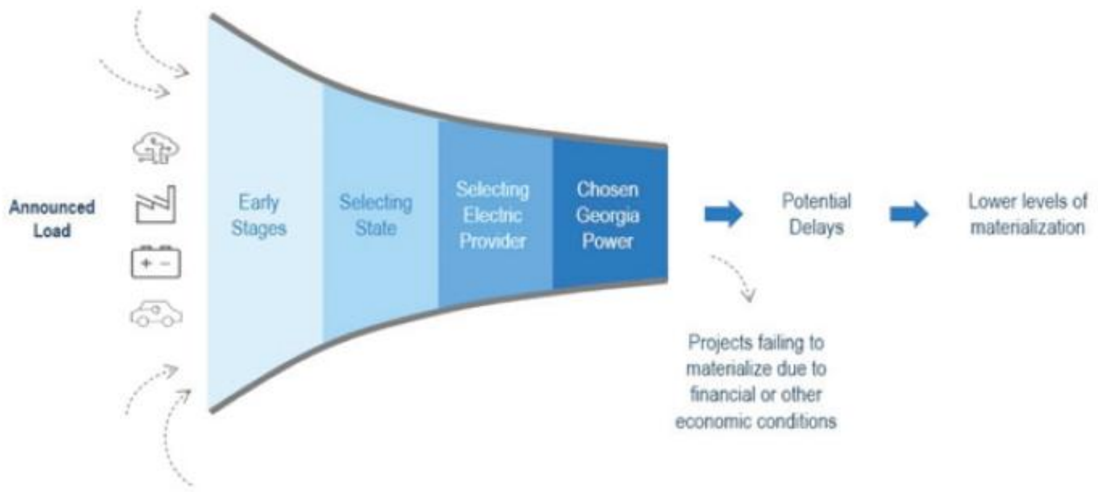
Synthetic weather records, spline regression, and Monte Carlo address thin historical tails

Source: ESIG (2025), Figure 6, pp. 22–26; Lafferty and Sriver (2023); EPRI (2024a)

Large Loads and Known New Customer Load

Gigawatt-scale interconnections, with no standardized forecasting method (Figure 9)

FIGURE 9
Example Large Load Forecast Model Considering Uncertainty



Four drivers of large-load growth

Data centers 65–90 GW of new load; AI facilities have higher power density and more aggressive ramps

Manufacturing ~20 GW; more predictable ramp schedules than data centers

Industrial electrification Arc furnaces, heat pumps, and electrified process heat

Hydrogen production Potentially large, but planned electrolyzer plants sit outside most forecasts today

Managing realization risk

Derating. Utilities and ISOs apply derating factors, but uncertainty is not uniform — some report full utilization of interconnection requests while others see actual load below 50% of requested capacity.

Confidence tiers. Eversource maintains a centralized tracking database classifying new customers as Certain · Probable · Possible · Uncertain · Forecasted, coordinated across distribution planning, customer groups, and load forecasting.

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Source: ESIG (2025), Figure 9, pp. 27–33; Wilson, Zimmerman, and Gramlich (2024)

Exogenous Factors: DER Adoption and Behavior

Two modeling steps — how many and where, then how they behave on the system

Step 1 — Modeling adoption

Top-down
Macro indicators model adoption at service area, state, or national level. Used for resource and financial planning. Cannot model individual adoption.

Bottom-up
Micro indicators produce site, parcel, or census-block forecasts that map directly to grid infrastructure. Mostly used to disaggregate top-down targets.

Disaggregation
Proportional allocation against load or customer count; or spatial allocation using adoption propensity and agent-based models.

Step 2 — Modeling behavior, by technology

Solar PV
Weather-driven; generation usually inferred from net load, not measured directly

Battery storage
Economics, back-up reliability, VPP participation — load, or dispatchable generation?

Building electrification
Heat pumps plus back-up resistance heat; may push East Coast ISOs to winter peaks by 2030–2035

Transportation electrification
"Mobile DERs" — home, workplace, and fast charging differ; rate design reshapes the profile

Efficiency & demand flexibility
Double-counting risk against SAE base load; demand response often sits outside the forecast

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Source: ESIG (2025), Table 3, pp. 34–40

Reconciling and Applying the Forecast

Report pages 41–47

Reconciliation: Three Challenges

System forecasts and aggregated local forecasts rarely agree (Figure 12)

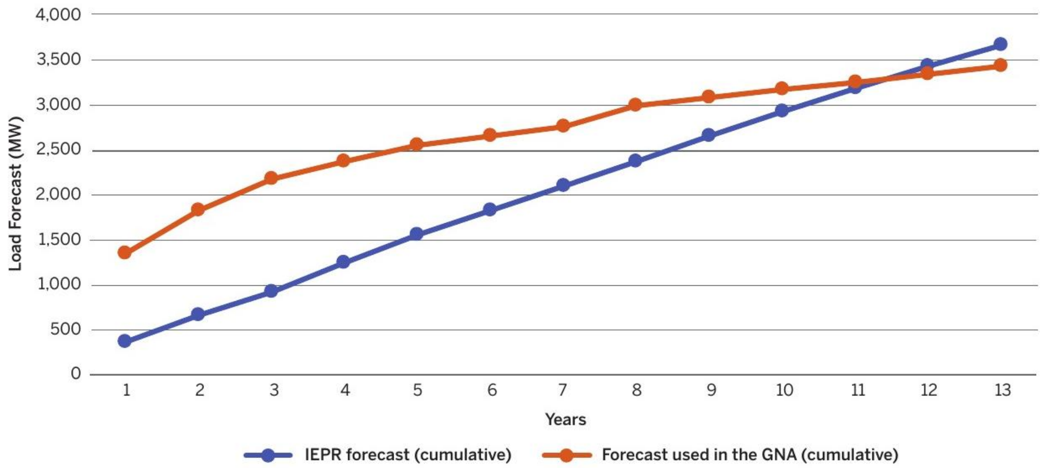
Where they diverge

Forecast components
Which base load assumptions and exogenous load and DER factors are actually included in each forecast?

Forecast reconciliation
The coincidence factor — system coincident peak over the sum of non-coincident peaks — is typically held constant, ignoring how DERs shift the timing of local peaks.

Forecast allocation
Contribution factors from historical records misallocate future resources — overstating rooftop solar in dense urban nodes, missing EV hot spots.

FIGURE 12
Comparison of the State System-Level Base Load Forecast with the Aggregate Distribution Utilities' Base Load Forecast in California



Interpreting the California example

- The aggregated bottom-up distribution forecast runs well above the state top-down forecast in early years, converging later.
- Either distribution planning is over-estimating demand and over-building, or the system forecast is under-predicting growth.

Source: ESIG (2025), Figures 11–12, pp. 41–44; Resource Innovations (2022)

Key Takeaways

Six themes for forecasters, planners, and regulators

1. **Move toward 8,760 time-series forecasting**
   Model hourly profiles at the asset level rather than disaggregating annual peak and energy values

2. **Increase geographic granularity**
   DER adoption is not uniform — concentrations trigger distribution upgrades best planned in advance

3. **Historical trends are losing explanatory power**
   Model the drivers of adoption at the end-use level, not the extrapolated past

4. **Scenario planning is essential**
   There is no single best methodology — bound the uncertainty rather than defend a point estimate

5. **Coordinate through integrated planning**
   Overlapping forecasts on different assumptions is inefficient and error-prone; data sharing is the fix

6. **Reconciliation remains genuinely hard**
   Top-down under-represents local growth; bottom-up can overestimate need. Both produce bad capital decisions

Granular methods, scenario-based approaches, and stakeholder data sharing are what make a long-term forecast usable.

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Questions?

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Read the report

esig.energy/long-term-load-and-der-forecasting

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