Long-Term Load and DER Forecasting

A Report by the
Energy Systems Integration Group's
Long-Term Load and DER Forecasting
Task Force

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Long-Term Load and DER Forecasting Task Force

Prepared by

Julieta Giraldez, Electric Power Engineers
Gregory Mandelman, Electric Power Engineers
Matthew Steffen, Electric Power Engineers

Task Force Members

Madeleine Balchan, Xcel Energy
Obadiah Bartholomy, Sacramento Municipal Utility District
Jonathan Black, ISO New England
Jon Bradshaw, Pacific Gas and Electric
Dominique Davis, Midcontinent Independent System Operator (MISO)
Brian DeMent, Ameren
Brad Decker, Midcontinent Independent System Operator (MISO)
Timothy Duffy, New York Independent System Operator (NYISO)
Brittany Farrell, Clean Power Research
Nicholas Fugate, California Energy Commission
Andrew Gledhill, PJM Interconnection
Elaine Hale, National Renewable Energy Laboratory
Ryan Hinkley, National Grid
Ludo Hintos, Dominion Energy
Ryan Jones, Evolved Energy Research
Daniel Kirk-Davidoff, EPRI
Kate Lamb, Electric Reliability Council of Texas (ERCOT)
Arthur Maniaci, New York Independent System Operator (NYISO)
Joseph Millard, Ameren
Brian Monson, Xcel Energy
Sean Morash, Telos Energy
Sam Morris, Electric Reliability Council of Texas (ERCOT)
Daniel Nelli, Pacific Gas and Electric
Joshua Novacheck, NextEra Energy
Valentin Rigoni, Kevala
Victoria Rojo, ISO New England
Priya Sreedharan, GridLab
Andy Sukenik, Itron
Brent Vastola-Lunghino, Kevala
John D. Wilson, Grid Strategies
Sophia Zhang, Eversource

This report was produced by a task force made up of diverse members with diverse viewpoints and levels of participation. Specific statements may not necessarily represent a consensus among all participants or the views of participants' employers.

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Contents

Abbreviations

AI	Artificial intelligence
AMI	Advanced metering infrastructure
DER	Distributed energy resource
EV	Electric vehicle
GCM	General circulation model
ISO	Independent system operator
PV	Photovoltaic
RTO	Regional transmission organization
SAE	Statistically adjusted end use

PHOTOS

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Executive Summary

Long-term load and distributed energy resource (DER) forecasting is critical for achieving clean energy and decarbonization goals, ensuring a reliable, resilient, and affordable energy system. Traditionally, these forecasts, conducted annually by entities like utilities, states, and ISOs, focused on total annual energy and peak demand. This approach was adequate for a grid dominated by centralized generation and a predictable demand pattern in which the past was representative of the future. However, the evolving energy landscape—marked by variable renewable generation, unprecedented load growth from electrification (buildings, transportation, data centers, manufacturing), and rising customer-sited DERs (solar, battery storage, electric vehicles)—necessitates a paradigm shift. Traditional forecasting practices are no longer sufficient for this complex, dynamic grid.

Addressing the Primary Forecasting Issues in a Transforming Grid

This report represents the culmination of the work of the Energy Systems Integration Group's Long-Term Load and DER Forecasting Task Force and addresses key forecasting issues in this transforming grid. It outlines the need for high-resolution, time-based forecasts (8,760 hourly profiles) to capture the correlated impacts of weather on demand, generation, and the nuances of DER behavior. Accurately predicting future energy demand requires explicit modeling of various demand-side modifiers—including energy efficiency, solar, battery storage, economic growth, new customer business loads, electric vehicle charging, and building electrification—to arrive at a net load forecast.

Policy-driven technology adoption introduces uncertainty, demanding careful modeling to avoid double-counting impacts, as well as the need to study multiple future scenarios. Improved time-series characterization and enhanced geographic granularity are vital for accurately forecasting future net load and localized demand variations, or load pockets. In addition, system operators, utilities, and other planning entities are realizing the need to reconcile their load projections to ensure consistency across diverse planning processes and use cases.

Key Takeaways

A Shift Toward 8,760 Time-Series Forecasting Can Significantly Improve Temporal Forecasting Accuracy

Moving toward 8,760 hourly time-series forecasting can significantly enhance temporal accuracy, providing a more precise assessment of how DERs, electrification, and climate trends influence load patterns.

Greater Geographic Granularity Can Address Several Forecasting Challenges

DER adoption is not uniform and can trigger significant local distribution system upgrades. Granular geospatial forecasting helps planners anticipate and manage these challenges.

Emerging Adoption and Behavior Trends Require New Forecasting Approaches

New industries and accelerating adoption of customer technologies are rendering forecasting based on historical trends less reliable. More granular, end use–focused methodologies that also model the drivers and patterns of technology adoption are becoming increasingly required.

Scenario Planning Is Essential for Capturing Uncertainty

Given the rapid changes in energy demand, technology, and policy, scenario-based forecasting is crucial for assessing a range of possible futures and improving system-wide preparedness.

Coordination Across Forecasting Entities Is Increasingly Critical Through Integrated Planning Approaches

Multiple entities often produce forecasts for overlapping regions, leading to inefficiencies and potential errors. Integrated planning approaches necessitate greater coordination and data-sharing among grid planning entities.

Incorporating Climate Change Models into Forecasting Remains Complex

Most current load-to-weather models rely on historical data, which may not fully capture climate change impacts. It is necessary to enhance methodologies to consider extreme weather and updated climate models.

Reconciliation Between Top-Down and Bottom-Up Forecasts Is Complex

System-level (top-down) and aggregated local (bottom-up) forecasts covering the same area often conflict. To improve forecast alignment, planners must manage differences in forecast components, reconcile how local and system peaks relate, and properly allocate system-level data to local grid areas.

Known New Customer Loads Must Be Carefully Integrated into Forecasts

Reconciling base load growth derived from economic indicators with known new customer load growth data (e.g., data centers, large manufacturing) is a key challenge to avoid double-counting.

Transportation Electrification Presents Similar Reconciliation Challenges

Like known new customer loads, transportation electrification forecasts need proper integration to avoid overestimation by overlapping with baseline or other load growth projections.

Future Price Signals May Influence Load Forecasting

Future price signals from dynamic rates, demand response, and local flexibility markets can significantly influence load patterns and should be incorporated into scenario analyses where relevant.

The challenges facing long-term load and DER forecasting present opportunities for innovation. Advanced, granular forecasting methods, coupled with scenario-based approaches and robust stakeholder coordination and data sharing, are vital for ensuring grid reliability and effective planning in the face of tomorrow's energy landscape.

Introduction

Long-term load forecasting is at the front and center of meeting clean energy and decarbonization goals. Forecasting load and distributed energy resources (DERs) is conducted to effectively plan for and implement system generation capacity, energy markets, grid infrastructure, DERs, and customer rates and programs to maintain a reliable, resilient, and affordable energy system while meeting customer and policy goals.

Long-term load and DER forecasting is typically performed annually by multiple entities and for multiple use cases in the electric grid planning process, including utilities, states, independent system operators, and research organizations. Traditionally, long-term (10 to 30 years) load forecasts estimated two key metrics: total annual energy and annual peak demand. These two metrics were sufficient to plan for future resource and grid infrastructure needs when power systems were shaped by large centralized thermal and hydropower generation units connected to load centers via the transmission system. However, three key changes are challenging this paradigm, including:

Long-term load forecasting is at the front and center of meeting clean energy and decarbonization goals.

- The introduction of variable, weather-dependent, and less-centralized renewable generation to the resource mix and the corresponding need for more temporally precise load forecasts to enable reliable demand and supply matching
- Unprecedented load growth from the electrification of the building and transportation sectors, and new large loads such as data centers and manufacturing expansion
- The increasing adoption of customer-sited distributed energy resources, such as solar photovoltaics (PV), battery energy storage systems, and electric vehicles (EVs)

Shifts in technology, policy, and consumer behavior are fundamentally altering the shape, timing, and location of electricity demand.

These shifts in technology, policy, and consumer behavior are fundamentally altering the shape, timing, and location of electricity demand. As a result, traditional forecasting practices—focused on annual energy and peak demand—are no longer sufficient. To effectively plan for a more complex and dynamic grid, energy planners must embrace new forecasting approaches that reflect the increasing influence of electrification, weather-driven variability, new large loads, and distributed energy resources. Several key forecasting issues must be addressed to meet the needs of a rapidly transforming grid.

Energy Planners Need High-Resolution, Time-Based Forecasts to Capture the Realities of a Changing Grid, Including Correlated Impact of Weather on Both Demand and Generation

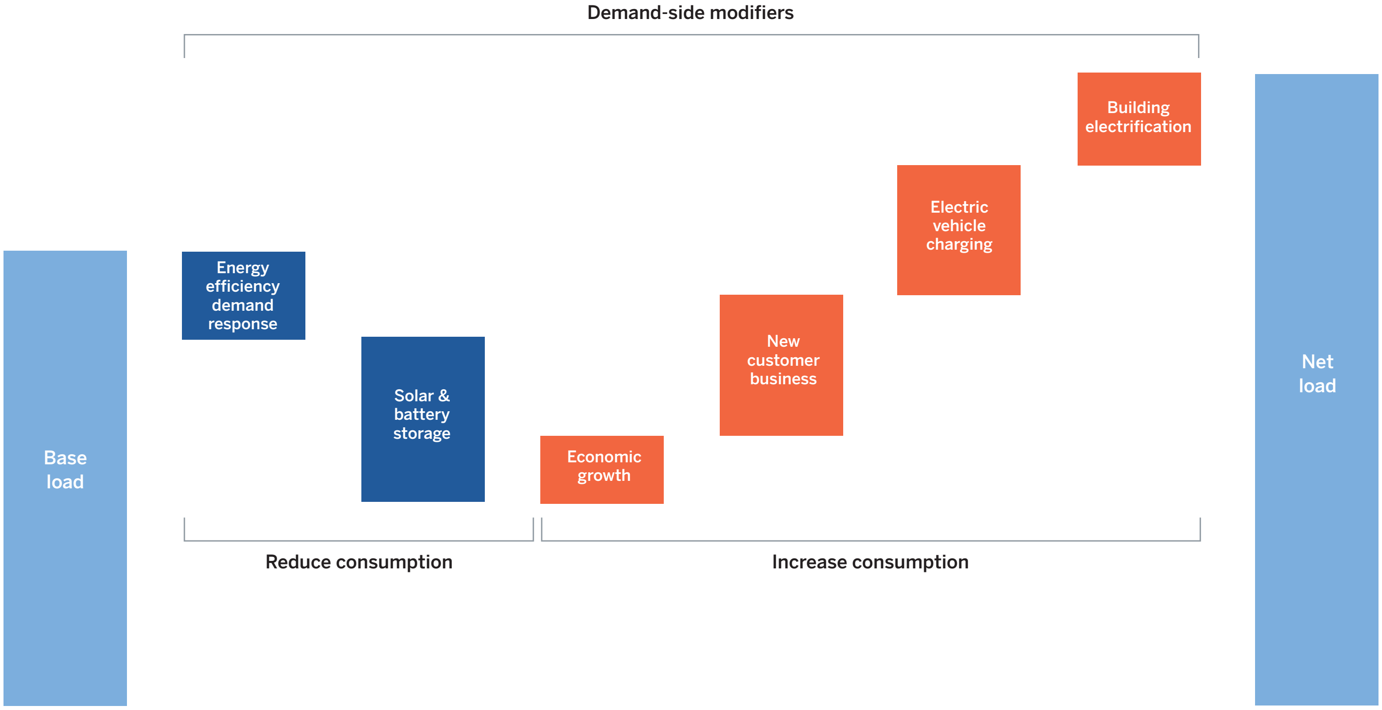
Traditionally, forecasts have focused on peak demand and total energy consumption, but with the rise of DERs like PV and EVs, these traditional practices are failing to address emerging planning objectives. High levels of DER generation, particularly from PV, can impact system resource dispatch, introducing new dispatch ramping requirements. EV charging often occurs outside of typical peak hours, introducing new and unpredictable load patterns. Relying solely on annual or peak demand estimates overlooks these emerging trends. To address this, the industry is shifting toward hourly or even sub-hourly forecasting, which provides a more granular view of demand and generation patterns.

More granular forecasting also enables advanced non-wires alternatives to traditional grid expansion, such as battery energy storage systems for peak shifting and demand management, or time-of-use rate structures that encourage off-peak consumption. With higher-resolution, hourly forecasting, planners can better align infrastructure investments with actual system needs, avoiding over- or under-investment while ensuring the grid is prepared for the future.

Another crucial aspect of high-resolution forecasting is capturing the correlated impact of weather on both energy demand and generation, particularly as DERs play a growing role in the grid. Temperature-dependent heating and cooling loads cause energy demand to fluctuate with seasonal and daily weather conditions. EV efficiency declines in extreme temperatures, increasing charging demand, and PV generation varies with time of day, cloud cover, and season. The increasing frequency and severity of extreme weather events adds another layer of uncertainty by causing sudden demand spikes, disruptions to generation, and other grid reliability challenges. To account for these impacts, weather must be modeled

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.

Source: Energy Systems Integration Group.

A crucial aspect of high-resolution forecasting is capturing the correlated impact of weather on both energy demand and generation.

at compatible temporal resolutions, providing a clearer picture of how its fluctuations influence both demand and generation.

Forecasting Demand-Side Modifiers Is Essential to Accurately Predict Future Energy Demand

Changing weather patterns, new load growth drivers, and evolving consumption behaviors challenge traditional forecasting models, which historically relied on past load and weather data alongside economic and demographic adjustments to predict energy and peak demand. While it is still necessary to model base load and extrapolate load to weather behavior, forecasting future demand now requires explicit modeling of multiple demand-side modifiers to ultimately forecast net load, as illustrated in an example of peak load forecasting with demand-side modifiers in Figure 1.

This approach can be applied to annual time-series profiles, total energy, and/or peak demand forecasts. A range of forecasting methods, varying in complexity, can be used to estimate net-load energy and peak demand. However, all approaches consider upward or downward adjustments to reflect long-term energy and peak demand trends.

Historically, long-term forecasts primarily focused on economic growth and new load additions (orange boxes in Figure 1), which was sufficient when electricity demand followed a steady growth trajectory. However, the ongoing transformation of the grid necessitates more dynamic forecasting approaches that incorporate time-series analysis. Customer energy programs and technologies such as energy efficiency and distributed generation (e.g., solar and wind generation) reduce overall consumption, impacting base load demand. Demand response programs and energy storage systems can shift consumption patterns and, along with distributed solar, alter peak demand periods, increasing the need for time-series modeling.

Electrification trends, particularly transportation and building electrification, are also reshaping demand patterns. Transportation electrification is primarily driven by replacing internal combustion engine vehicles with EVs and developing the necessary charging infrastructure. Building electrification involves replacing natural gas heating and cooling systems with electric alternatives, further increasing electricity demand and contributing to new system peaks.

Additionally, new large energy consumers, such as data centers and manufacturing, introduce significant new loads that are challenging to model due to their rapid technological evolution. These new demand drivers underscore the need for flexible, high-resolution forecasting approaches that capture shifting consumption patterns and account for both long-term trends and emerging technologies.

Policy-Driven Technology Adoption Introduces Uncertainty in Load Forecasts, Requiring Careful Modeling to Avoid Double-Counting Impacts

Policy goals and incentives influence consumers' adoption of new technologies that underpin many demand-side modifiers. However, the implications of these policies are complex, are hard to quantify, and can shift rapidly, introducing significant uncertainty into load forecasts. Historical technology adoption data are sparse, making it difficult to create robust consumer adoption models and to avoid double-counting demand-side modifier impacts when a technology is present in historical data that are used to forecast base load.

Accurately Forecasting Future Net Load Requires Improved Time-Series Characterization as Well as Enhanced Geographic Granularity to Account for Localized Demand Variations

Demand-side modifiers resulting from customer adoption of technologies have exacerbated the need for improving the time-series characterization of future net load. They have also increased the need for more granular geographic resolution of demand forecasts and for accurately forecasting the so-called load pockets in multiple load forecasting use cases.

System Operators, Utilities, and Other Planning Entities Must Reconcile Load Projections to Ensure Consistency Across Planning Processes and Use Cases

With multiple entities producing forecasts for overlapping service areas and varying planning horizons, alignment and transparency are increasingly important. Reconciling assumptions, methodologies, and scenarios across entities and departments improves coordination and reduces the risk of planning misalignment.

The Energy Systems Integration Group (ESIG) convened the Long-Term Load and DER Forecasting Task Force, a diverse group of grid planners, utilities, researchers, technology providers, and others. This report synthesizes the task force's insights, outlining key actors and use cases for long-term forecasting, reviewing current methods and their trade-offs, identifying gaps in reconciling different forecasts, and describing existing and advanced practices to improve the accuracy, resolution, and relevance of load and DER forecasts for modern grid planning.

Forecasting Stakeholders and Use Cases

Key Actors and Roles

Long-term load and DER forecasting involves multiple stakeholders, each playing a distinct role in shaping forecasts, setting policies, and using forecast data for planning and investment decisions. The key actors include:

- **Utilities:** Electricity providers and asset owners are responsible for distribution systems and, in some cases, transmission and generation assets. Utilities conduct forecasting to support infrastructure planning, regulatory filings, and operational decisions. Load forecasts developed by load-serving entities are the foundation for most regional and national forecasts.
- **Independent system operators (ISOs) and regional transmission organizations (RTOs):** These federally regulated entities manage regional transmission planning, coordinate energy markets, and ensure grid reliability. ISOs and RTOs develop system- and zonal-level load and DER forecasts for resource and transmission planning. They may simply aggregate members' forecasts, or they may perform an independent forecast supplemented by information obtained from members.
- **State agencies and utility regulators:** State governments legislate and set policies related to energy and technology adoption. State utility regulators oversee utility programs, approve investment applications, and enforce policies that influence forecasting assumptions. Some state agencies develop models and datasets as well: the California Energy Commission is unique in that it prepares a statewide load forecast that is used by utilities and the California Independent System Operator (with their input).
- **Federal agencies and regulatory entities:** The federal government enacts legislation, provides incentives, and implements programs that influence long-term load and DER growth. Agencies like the U.S. Department of Energy support forecasting efforts through public datasets, tools, and research.
- **National laboratories, research institutions, and utility associations:** National labs, independent research organizations, and utility associations also develop models, data sets, and long-term energy outlooks that inform load and DER forecasts. They often leverage and enhance data from government agencies and are sometimes able to aggregate confidential information for public release. Many of these sources provide free or low-cost data and scenario analysis used in grid planning.
- **Consultants and vendors:** Private companies provide forecasting services, proprietary datasets, analytical tools, and modeling expertise. These vendors often enhance publicly available data with additional methods and insights.

Each of these stakeholders plays a distinct role in shaping, developing, and applying load and DER forecasts. However, their forecasting objectives vary based on their specific functions and responsibilities, which can include

Stakeholders play distinct roles in shaping, developing, and applying load and DER forecasts, with their forecasting objectives varying based on their specific functions and responsibilities.

ensuring grid reliability, planning infrastructure investments, designing energy policies, or managing market operations. The following section outlines the primary use cases for long-term load and DER forecasting, highlighting how different entities rely on these projections to inform critical decision-making processes.

Forecast Use Cases

Long-term load and DER forecasts serve a variety of critical planning functions across the electricity sector. These forecasts guide financial and operational decision-making, helping utilities, system operators, and policymakers prepare for future energy demand and technology adoption. Below are the most common use cases.

- **Resource planning and market design:** Utilities and ISOs use long-term annual energy and peak load forecasts in capacity expansion planning and production cost models to determine the optimal mix of generation and capacity resources, as well as energy market design parameters, to achieve specific goals. These goals include safe and reliable grid operations, resource adequacy, and compliance with clean energy standards at least cost. Integrated resource plans evaluate new energy resources by considering all available alternatives, including conventional generation, renewable energy, storage, power purchases, and demand-side management programs. Historically, integrated resource plans have emphasized meeting annual forecasts of energy and peak demand. For some regions and utilities, resource planning has or will soon adopt more granular hourly forecasts to better reflect grid dynamics.
- **Transmission planning:** System operators and transmission owners use long-term load and DER forecasts to produce key seasonal snapshots—such as summer and winter peaks—to identify transmission expansion needs. These forecasts help ensure system reliability while accommodating new generation and load growth, as well as inform decisions on upgrading or replacing aging infrastructure.
- **Distribution planning:** Many distribution utilities develop medium-term (3- to 10-year) load and DER forecasts to guide investments in the distribution system by identifying where system upgrades are needed to maintain reliability while accommodating local DER adoption and load growth. Historically,

some utilities have relied on historical trends in distribution investments to inform budgets, but more detailed distribution system forecasts are being used to improve investment alignment with future customer requirements. As with transmission planning, distribution planning also considers asset retirement and replacement decisions based on forecasted demand changes.

- **Financial planning and rate design:** Utility financial planning departments rely on long-term forecasts of total energy sales and peak demand to inform corporate financial projections. Some utilities use load forecasts to inform annual revenue requirement calculations. Revenue needs are, in turn, used to set rates based on cost-of-service studies.
- **Customer programs:** Utility customer departments use load and DER forecasts to design demand response, energy efficiency, solar adoption, and electrification programs. By understanding projected energy usage trends, customer programs can be tailored to enhance grid reliability, support policy goals, and optimize cost-effectiveness.

Expanding Requirements of Load Forecasting Across Use Cases

Regardless of use case, the increasing complexity of load patterns necessitates a shift toward an annual hourly ("8,760") forecast. Traditional forecasting approaches focus primarily on system-wide peak and total energy demand, but modern grid planning requires a more granular understanding of load characteristics. Key drivers for this transition include:

- **Diverse peak day profiles:** Different customer segments, DERs, and electrification trends are creating multiple peak demand patterns that vary by location, season, and economic activity. Understanding these variations is essential for resource adequacy planning.
- **Mid-day minimum loads:** The proliferation of behind-the-meter solar generation is causing significant dips in net demand during midday hours. Accurately forecasting these minimum loads is critical for evaluating ramping needs, energy storage integration, and reliability planning.

The increasing complexity of load patterns necessitates a shift toward an annual hourly forecast.

- **Zonal non-coincident load characteristics:** While traditional planning has focused on system-wide coincident peaks, local or zonal non-coincident peaks—when subsets of the system reach their highest demands at different times—often do not align with the overall system peak. Accounting for non-coincident peaks ensures that planners do not overlook localized constraints that arise outside of the coincident system peak.
- **Seasonal peaks on weekends, holidays, or atypical months:** Climate change, changing consumption behaviors, and new technologies (e.g., EV charging, heat pumps) are shifting peak demand patterns, sometimes resulting in unexpected seasonal peaks occurring outside of historical norms. These trends must be captured in load forecasts to prevent planning deficiencies.

In some cases, utilities are developing 8,760 hourly forecasts, and in others the energy and peak demands are being adjusted using representative load profiles. Adopting these more nuanced forecasting approaches empowers planners with the insights necessary to improve grid reliability, optimize investments, and better manage the uncertainties introduced by evolving demand patterns and DER adoption.

TABLE 1

Long-Term Load and DER Forecast Actors, Use Cases, Time Horizons, and Spatial Granularities

Actors	Use Cases	Time Horizon and Variables	Spatial Granularity
States **Regional planning entities** (independent system operators, regional transmission organizations (ISOs/RTOs))	Resource planning/integrated resource plans Market design	A 10- to 30-year annual energy and peak load forecast with different weather variants	Forecast produced at load-zone and ISO-system levels
	Transmission planning	A 10- to 30-year annual peak load forecast with different weather variants	ISO load zone forecast allocated to transmission node level
Utilities	Resource planning/integrated resource plans Financial planning and rate design Consumer programs	A 10- to 30-year annual energy and peak load forecast with different weather variants	Utility service territory level by customer class or revenue class
	Transmission planning	A 10- to 30-year annual peak load forecast with different weather variants, including both peak and low-load conditions	Utility service territory level or ISO load zone level forecast allocated to transmission node (most common) or distribution substation–level forecast aggregated up to transmission node level (less common)
	Distribution planning	A 5- to 10-year annual peak load forecast. (If weather modeling is used, a 1-in-10 or 90th percentile load forecast is common.)	Distribution substation or feeder level

Source: Energy Systems Integration Group.

Table 1 summarizes how different entities use long-term load and DER forecasts, highlighting the key actors, use cases, time horizons, and forecast granularity levels.

Ensuring Consistency and Reliability Across Different Use Cases

Given the wide range of applications for load and DER forecasts, it is essential to ensure consistency and reliability across different use cases. However, multiple forecast stakeholders are developing and relying on these forecasts, which makes it challenging to avoid discrepancies in data, assumptions, and methodologies. Even within a single utility or regional entity, there may be more than one long-term load forecast due to different business unit requirements, which can result in confusion.

Effective coordination among stakeholders is necessary to align forecasting inputs, share data, and establish common assumptions, ultimately improving the accuracy and usefulness of forecasts. The following section explores existing coordination steps and the mechanisms used to facilitate collaboration in forecasting efforts.

Coordination Among Stakeholders and Use Cases

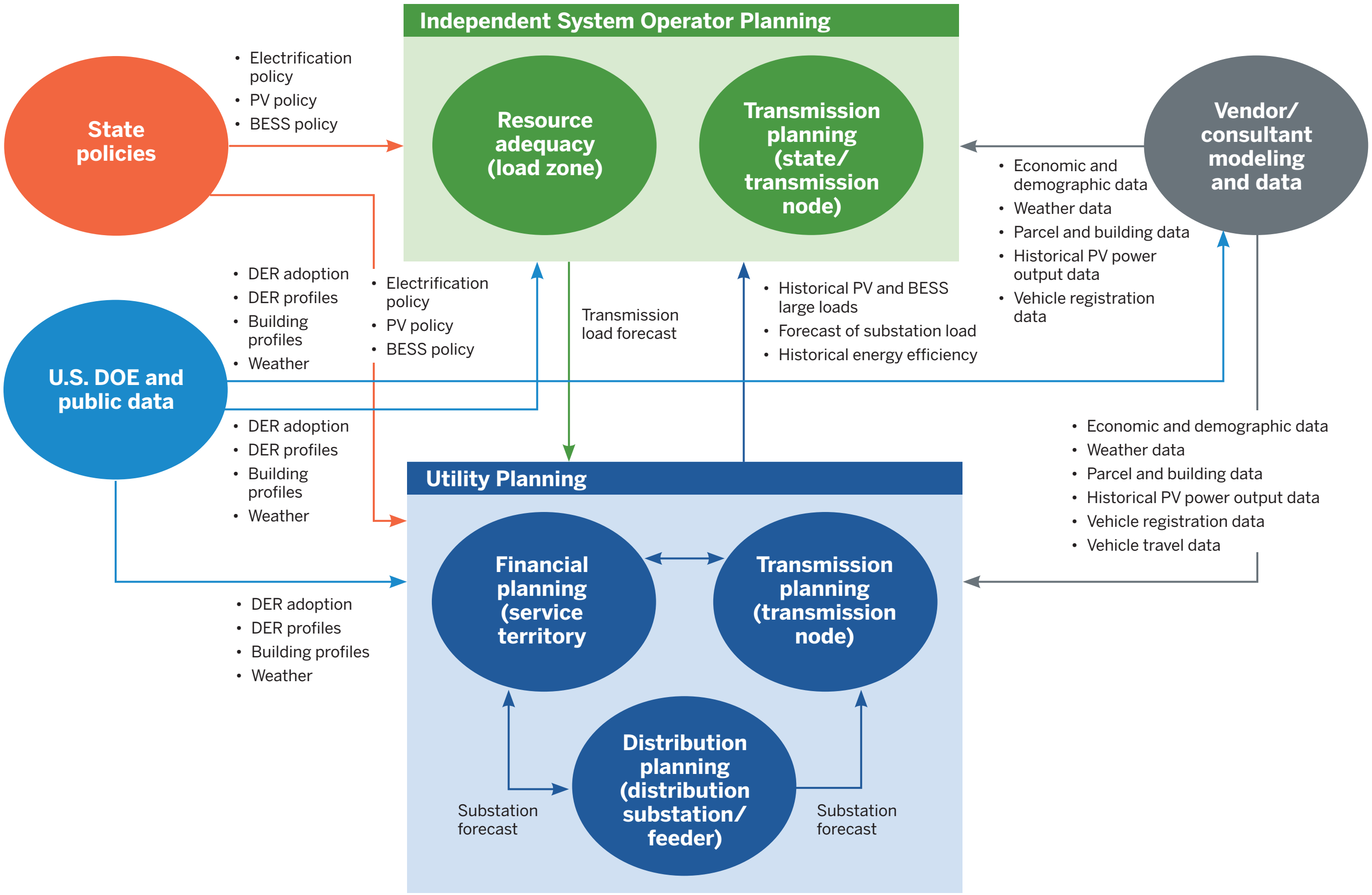
The key coordination and data-sharing steps that might occur between the actors involved in annual load and DER forecasts for grid planning are generically depicted in Figure 2 (p. 9) for regions with market operators. Some coordination is already taking place among these actors, though several key alignment challenges remain, described below.

Current Areas of Coordination

ISOs and RTOs use data from load-serving entities to assess present and future energy consumption. These data increasingly include programmatic data from energy efficiency program savings, existing distributed solar, and

FIGURE 2

Data Sharing and Coordination in a Region or State with Market Operators



These are the key coordination and data-sharing steps that might occur between the actors involved in annual load and DER forecasts for grid planning in regions with market operators. Arrows indicate the direction of data sharing.

Notes: BESS = battery energy storage system; DER = distributed energy resource; PV = solar photovoltaics.

Source: Energy Systems Integration Group.

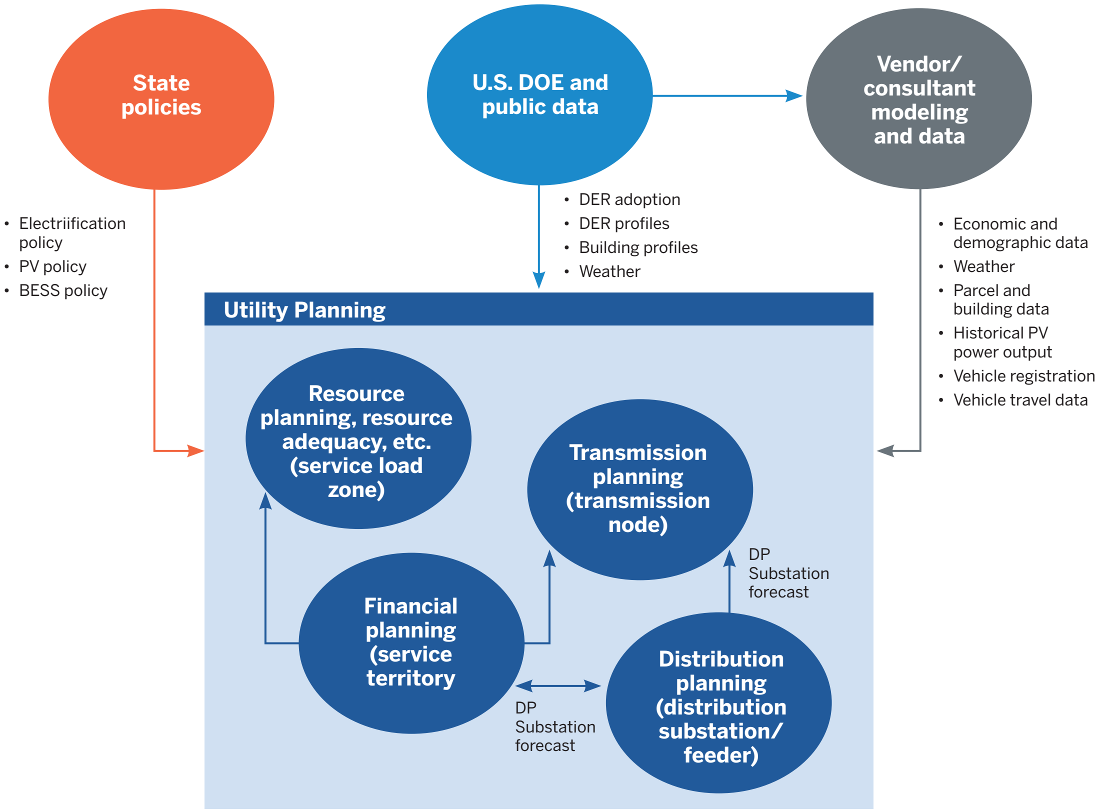
new large load requests such as data centers. The ISO uses these data to produce system- and zonal-level load and DER forecasts for resource planning. It also allocates these system-level forecasts to transmission nodes for transmission planning. Allocation to transmission nodes is often done with transmission owner input.

Vertically integrated utilities rely on system-level load and DER forecasts for resource planning. These forecasts are also allocated to transmission nodes for transmission planning, often using distribution-level forecast values to guide the allocation process (Figure 3, p. 10). In vertically integrated utilities, the key difference is that resource planning is also a planning function performed by the utility, versus the market entity.

Distribution planning in both market and non-market regions typically produces its own local area forecasts, which may or may not be coordinated with the system-level ISO or utility-level forecast used for resource and transmission planning. The distribution planning forecast or historical data are sometimes used to allocate system-level forecasts to transmission nodes. For many utilities, some or all aspects of distribution planning rely on historical trends or other highly simplified forecasting techniques that are largely disconnected from system-level forecasts.

FIGURE 3

Data Sharing and Coordination in a Vertically Integrated Utility



Vertically integrated utilities rely on system-level load and DER forecasts for resource planning. These forecasts are also allocated to transmission nodes for transmission planning, using distribution-level forecast values to guide the allocation process.

Notes: BESS = battery energy storage system; DER = distributed energy resource; PV = solar photovoltaics.

Source: Energy Systems Integration Group.

State actors can play an important role in the long-term load forecasting process as they approve legislation to help support energy affordability, improve reliability, reduce greenhouse gas emissions, advance clean energy deployment, and set targets that influence consumer technology adoption and behavior. In California, state agencies are also responsible for developing the load and DER forecasts used by regulated utilities and grid operators.

States may also specify certain energy outlook scenarios and policies related to transportation and building electrification, behind-the-meter PV and battery energy storage systems, and energy efficiency. These policies serve as key inputs for load and DER forecasting, either by setting targets for scenario development or informing adoption models. ISOs and utilities then incorporate these policies and technology adoption targets as inputs into their forecasts of net demand.

Consultants and vendors also play a role in load and DER forecasting, not only by providing data and analytical services, but also by developing forecasts directly for states, ISOs, and utilities. Within a given state or region, different entities involved in forecasting may rely on different datasets, modeling approaches, and vendor services, leading to inconsistencies in inputs and methodologies.

Public data serve as a foundation for many forecasts, as vendors often clean, organize, and repackage publicly available datasets. In some cases, they enhance these datasets by incorporating proprietary data or applying specialized analytical methods to create streamlined forecasting products for end users.

Coordination Challenges Remaining

Although some coordination is already happening among the different entities and utility departments, several key alignment challenges remain:

- **Cross-organization data-sharing:** As the volume and diversity of data needed for forecasting increases, data availability and standardization remain critical constraints. Enhanced data-sharing within and across state agencies, utilities, ISOs, and regional planning entities can improve forecasting accuracy, particularly through the exchange of more detailed customer usage, weather patterns, renewable generation, and demand-side management programs.
- **Standardized load forecasting practices:** Establishing industry-wide forecasting practices—such as standardized data formats, accuracy benchmarks, and planning time horizons—can improve consistency across organizations and support better coordination in integrated resource and infrastructure planning.
- **Policy and program alignment:** DER adoption and electrification are heavily influenced by federal/state/utility/local policies and initiatives, and it is important to align on technology adoption levels and achievability across stakeholders. However, policies and programs often do not prioritize data inputs and assumptions needed for forecasting.
- **Operational characteristics of technologies:** Improved coordination is needed around the assumptions used to model the operational characteristics of DERs and new loads. These characteristics are influenced by factors such as consumer behavior, policy drivers, utility tariffs, and market participation models (whether distributed non-wholesale market or distributed market-facing). Installation practices and use cases further shape how these technologies affect system load and should be reflected in forecasts.

Enhanced data-sharing within and across state agencies, utilities, ISOs, and regional planning entities can improve forecasting accuracy.

Improved coordination and data-sharing across forecasting stakeholders lays the foundation for more consistent and actionable forecasts. However, even with aligned inputs and assumptions, the structure and resolution of the forecast models themselves play a critical role in shaping outcomes. Forecast model granularity affects how well forecasts capture localized trends, operational variability, and emerging demand-side behaviors. The next section explores how different entities approach granularity in their forecasting models, and the implications of those choices for planning accuracy and resource alignment.

Forecast Model Granularity

The choice of forecast model granularity depends on the entity performing the forecast, the available historical data, and the intended use case. More granular forecasts provide more detail but come with increased data processing, modeling complexity, and computational demands. Load forecasting is performed by multiple entities, and often different departments within the same entity, using different historical load datasets measured at distinct granularity levels of the grid. As shown in Table 2, ISOs use load zone–granularity data, while utilities often use billing data for financial base load forecasting and substation transformer or feeder head data for determining historical load for system planning use cases. The use of distinct historical load datasets at different temporal and spatial granularity levels is a challenge for load forecasting reconciliation. This topic is further elaborated in "Reconciliation of Different Load and DER Forecasts" (p. 41).

Table 2 outlines the various levels at which different load forecasting models for base load forecasting are applied.

Choosing Forecast Granularity: Spatial and Temporal Considerations for Long-Term Forecasting

Load forecasting models rely on historical consumption data, which vary in temporal and spatial granularity. More granular temporal data (e.g., hourly or sub-hourly advanced metering infrastructure (AMI) data) provide detailed consumption pattern analysis but require significant processing capabilities. Conversely, less granular data (e.g., daily or monthly meter reads) reduce computational complexity but lack detail. When selecting model granularity, forecasters must consider the following factors.

TABLE 2

Measured Historical Load, and Forecast Model Granularity by Multiple Entities and Use Cases

Entity/Type of Forecast	Measured Historical Load Used in the Forecast	Model Granularity
ISOs'/utilities' resource planning load forecast	Hourly load zone	Model by load zone (1 to 20 zones)
Utilities' financial load forecast	Customer monthly energy consumption and service territory annual peak load or AMI hourly energy consumption	Model by customer class or revenue meter (3 to 30 customer classes or rate types)
Utilities' distribution load forecast	SCADA annual peak load or hourly load AMI annual peak or hourly load	Model by distribution substation and/or feeder (tens to thousands of substations and feeders) Model at the customer level (hundreds to millions of customers)

Notes: AMI = advanced metering infrastructure; ISO = independent system operator; SCADA = supervisory control and data acquisition.

Source: Energy Systems Integration Group.

- The availability and quality of historical data (e.g., AMI, supervisory control and data acquisition (SCADA), revenue meters)
- The intended use case (e.g., financial planning vs. system planning)
- Required forecast accuracy for different time horizons
- Available computational and staffing resources

Specific data types, availability, and processing requirements are discussed in "Historical Load Data and Preprocessing" (p. 21).

While trade-offs are inevitable, emerging load patterns, DER integration, and localized planning needs increasingly demand more spatial and temporal detail. Forecasters should aim to use the highest granularity feasible for their data and modeling constraints to capture evolving system behaviors and avoid missing critical insights at the edge of the grid.

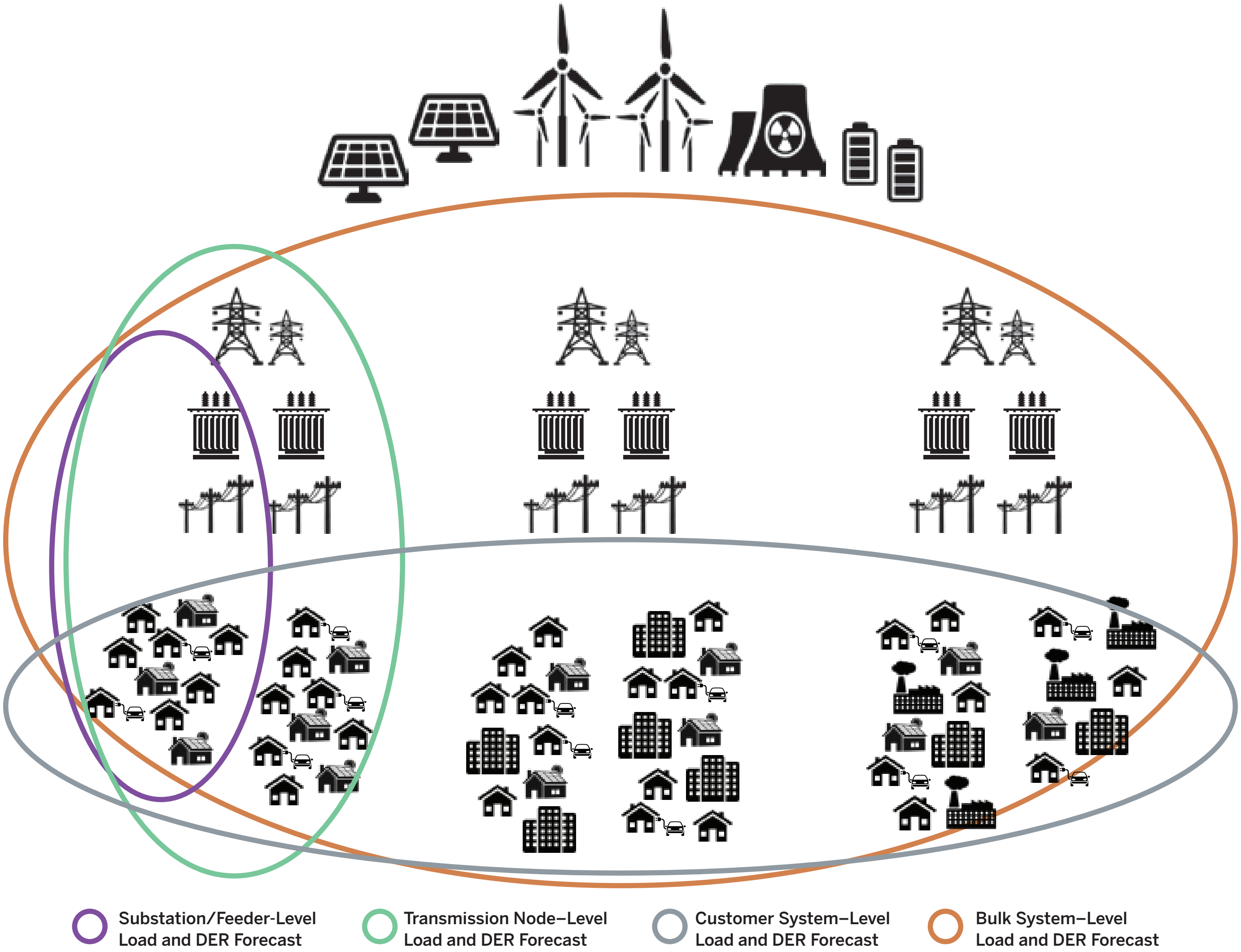
Trade-Offs Between Hourly, Daily, Monthly, and Annual Long-Term Forecasting Models

Selecting a temporal resolution for long-term load and DER forecasting involves balancing data complexity, precision, modeling effort, and the intended use case. While granular temporal data (e.g., hourly) provide detailed information, they can dramatically increase data and computational requirements—especially when forecasting over long horizons or aggregating bottom-up from local datasets. Below we discuss some of the high-level benefits and challenges associated with using different levels of temporal granularity.

- **Hourly forecasting** enables detailed modeling of DER behavior, ramping needs, and intra-day variability. However, for long-term forecasting, generating 8,760 data points per year across multiple feeders or customer segments over 20 or more years can be resource intensive.
- **Daily forecasting** captures weather patterns and behavioral variation while reducing computational complexity, making it a practical choice for modeling specific end uses or aggregated DER profiles over time.
- **Monthly forecasting** smooths out day-to-day noise and reduces model run times, making it a practical choice for financial planning and regulatory reporting. However, it may mask critical short-term dynamics relevant to DER integration or grid flexibility planning.

FIGURE 4

Grid Hierarchy and Use-Case Forecast Resolution



An illustration of one example of the hierarchical topology of the electricity distribution system. Aggregation in the context of load forecasting refers to the hierarchical relationship between data from "lower" levels in the hierarchy to data at "higher" levels in the hierarchy. Typically, the hierarchical reference is to the topology of the electricity system, with the meter at the lowest level of the hierarchy, moving up to assets such as the service transformer or the feeder, to higher levels of the hierarchy like the substation or transmission zone.

Source: Energy Systems Integration Group.

- **Annual forecasting** is still common in many long-term planning exercises—annual models simplify complexity and enable straightforward integration into investment planning. However, they may miss important seasonal or temporal trends introduced by emerging technologies, especially when used as the sole modeling resolution.

Choosing the resolution for a long-term demand forecast involves trade-offs between detail and complexity. Annual resolution provides a broad overview with minimal data requirements, making it easier to manage but less responsive to seasonal or operational variability. Monthly resolution offers a better balance, capturing seasonal trends while remaining relatively simple. Daily

Choosing the resolution for a long-term demand forecast involves trade-offs between detail and complexity.

resolution increases accuracy for variable resources like solar or wind but requires significantly more data and computational effort. Hourly resolution provides the highest granularity, allowing for detailed modeling of demand and generation patterns, but it dramatically increases data needs, model complexity, and computational time for long-term forecasting purposes.

Considerations for Different Levels of Aggregation

In the context of load forecasting, aggregation refers to the hierarchical relationship between data from "lower" levels in the hierarchy to data at "higher" levels in the hierarchy. Typically, the hierarchical reference is to the topology of the electricity system, with the meter at the lowest level, moving up to assets such as the service transformer or the feeder, to higher levels of the hierarchy like the substation or transmission zone. Figure 4 (p. 14) illustrates one example of the hierarchical topology of the electricity distribution system.

The function of summing data from lower levels in the hierarchy up to higher levels in the hierarchy is known as aggregating the data. Conversely, when data from higher levels in the hierarchy are separated and allocated to lower levels in the hierarchy, the function is known as disaggregation.

Forecasting models can be applied at various levels of spatial granularity, depending on the intended use case:

- **System-wide forecasts:** Typically used by ISOs and large utilities for regional demand planning
- **Substation- or feeder-level forecasts:** Essential for distribution planning, ensuring grid reliability at localized levels
- **Customer- or meter-level forecasts:** Advanced approach that uses AMI data to provide detailed insights into consumption patterns across different customer classes

Components of a Long-Term Load and DER Forecasting Process

As forecasting practices evolve to meet the demands of a rapidly changing energy system, energy planners must move beyond traditional approaches centered on annual peak demand and total energy consumption. Today's forecasting challenges stem from the increasing variability of weather-dependent generation, accelerating electrification, and the proliferation of distributed energy resources. To address these complexities, planners require high-resolution, time-based forecasts that can account for the influence of demand-side modifiers and reflect localized demand variations. This section outlines the core components of a robust long-term load and DER forecasting process that is capable of delivering insights at the temporal, spatial, and structural levels needed to guide future grid investments and operations.

As previously described, multiple entities within the same region often develop base load forecasts using different historical datasets, modeling methods, and levels of spatial and temporal granularity. Reconciling these forecasts across organizations and aligning them with shared planning objectives remains a significant challenge. One area where these differences frequently arise is in the choice between "top-down" and "bottom-up" forecasting approaches, which we define in the following section.

Top-Down Versus Bottom-Up

In discussions of load and DER adoption forecasting, the terms "top-down" and "bottom-up" are often used in two distinct ways: to describe either grid resolution (i.e., spatial scale) or forecast methodologies. While the grid resolution perspective may be more intuitive, this report uses these terms primarily in reference to forecast methodologies.

In terms of grid resolution, "top-down" refers to forecasts produced at the system level (e.g., ISO, state, or utility service territory), while "bottom-up" refers to those developed at the local or distribution level. However, the resolution of a forecast does not dictate the methodological approach. For example, a distribution substation forecast could be built using either a top-down method (e.g., disaggregating a system-wide projection) or a bottom-up method (e.g., aggregating customer-level adoption forecasts).

While "top-down" and "bottom-up" can also be used to describe grid resolution, this report uses these terms to describe forecasting methodologies.

Top-Down and Bottom-Up Forecasting Methodologies

This report uses "top-down" and "bottom-up" to describe forecasting methodologies. In a top-down forecasting approach, aggregate customer behavior is modeled using macro-level variables such as regional gross domestic product, population growth, or economic and demographic trends. These forecasts are typically easier to execute and are often used for long-term, system-level planning conducted by ISOs or utilities. For example, top-down forecasts commonly inform transmission planning, resource adequacy studies, and financial modeling. A typical top-down adoption model assumes that customers make decisions based on economic factors, often modeled using techniques such as Bass diffusion. However, the coarseness of top-down forecasts limits their direct applicability to distribution planning, where higher geospatial resolution is required.

In contrast, a bottom-up forecasting approach starts with micro-level inputs, such as customer-class usage, end-use equipment stock, or DER adoption at the site or neighborhood level, and aggregates them to develop broader system forecasts. Micro-level indicators represent characteristics of a granular unit (e.g., households, buildings, feeders, or census blocks), allowing for more precise modeling of customer decisions and localized impacts. These models are more data- and labor-intensive and may require substantial preprocessing and coordination, but they can offer valuable insight into spatial variation in technology adoption and load growth.

Spatial and Temporal (Dis)Aggregation

To use a top-down forecast for local distribution planning, a disaggregation step is required, typically using proportional or spatial allocation methods (discussed further in the section "Allocation of Top-Down Forecasts" (p. 43)).

The temporal output from top-down and bottom-up forecasts can also be decomposed or combined to different temporal resolutions, such as annual 8,760 hourly load profiles or 12 monthly coincident peak values, for various levels of geospatial granularity. For example, the California Energy Commission uses its Hourly Electric Load Model (HELM) to convert top-down system- and forecast zone–level energy use forecasts to hourly demand forecasts using a range of standardized dynamic load shapes, which are then used to project annual peak load forecasts. Thus, assuming forecasters have the necessary data, methodological assumptions, and modeling tools, top-down or bottom-up approaches can typically be utilized effectively to address the needs of most traditional use cases, regardless of geospatial resolution.

Understanding both the methodological and spatial meanings of top-down and bottom-up is essential for aligning forecasts across planning levels and use cases. Most forecasting approaches follow similar steps, including establishing base load, integrating demand-side modifiers, and producing final outputs. The next section describes these core steps, which serve as the foundation for the remainder of this report.

FIGURE 5
Load and DER Forecasting Steps

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

Source: Energy Systems Integration Group.

Long-Term Load and DER Forecasting Steps

As described in the introduction, load forecasting has evolved significantly over the past decade. Figure 5 presents three key steps that represent best practices for forecasting load over time. These steps serve as the foundation for the next three sections of this report.

Entities differ in their ability to implement the load and DER forecasting steps outlined in Figure 4, while the sophistication required for different use cases varies accordingly. As the industry evolves to address emerging technologies and policy shifts, an effective net load forecasting approach must follow a structured process:

- **Step 1: Establishing a base load forecast.** This step involves isolating base load by removing the effects of weather-dependent DERs (such as solar and demand response) and extrapolating trends using historical load data, weather patterns, and economic variables.

- **Step 2: Adjusting for known new loads.** The base forecast is refined by incorporating exogenous forecasts for anticipated customer growth and large new loads, such as industrial expansions or data centers, ensuring a more accurate representation of future demand.
- **Step 3: Adjusting for new consumer-adopted technologies.** Additional adjustments account for the adoption of DERs such as solar and battery storage, electrification of buildings and transportation, and demand response measures (if not already addressed in Step 1).

While structured load forecasting steps provide a foundation for anticipating future demand, inherent uncertainties remain due to evolving technologies, policy shifts, and economic factors. To ensure robust grid planning, uncertainty analysis and scenario planning must complement load and DER forecasting, accounting for a range of potential future conditions and their impact on long-term system reliability.

Uncertainty and Scenario Planning

Uncertainty is inherent in load and DER forecasting due to variability in inputs, model structures, and assumptions. As grid planning relies on these forecasts, it is essential to incorporate uncertainty analysis rather than rely solely on point estimates.

Uncertainty in load and DER forecasting can be classified into three main categories:

- **Natural variability:** Uncertainty in historical load and weather data, often 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

There are four core techniques for conducting uncertainty analysis:

- **Deterministic analysis:** Examining the impact of one factor at a time
- **Deterministic joint analysis:** Simultaneously adjusting multiple factors to explore interaction effects (e.g., economic growth and DER adoption trends)
- **Parametric analysis:** Varying input values within a predefined range
- **Probabilistic analysis:** Using statistical techniques (e.g., Monte Carlo simulations) to examine how forecast outputs vary as a function of uncertain inputs

These techniques support scenario development, a widely used tool for addressing uncertainty. The most common approach is using parametric analysis to create multiple scenarios (e.g., low, medium, and high levels of adoption), typically with multiple variables adjusted in what is understood to be a reasonably correlated manner. These scenarios may be framed around drivers such as regulatory shifts, technological advancements, and economic conditions. The selection of scenarios is a critical step in long-term load and DER forecasting, ensuring alignment with future trajectories used in grid planning.

Use Cases for Uncertainty and Scenario Analysis

Distribution planning: Traditionally, utilities have relied on either trend-based or "worst-case" scenarios, but multi-scenario approaches are gaining adoption. Utilities such as Dominion Energy South Carolina, Xcel Upper Midwest, DTE Electric (Synapse Energy Economics and LBNL, 2024), and National Grid now incorporate multiple scenarios to reflect varying EV, heat pump, and DER adoption levels (National Grid, 2024).

> These four core techniques support scenario development, a widely used tool for addressing uncertainty.

Transmission planning: Adoption of scenario-based planning varies, but FERC Order 1920 encourages ISOs to develop multiple future portfolios. For example, MISO uses three 20-year planning scenarios to assess different economic, policy, and technological futures.

Integrated resource planning: Load growth pathways in integrated resource plans commonly include low, medium, and high growth scenarios, incorporating macroeconomic trends and structural shifts. Some utilities focus on a single selected forecast for portfolio design and reliability analysis, while others prefer to create a wide bracket within which a range of resource acquisition decisions may be justified. A growing number of large utilities are using probabilistic analysis. Its usage depends on whether the users and stakeholders have confidence in whether meaningful input distributions are used to measure uncertainty.

Long-term load and DER forecasting must account for the growing complexity around shifting customer behavior, emerging technologies, and regional variability. Forecasting approaches—whether top-down or bottom-up—must align with the spatial and temporal resolution required for each planning application. Effective forecasts begin with a clear view of base load, incorporate expected new developments such as data centers, and adjust for the adoption of electrified end uses and distributed resources. Given the uncertainty surrounding these drivers, scenario planning and sensitivity analysis are essential to ensuring that forecasts remain useful across a range of future conditions. The next section begins with the foundation of this process: establishing a consistent and accurate base load.

Long-Term Base Load Forecasting

Here we outline methods for forecasting base load, defined as the projection of foundational historical load trends into the future without considering exogenous factors such as known new business growth, large loads, or the impacts of projected DERs and electrification in buildings and transportation. The discussion covers forecast approaches, forecast model granularity, historical load data and preprocessing, and forecasting steps.

Base-Load Modeling Methods

Long-term base load forecasting relies on different modeling techniques, each suited to specific use cases and data availability.

Before using historical load data for forecasting, it is often necessary to adjust for existing weather-dependent DERs to ensure accurate representation of native demand. Without these adjustments, embedded solar and/or demand response programs can distort load patterns, particularly by altering the timing of system peaks and modifying coincidence factors across different load zones or substations. Approaches for accounting for each DER's impact on base load is explored in more detail in "Exogenous Load Forecasting Factors: DERs" (p. 34).

The three primary approaches are time-extrapolation models, econometric models, and statistically adjusted end-use (SAE) models. Each of the models described below can forecast energy demand at annual, monthly, weekly, or daily granularities, as well as estimate peak load. At hourly granularity, the output can directly determine the peak load.

Time-extrapolation models use historical growth rates to project future load trends. These models assume that past patterns of load growth will persist into the future and are relatively simple to implement, requiring minimal data and computational resources. The main limitation of time-extrapolation models is that they do not account for economic, demographic, public policy, or weather-related factors that may influence load growth or reduction.

Econometric and machine learning models, such as regression analysis, can be used to understand complex relationships between historical load and external variables like weather, economic activity, and population growth. More advanced machine learning models, including neural networks and boosting techniques, can capture non-linear interactions between variables, improving forecast accuracy. The main limitation of these models is that they require high-quality historical data and computational resources and skills. Depending on the granularity of available data, these methods can work well for both top-down and bottom-up forecasting.

SAE models are econometric approaches that also incorporate components of an end-use modeling framework. An end-use modeling framework forecasts energy use by equipment (e.g., appliances, heating and cooling systems) and accounts for end-use changes such as equipment saturation, energy efficiency, demand-side management programs, building square footage, and thermal shell integrity improvements. By capturing long-term shifts in customer behavior and equipment adoption, these models are well suited for running scenario analysis on policy, technology adoption, energy efficiency, and electrification trends. While not as technically challenging to implement as machine learning, these models also require detailed end-use data. They often require more engagement with stakeholders in development of key assumptions.

While each model offers distinct advantages, their usefulness depends on the quality, availability, and granularity of historical load data. These factors strongly influence how base load forecasts are developed and which modeling approaches are most appropriate in practice.

Historical Load Data and Preprocessing

Forecasters require historical consumption data to estimate existing load, which can then be used for extrapolation and establishing relationships between changes in load consumption and external variables such as economic growth and weather. Often, the granularity of available historical consumption informs the level at which the base load forecast is modeled. The forecasting entity's capacity to collect, clean, and use large data volumes is an important factor that may influence forecast granularity, as the cost and complexity to manage more granular data may discourage utilities from collecting data that are only used for planning purposes.

Forecasters require historical consumption data to estimate existing load, which can then be used for extrapolation and establishing relationships between changes in load consumption and external variables such as economic growth and weather.

Historical load data are sourced from a variety of systems, including ISO market settlements, supervisory control and data acquisition (SCADA) systems, and AMI meters (i.e., smart meters). Notably, these major data sources were not built to support forecasting, but rather to achieve utilities' reliability and financial objectives. However, as the grid becomes increasingly dynamic and decentralized, these datasets have become important for forecasting, as they reveal patterns in load, DER behavior, and customer usage. As a result, forecasters must now adapt and find ways to effectively integrate and interpret these data for planning purposes.

Over time, these data sources have become more granular, both temporally and geographically, particularly with the widespread deployment of smart meters. For example, data from smart meters provide higher-resolution insights that are easier to aggregate at the customer class level. However, accessing longer historical records often requires using older datasets, which typically offer less temporal or spatial detail, highlighting a trade-off between historical depth and data granularity. Ensuring data quality is a critical step in preprocessing historical load data. Common challenges include missing or erroneous data points, inconsistencies between different data sources, and aggregation discrepancies when integrating datasets from multiple systems. In some cases, representative synthetic time-series data must be generated to fill gaps in historical records. Best practices for data cleaning include detecting and handling outliers, interpolating missing values, and cross-checking modeled data with validated historical load.

Incorporating Weather, Climate, and Extreme Weather into Long-Term Load Forecasting

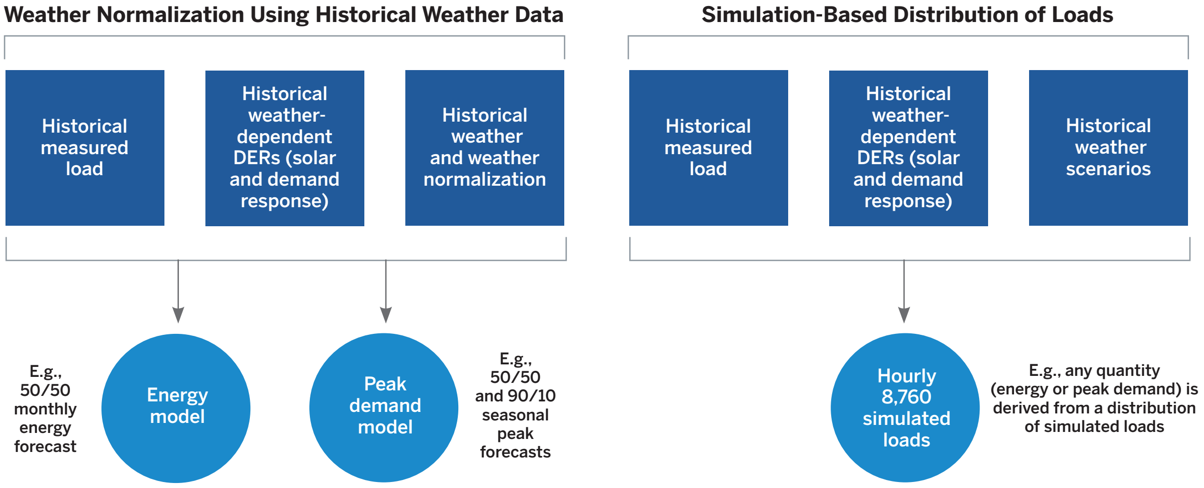
While uncertainty analysis and scenario planning help account for a range of potential futures, another critical dimension in load forecasting is the influence of weather conditions, climate trends, and extreme weather events. Short-term fluctuations in weather directly impact electricity demand, while long-term climate trends shape baseline consumption patterns and the variability of renewable generation. Integrating weather and climate data into load forecasting models enhances their accuracy and resilience, ensuring that planners can anticipate and mitigate the risks associated with both routine and extreme weather conditions.

Extreme weather events may be more pronounced in certain years, but their impact on energy use depends on timing and context—for example, a heat wave occurring on a weekend or holiday may have a lower impact on energy demand than one occurring during peak business hours. To account for these variations, forecasters apply statistical methods to historical weather and consumption data to establish representative load conditions.

By analyzing 25 to 30 years of historical weather data, forecasters can estimate load conditions that are typical (1-in-2 or 50th percentile) and extreme (1-in-10 or 90th percentile) for a given region. These estimates serve as a foundational reference for base load forecasting across multiple levels of aggregation, including load zones, customer classes, distribution substations, feeders, and individual customer-level models. Weather normalization

FIGURE 6

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



Two primary approaches for statistical load analysis are shown: weather normalization (left) and simulation-based (right).

Source: Energy Systems Integration Group.

is then used to adjust historical load data, removing the short-term variability caused by abnormal weather fluctuations.

Weather Normalization

Normalization techniques adjust historical load data to account for variations in weather, ensuring that forecasts reflect underlying consumption trends rather than temporary weather anomalies.

Two primary approaches exist for weather normalization, based on historical weather data or on probabilistic simulations of load.

Weather normalization based on historical data is the most commonly used method for all use cases. This method pre-defines typical weather conditions and then models load under that weather. Under this approach, a normal weather pattern is constructed using historical weather data for the aggregation level under study. The constructed series of normal weather is then pushed through the base load forecast model to simulate loads under normal weather conditions. There are several schemes for constructing a normal weather pattern, such as calculating the average weather by calendar day, using a ranking method to sort each month of historical weather data from the coldest day to the hottest day (McManamin, 2008), or using typical meteorological year data from the National Renewable Energy Laboratory (NREL, 2025).

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—particularly heating degree days and cooling degree days.

Simulation-based load distribution is more advanced than historical-based normalization and simulates multiple weather scenarios to generate hourly load profiles. As shown in Figure 6, these simulations can consider other weather factors that drive load and can reflect the fact that normal weather does not necessarily lead to normal load. The average, or any other probability of load, is derived from the distribution of simulated loads (Fox et al., 2022).

Increasing load volatility associated with distributed solar PV and electrification is driving greater interest among system operators and planners in quantifying hourly load uncertainty. Compared to historical approaches, weather-driven load simulations provide a more effective means of capturing load volatility and constructing distributions of hourly ramp rates, which are expected to evolve significantly with the increasing levels of solar PV generation and EV charging.

The next section explores different sources of historical weather data and the methodologies used to integrate climate-adjusted forecasting, ensuring robust long-term load projections in the face of changing conditions.

Weather and Climate: Historical Data and Modeling the Future

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—particularly heating degree days and cooling degree days, the biggest drivers of electricity consumption. While historical weather data have long been the foundation for load forecasting, they may not fully represent the variability and trends introduced by climate change. This section explores the sources of historical weather data and methodologies for incorporating climate-adjusted forecasts (see also ESIG's report *Weather Dataset Needs for Planning and Analyzing Modern Power Systems* (ESIG, 2023b)).

Historical Weather Data

There are two categories of historical weather data:

- **Weather station measurements** provide direct, sensor-based records of temperature, precipitation, wind speed, and other meteorological variables. Their key advantage is that they are based on direct observations with minimal modeling assumptions. However, their limitations include limited geographic coverage, data gaps, and limited historical records.
- **Reanalysis datasets** combine past observations with atmospheric models to generate spatially and temporally consistent time-series reconstructions of historical climate conditions. These publicly available and regularly updated datasets provide gridded meteorological fields covering multiple decades and describe the observed climate for multiple decades at sub-daily intervals. However, because they are modeled outputs rather than direct observations, they introduce uncertainties associated with data assimilation and model bias. (ESIG (2023b) includes an in-depth discussion of reanalysis datasets.)

Long-term load forecasting has typically relied on historical weather as the key explanatory input for developing associations between temperature and energy usage. However, many load forecasting approaches are evolving to also consider how climate change is influencing weather.

Methods for Incorporating Climate Change into Load Forecasting

While historical weather data reflect past climate patterns, climate change is altering temperature distributions, seasonal trends, and the frequency of extreme events. Historical conditions are not guaranteed to persist in the future, especially for longer time horizons over which the global mean temperature is expected to continue increasing. Forecasters can use more or less complicated approaches to account for uncertainties in past and future climate trends.

Trend-based adjustments (simple): This approach applies observed historical trends in cooling degree days and heating degree days to adjust load forecasts (U.S. EPA, 2025). While simple to implement, it assumes that future trends will continue at the same rate, potentially underestimating the frequency of extreme events. Examples of these trends could include:

- Cooling degree days are increasing, leading to higher summer energy consumption
- Heating degree days are decreasing, leading to lower winter energy consumption and altering winter load profiles
- Extreme temperature events are becoming more frequent, increasing peak demand volatility

Climate model-based adjustments (advanced): Climate models, such as general circulation models (GCMs), provide long-term projections of temperature and precipitation patterns. However, the outputs of these models must be spatially and temporally downscaled to

be relevant to modeling grid impacts. The three main downscaling approaches are:

- **Dynamical downscaling**, which uses GCM outputs as boundary conditions to a regional climate model that numerically solves the physical equations governing the climate at more granular levels. Dynamical downscaling is computationally expensive but produces physically coherent outputs and is capable of modeling weather events that are not in the historical record.
- **Statistical downscaling**, which uses properties of historical weather data to build a statistical relationship between GCM outputs during the historical period and local weather events. Statistical downscaling is less computationally expensive but may not preserve the spatial correlation between weather events in different locations.
- **Machine learning downscaling** is a subtype of statistical downscaling that uses computer vision algorithms to perform highly granular analysis on GCM outputs. One source of statistical downscaling data is Carbon Plan, which has applied a variety of statistical downscaling techniques to CMIP6 data.[1] Another useful data source is sup3rCC from the National Renewable Energy Laboratory, a machine learning downscaled climate data product that has hourly granularity and irradiance variables, which are not typically features of more generic downscaling datasets.[2]

Different climate models give different results, especially after downscaling. One study found that in some cases the variance in climate model output due to downscaling methodology can be larger than the variance due to CO_2 emissions and the natural inter-annual weather variability, depending on the location and climate variable (Lafferty and Sriver, 2023). Therefore, basing a load forecast on climate projections from a single climate model represents one potential climate future with a great deal

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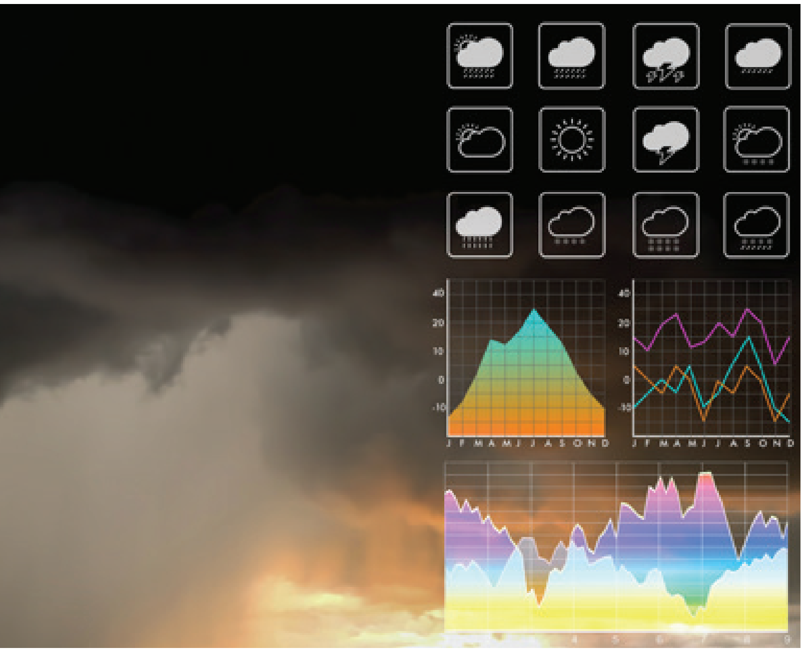
[1] https://carbonplan.org/research/cmip6-downscaling-explainer

[2] https://www.nrel.gov/analysis/sup3rcc



of uncertainty associated with it. This uncertainty can be reduced by drawing on multiple climate models when performing a load forecast.

Modeling Extreme Weather

Climate change is also leading to the increased frequency and severity of extreme weather events across many jurisdictions, which have more immediate and often unpredictable impacts on load. These events have local drivers and require short-term, highly granular forecasting to ensure system resilience and reliability.

Challenges in Forecasting the Load Impacts of Extreme Weather

Because extreme weather events are significant aberrations from typical weather patterns, there are very limited data in historical records from which load models can derive the associations between extreme weather and corresponding electricity demand. Approaches rooted in typical historical data can under-predict these events, and traditional econometric models struggle to predict energy demand during heat waves, polar vortexes, and severe storms.

Research by EPRI that analyzed data from over 60 balancing authority areas using leading machine learning techniques indicates that in most load zones, modeling error associated with accurately predicting load based on temperature was greatest at high temperatures (EPRI, 2024a). Researchers indicated that the negative bias at extreme high and low temperatures is likely due to the limited number of observations in these ranges. While a more sophisticated training approach could mitigate this issue, the fundamental challenge of accurately modeling extreme temperature events with limited historical data remains.

Addressing Extreme Weather in Load Forecasting Models

To improve the accuracy of load forecasts in extreme weather conditions, several advanced modeling techniques can be employed, including:

- **Expanding training datasets using synthetic weather records**, which allows models to account for conditions beyond the limited scope of historical observations. By incorporating simulated extreme weather scenarios, these datasets help improve model performance under rare but high-impact events.
- **Spline regression and non-linear modeling**, which better captures the complex relationships between temperature and electricity demand. Unlike traditional linear models, these techniques recognize that the relationship between temperature and energy consumption is not linear. Instead, they accommodate variations such as the rapid increases in cooling demand during heat waves, the non-linear heating demand response in extreme cold, and that result from heating and cooling systems having system capacity limits at which they stop increasing load.
- **Uncertainty analysis using Monte Carlo simulations** plays a crucial role in forecasting extreme weather impacts. By generating thousands of possible weather-load scenarios, Monte Carlo methods help assess a range of potential outcomes and quantify the probability of extreme demand spikes. This approach enables grid operators to plan for worst-case scenarios and develop more resilient infrastructure strategies.

Together, these methodologies enhance the robustness of load forecasting models, ensuring that energy planners can anticipate and mitigate the challenges posed by increasingly frequent and severe weather events.

Exogenous Load Forecasting Factors: New Customer Business Growth and Large Loads

Base load models that capture weather- and demographics-driven base load forecasting trends need to be enhanced with exogenous forecasts estimating new customer growth. In this section, we describe options for adjusting or overlaying exogenous factors of load growth onto base load forecasting models.

Distribution-Level New Customer Load

It is important for utility customer account teams and distribution planning departments to coordinate on known new customer loads seeking interconnection to local distribution grids. These loads are new sources of demand that are identifiable and planned, have a significant impact on the distribution system, and are location specific. Known new loads are distinguishable developments that are distinct from—but potentially associated with—general economic or demographic growth trends. To consistently and appropriately reflect known new customer loads within a long-term load forecast, forecasters and stakeholders need to promote careful coordination between customer and distribution planning departments, effectively characterize the uncertainty around whether a load will show up, and appropriately incorporate new loads into long-term forecasts, while also making sure these new loads are not double-counted once the customer's service has been connected and their usage is incorporated into recorded meter loads.

These new customer loads often provide valuable bottom-up data that can be used to adjust local substation or feeder forecasts. However, formal coordination between customer account and distribution planning departments is not always in place. As a result, data from new medium or large customers—whether obtained via a formal "load letter" request or a less structured inquiry—can fail to reach the distribution planning department. If the distribution planning department is unaware of new known loads, then these are unlikely to be reflected in feeder and substation forecasts, which in turn may lead to infrastructure capacity issues.

To consistently and appropriately reflect known new customer loads within a long-term load forecast, careful coordination is needed between customer and distribution planning departments.

There is often substantial uncertainty around whether a potential new load will ultimately materialize in a given location. The three investor-owned utilities in California and Eversource in Massachusetts are good examples of utilities that formally track and report "known loads" or "spot loads" to adjust the local 5- to 10-year substation and feeders peak load forecast. Eversource has an internal initiative that coordinates multiple departments—including distribution planning, customer groups, and load forecasting—to maintain a centralized tracking database and classify new customers into five confidence levels:

- **Certain:** A work order is in place and payment has been received from the new customer.
- **Probable:** Public statements have been made and permits requested, or other actions have been taken that announced the customer's intention to the broader public, making a withdrawal less likely.
- **Possible:** The customer is engaging with the utility in earnest discussion about the project, distribution engineering is included, and some public statements are issued.

- **Uncertain:** Discussions with the utility have happened only with strategic and national customer accounts and at a conceptual level.
- **Forecasted:** A step load assumption is made from extrapolating historical data.

For the California utilities and Eversource service territories, new customer business loads are integrated into the 5- and 10-year distribution load forecasts. In these forecasts, new customer business loads are the primary driver of load growth and are solely responsible for nearly all capacity-related projects currently underway.

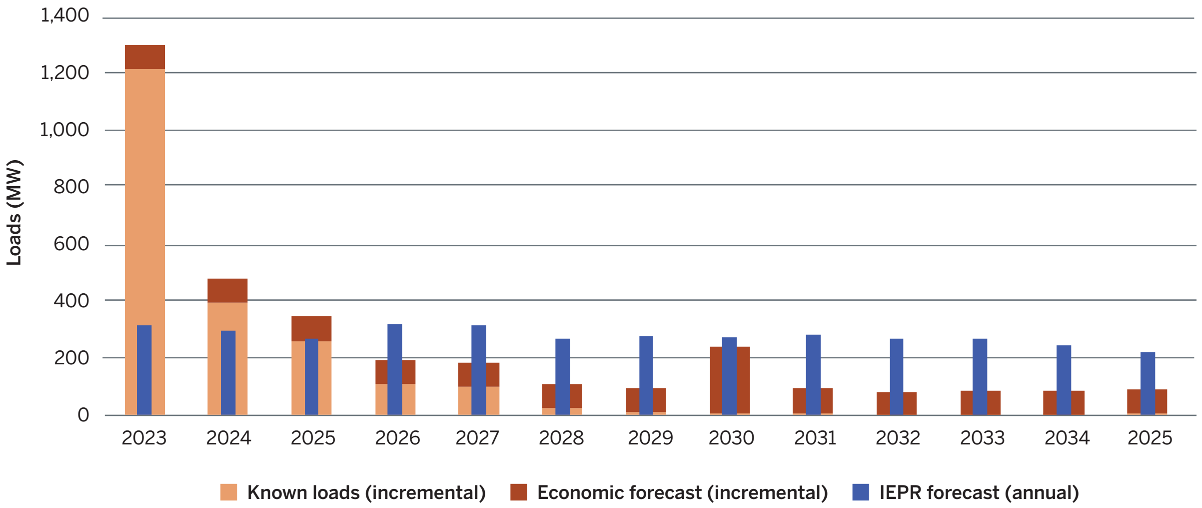
However, these new customer business loads are not incorporated into longer-term load forecasts (of greater than 10 years). The key challenges to incorporate known new distribution loads into long-term load forecasts are:

- Most projects must interconnect within five years, meaning that within a 10-year horizon, most will be online or near completion.
- Long-term load growth trends are difficult to determine as these loads are sporadic and unpredictable, making linear regression or extrapolation ineffective.
- The confidence level of a project may change at any time due to factors like funding availability, supply chain constraints, and other uncertainties.

California—as the only state where the distribution utilities use a single state's forecast for multiple grid planning use cases—offers a helpful illustration of the challenge of reconciling distribution-level base load growth with system-level base load growth projections. Figure 7 shows the challenge that exists reconciling the state agency's top-down base load growth projections ("IEPR forecast") (CEC, 2022) with the load growth estimates drawing from distribution-level known new customer business loads (known loads) and distribution economic forecasted trends. As shown in the figure, this discrepancy is most pronounced in the first years of the forecasting period for which known new loads are included in the distribution forecast, versus the later years where only the economic forecasted trend is included in the base load forecast. This challenge of reconciling the two types of load growth projections is not unique to California and is a challenge across the country.

FIGURE 7

Comparison of Distribution Known New Loads and Economic Forecasted Base Load Growth with the System-Level Base Load Growth in California



Known new customer loads from the three investor-owned utilities in California, as well as incremental economic growth (no DERs) compared to the California's *Integrated Energy Policy Report* (IEPR) load forecast (no DERs) (https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report-iepr).

Source: Resource Innovations (2022).

Lastly, historical known new loads eventually become embedded within recorded electricity usage data, and there are limited data on whether and how load forecasts for local distribution planning account for and adjust for past and future known new loads so that their impacts are not double-counted as pure economic or demographic growth.

Large Load Growth Forecasting

With large-scale loads reaching gigawatt levels for individual interconnections, accurately forecasting this growth has become essential for bulk power system planning, resource adequacy assessments, and transmission expansion strategies. National electricity demand forecasts have surged from 2.8% to 8.2% growth over five years, with an anticipated increase of 128 GW in peak demand by 2029 (Wilson, Zimmerman, and Gramlich, 2024). This sharp rise is primarily driven by four major sectors: data centers, new manufacturing, electrification of existing industry, and hydrogen production. Each of these load categories presents unique forecasting challenges due to variations in deployment rates, regional economic factors, and interconnection requirements.

> With large-scale loads reaching gigawatt levels for individual interconnections, accurately forecasting this growth has become essential for bulk power system planning, resource adequacy assessments, and transmission expansion strategies.

Data center load growth is the single largest component of growth in utility load forecasts and is expanding at an unprecedented rate, with forecasts ranging between 65 GW and 90 GW of new load by 2029 (Wilson, Zimmerman, and Gramlich, 2024). The proliferation of artificial intelligence (AI)–driven facilities is amplifying demand and shifting siting priorities toward regions with both low-cost land and grid access. Unlike traditional data centers, AI-focused facilities require higher power densities than conventional data centers (they use more energy per square foot), making their ramp-up profiles more aggressive and unpredictable. However, the release of more compute-efficient AI models could temper these ramp profiles and long-term load growth by reducing energy intensity per unit of compute.

While there is substantial growth in data center demand, there is also significant uncertainty associated with this category of large loads. Utilities and ISOs often apply derating factors to reflect the uncertainty in data center forecasts. But this uncertainty is not uniform across regions. Some ISOs and utilities report full utilization of interconnection requests, while others observe significant underutilization, with actual load reaching less than 50% of requested capacity. Additionally, speculative land developers building substations without confirmed end users introduce further planning risks. Proposals such as Duke Energy's "take-or-pay" model, which require data centers to pay for a certain amount of power regardless of how much they consume, seek to mitigate financial risks but do not directly enhance forecasting certainty.

Despite these challenges, research on data center energy consumption provides a foundation for improving forecasting. For example, bottom-up methods for forecasting data center loads that account for factors like information technology hardware specifications, cooling infrastructure, and operating characteristics offer a more reliable, accurate, and transparent approach for estimating data center energy use than "short-cut" methods that simply extrapolate previous trends. To assume that because data center energy use doubled over the past decade it will do the same over the next decade may overestimate future data center energy use by ignoring other trends, namely countervailing energy efficiency trends (Masanet et al., 2020).

For bottom-up forecasting to be effective, greater transparency is needed on key data center parameters. Given that a small number of technology companies account for a large share of global AI installations, collaboration between these companies, utilities, ISOs, and researchers is feasible and could facilitate the necessary data-sharing to improve forecasting. Establishing standardized tools and methodologies will be critical to ensure that utilities and ISOs can effectively plan for the growing role of data centers in bulk power system demand.

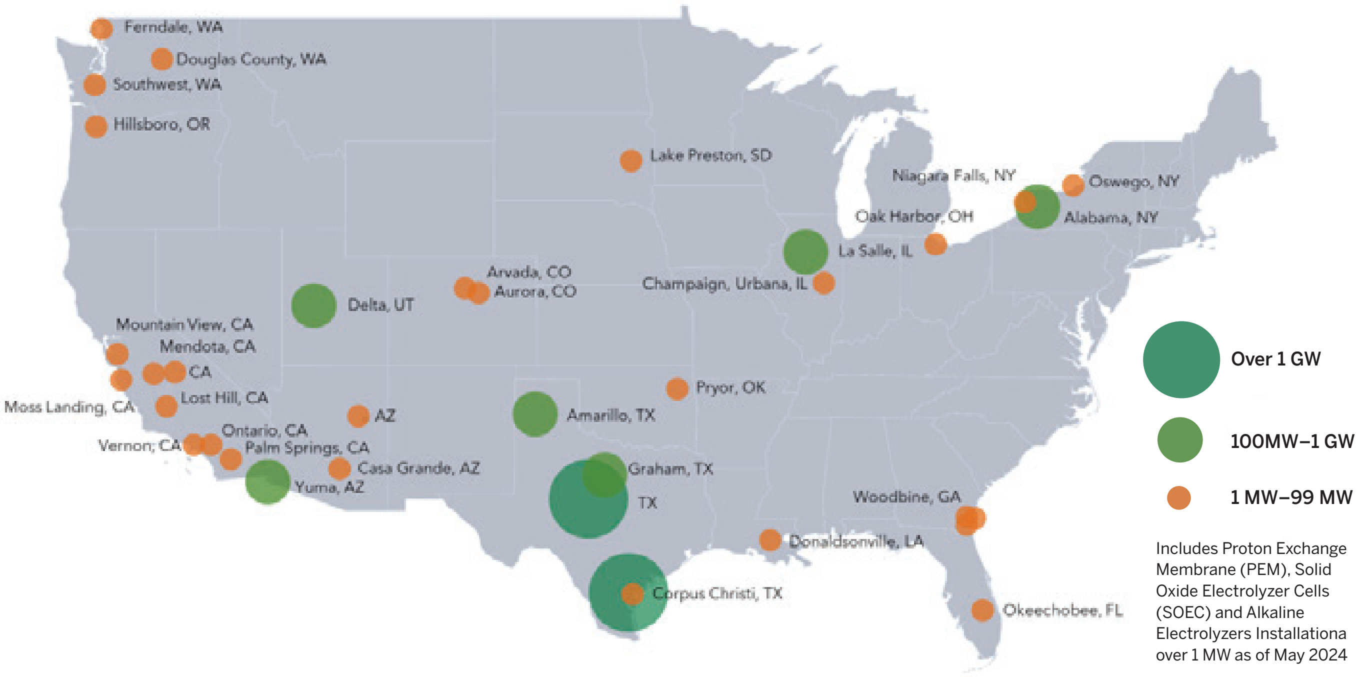
Manufacturing load growth, particularly in semiconductor fabrication, battery production, and heavy industrial facilities, is poised to add approximately 20 GW of new load through 2029 (Wilson, Zimmerman, and Gramlich, 2024). Federal policies incentivizing domestic production in the U.S., such as the CHIPS Act, are accelerating project timelines, necessitating rapid infrastructure build-outs. Unlike data centers, manufacturing loads tend to follow more predictable ramp-up schedules but are still subject to economic cycles and policy shifts.

Electrification of existing industry is another significant driver of load growth, with many sectors transitioning from fossil fuel–based processes to electric alternatives, such as electric arc furnaces, heat pumps, and other electrified industrial processes. This shift is expected to contribute substantial new load over the coming decade, particularly in steel production, chemical processing, and other high-energy industries.

Hydrogen production load growth, particularly for green hydrogen using electrolysis also represents a large potential load driver in the long term. The scale of hydrogen-related electricity demand over the longer term remains uncertain as it is heavily influenced by policy incentives, market developments, and technology adoption. However, early projections suggest that hydrogen production could become one of the largest new sources of electricity demand in the next decade,

FIGURE 8

Operational or Planned Hydrogen Production Facilities, as of May 2024



Includes Proton Exchange Membrane (PEM), Solid Oxide Electrolyzer Cells (SOEC) and Alkaline Electrolyzers Installationa over 1 MW as of May 2024

This map shows hydrogen production projects greater than 1 MW that are operational or have been announced as of May 2024 (bubbles are not to scale). Installed capacity in the U.S. is currently 116 MW, equal to one orange bubble, with 657 MW under construction. Most of the projects in the figure (a total of 3.8 GW) are not operational but rather announced/planned, 30 times present capacity.

Source: Hubert and Arjona (2024); U.S. Department of Energy.

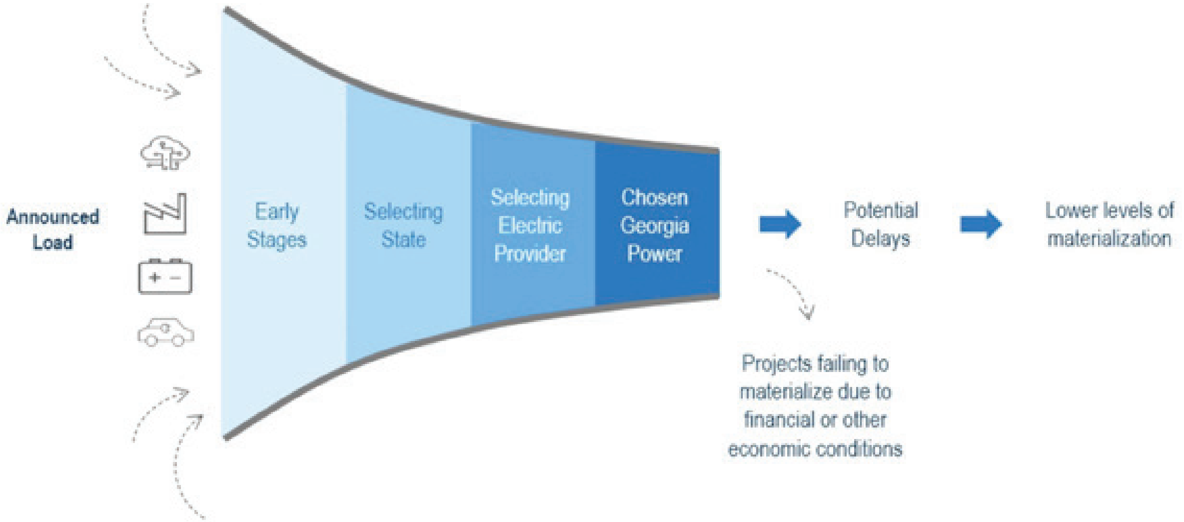
especially in designated regional hydrogen hubs, as shown in Figure 8. But despite this potential growth, planned hydrogen fuel plants are not currently included in most long-term load forecasts (Wilson, Zimmerman, and Gramlich, 2024).

Despite these projections, significant challenges remain in modeling large load growth, including:

- **A lack of standardized forecasting methods:** The power industry needs an initiative to develop standard data sources and load forecast methods for these drivers, as well as for building and transportation electrification. Currently, there is no standardized methodology for modeling and forecasting large loads.
- **Uncertainty in realization rates:** Many interconnection requests do not fully materialize, leading to discrepancies between planned and actual loads. Figure 9 (p. 32) presents one approach for reflecting this uncertainty in forecasts, showing how announced load progresses

FIGURE 9

Example Large Load Forecast Model Considering Uncertainty



The model considers a spectrum of uncertainty, beginning on the left with announced load, where a large amount of uncertainty exists. Uncertainty diminishes as projects move through stages of selection, such as choosing an electric provider, and may result in potential delays or projects failing to materialize due to financial or other economic conditions, leading to lower levels of actual materialization.

Source: Georgia Power Company, 2023 IRP Update Load and Energy Forecast, October 2023.

through stages where uncertainty is reduced as decisions are made, ultimately impacting the level of materialization.

- **Regional variation:** Economic conditions, permitting timelines, and infrastructure readiness differ widely across jurisdictions.
- **Load clustering effects:** Certain regions may experience disproportionate growth, exacerbating transmission constraints and resource adequacy concerns. Figure 10 (p. 33) shows the clustering of data centers (EPRI, 2024b), while new manufacturing plants are clustering in the Southeast, MISO, PJM, and the West (Rhodium, 2023).

To address these challenges, ESIG has launched a Large Loads Task Force to unite stakeholders, identify practical solutions, and develop harmonized practices that ensure reliable and efficient grid integration while supporting industry growth.[3] One focus area of this task force is forecasting these loads.

Approaches to Improving New Customer and Large Load Forecast Accuracy

To enhance forecasting methodologies, utilities and ISOs are adopting a mix of top-down and bottom-up approaches, incorporating:

- **Historical load or probabilistic trends:** Derating factors based on past large load realization rates or probabilistic approaches
- **Direct industry engagement:** Continual dialogue with data center operators, manufacturers, and industrial and hydrogen producers
- **Scenario-based modeling:** Sensitivity analyses to account for high and low realization scenarios
- **Standardized methodologies:** Efforts to establish consistent forecasting frameworks across regions

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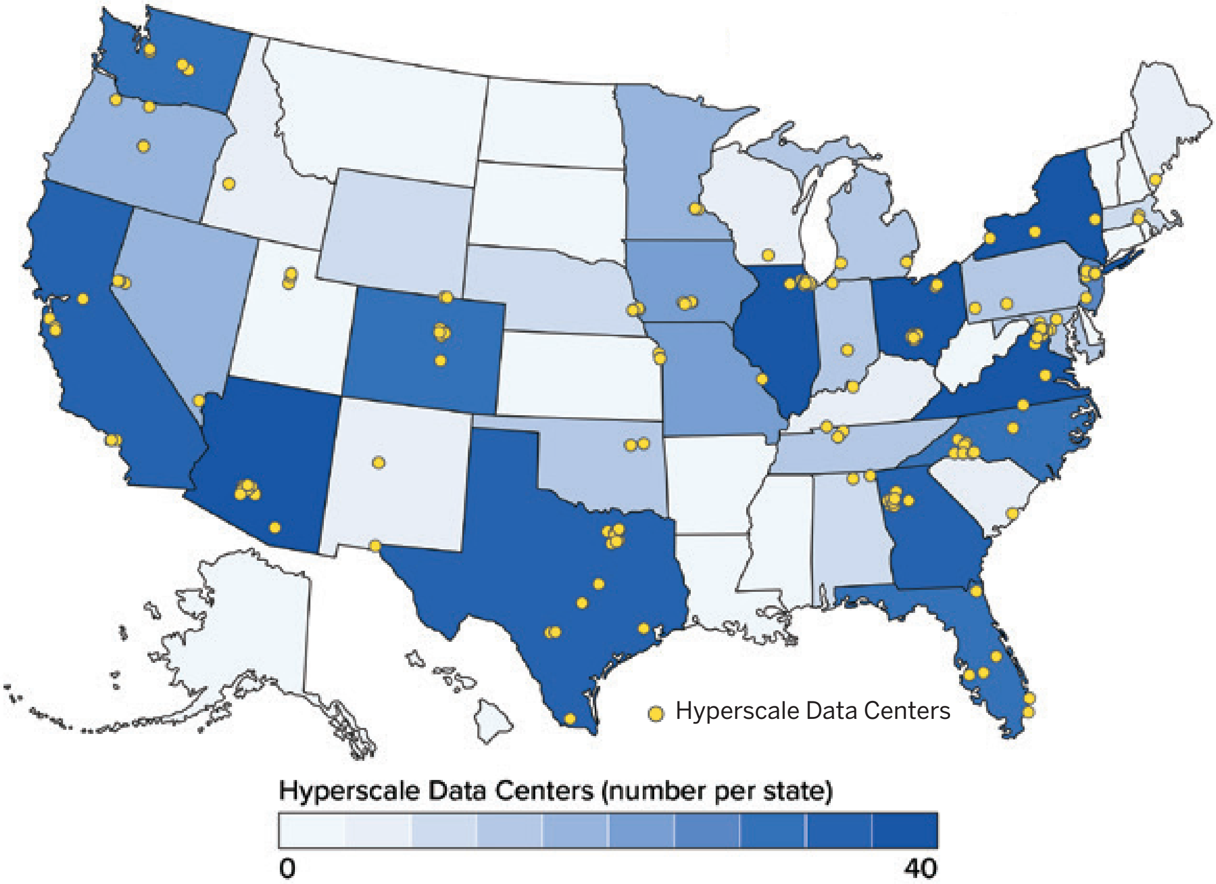
[3] https://www.esig.energy/large-loads-task-force/

FIGURE 10

Hyperscale Data Centers by State, as of 2022



Fifteen states accounted for 80% of data center load in 2022. Data center load growth is the single largest component of growth in utility load forecasts.

Source: EPRI (2024b), "Powering Intelligence."

Exogenous Load Forecasting Factors: DERs

Explicitly modeling the impact of customer technology adoption is essential for long-term load forecasting across all use cases. As the adoption rates of DERs grow, including EVs and building electrification, so does their influence on both energy consumption and peak load. DERs are introducing a greater need to increase the spatial and temporal granularity of load forecasts to better capture localized adoption and behavior patterns, and are further driving the need to perform hourly modeling.

Most ISOs incorporate behind-the-meter solar, battery storage, EV charging, and energy efficiency into their long-term load forecasts. Utilities are also increasingly considering these impacts in financial and resource planning. However, while some utilities explicitly account for DERs and electrification in their distribution planning, many still rely on traditional forecasting methods that do not fully capture these technologies' effects. As customer adoption of these technologies increases, modeling them as factors in forecasts is becoming necessary practice.

DERs are introducing a greater need to increase the spatial and temporal granularity of load forecasts to better capture localized adoption and behavior patterns, and are further driving the need to perform hourly modeling.

Modeling DER Adoption

DER Forecasting Models: Top-Down Versus Bottom-Up

DER adoption forecasting efforts generally use either a top-down or bottom-up approach. The difference between macro-level (top-down) and micro-level (bottom-up) indicators is their specificity: micro-level indicators represent the traits of a granular unit—typically a site, building, or a household, but it can also be a spatial area such as a census block, and macro-level indicators represent an aggregate area or customer base, such as a state, service area, or even an entire country. Top-down approaches use macro-level indicators (such as financial analysis parameters, population, etc.) to model adoption trends at the service area, state, or national-level, whereas bottom-up approaches use micro-level indicators (for example, household income or building ownership) to create high-resolution (site, customer, census block, or zip-code) forecasts, which can then be aggregated up to a system-level forecast. Bottom-up approaches are most commonly being used to geospatially disaggregate top-down forecasts or technology targets, rather than as a method to determine a technology system-level forecast. A top-down approach cannot model individual-level adoption; however, micro-level indicators are more difficult to collect and process at scale, making top-down models easier to execute.

Top-down models are currently being used by ISOs and utilities for system-level DER forecasting for resource planning and financial planning use cases, while bottom-up models are being developed and used by utility infrastructure planning to inform more localized DER forecasts. There is no publicly available information comparing top-down and bottom-up DER forecasts, and more information regarding reconciliation of DER forecasts is provided in "Reconciliation of Different Load and DER Forecasts" (p. 41).

A list of common model inputs by DER is given in Table 3 (p. 36).

System-level DER forecasts, such as the ones produced by ISOs or utilities, typically use top-down technology forecasts for resource, transmission, and financial planning. However, these top-down technology forecasts are not directly applicable to infrastructure planning use cases, since the latter require higher geospatial resolution at the substation or feeder level.

Distribution utilities have a few different options for modeling the impact of customer-adopted technologies at the level of granularity they require. The most common approach is to disaggregate top-down state, regional, or utility system-wide targets using higher geographic resolution allocation or geospatial disaggregation methods.

Disaggregation methods of top-down forecasts or targets can be done using:

- **Proportional allocation methods** allocating technologies proportional to one or more variables of the lower-resolution area, such as load or number of customers
- **Spatial allocation methods** based on propensity for adoption of technologies or agent-based models for spatial allocation of technologies to individual consumer/site or smaller spatial area

A key advantage of bottom-up models for geospatial disaggregation at the customer level (parcel or site) in distribution planning is the ability to map the unit of adoption (i.e., the parcel or site) directly to grid infrastructure. In contrast, using less granular units, such as zip codes, presents challenges because zip code boundaries do not align neatly with the distribution grid. Feeders often span multiple zip codes, requiring additional processing, assumptions, and/or heuristics to relate adoption data to grid infrastructure. This translation process may limit the usability of forecasts for infrastructure planning. However, it is important to consider the "precision vs. accuracy" trade-offs that are made when forecasting the adoption and behaviors of certain DERs in a granular, bottom-up manner. While customer- or parcel-level bottom-up models may provide a high degree of precision (i.e., the model will output adoption at a very specific geolocation, such as parcel, and the model will be consistent in its predictions), because the overall adoption rate of many important DERs, such as battery storage or EVs, is very low in the overall population, the accuracy of a bottom-up model to predict adoption at a granular geospatial level may be low. As such, when leveraging a bottom-up model, forecasters should consider and be aware of the level of uncertainty at the unit level (i.e., the customer or the premise) and communicate that uncertainty to stakeholders.

Modeling DER Behavior

Once future DER adoption is forecasted, load forecasters model the time-series behavior and associated grid impacts of these technologies to reflect the influence of weather, their hourly patterns, and the subsequent coincident peaks that result. Simulating DER behavior profiles may be integrated within the technology adoption forecast model—as is common for solar PV, batteries, and heat pumps—or performed separately after adoption modeling. Regardless of when this step occurs, the assumptions and inputs used to model DER behavior profiles, such as the presence or absence of price signals to modify the size and timing of future consumption patterns, significantly influence load forecasting outcomes. Accurately representing these behaviors is essential for understanding and comparing different forecasts.

TABLE 3

Common Model Inputs for DERs and Flexible Demand

Category	Data Stream	Source	Current Granularity	
			Spatial	Temporal
Energy efficiency	Historical savings, costs	Utilities	State, utility	Annual
	Projected budgets, savings, measures	States, utilities	State, utility	Annual
	Technology efficiencies, saturations	U.S. Energy Information Administration, industry reports	State, utility	Annual
Demand response programs	Historical program enrollment	Utilities	Customer	Hourly
	Historical (ex post) per customer load impacts	Utilities	Customer	Hourly
	Forecasted customer enrollment	Utilities	Customer	Hourly
	Forecasted (ex-ante) per customer load impacts	Utilities	Customer	Hourly
Time-varying rates	Historical program enrollment	Utilities	Customer	Hourly, time-of-use period
	Historical (ex post) per customer load impacts	Utilities	Customer	Hourly, time-of-use period
	Forecasted customer enrollment	Utilities	Customer	Hourly, time-of-use period
	Forecasted (ex-ante) per customer load impacts	Utilities	Customer	Hourly, time-of-use period
Behind-the-meter PV	Historical installed capacity	Utility	Customer	Install date
	Power output (ground truth or simulated, e.g., PVWatts)	Vendors, U.S. Department of Energy	Town (sample), 4 km grid	5-minute to hourly
	Information to guide future adoption	State policies	State, utility	Multi-year targets
Battery energy storage systems	Historical installed capacity	Utilities	Customer	Install date
	Expected charging/discharging	Utilities	Customer	Hourly
	Future adoption	State policies	State, utility	Annual
Transportation electrification	Vehicle registration	Vendor	State, county	Annual
	Vehicle miles traveled	Federal Highway Administration, vendor	State	Annual
	Vehicle efficiency	Consultant	State	Static*
	Charging profiles	Consultant	State	Hourly
	Managed charging programs	State	Utility	
Building electrification	Installations	States, municipalities, cities, utilities,	State	Annual
	Building stock characterization	U.S. Department of Energy, research organizations, vendors	County, parcel/ building	Static*
	Technology coefficient of performance (COP) curves	Consultant	State	Static*

*Static means that the data variable is constant over time.

Source: Energy Systems Integration Group.

Solar PV

Solar PV systems are weather-dependent resources that influence the net load profile due to behind-the-meter generation.

- **Key behavior drivers:** Solar PV behavior is driven by weather conditions, the size of the installed system, whether battery storage is co-located, and assumptions regarding system efficiency.
- **Modeling approaches:** The National Renewable Energy Laboratory's PVWatts tool is publicly available and commonly used to model solar generation based on location, system configuration, and typical meteorological year data.[4]
- **Key challenges:**
  - Forecasting solar PV requires aligning weather and irradiance/insolation datasets to ensure consistency across forecasts and often needs to be derived from net load.
  - Solar generation often must be inferred from net load rather than directly measured, which can lead to inaccuracies if weather data or customer usage assumptions are off.

Battery Energy Storage Systems

Behind-the-meter battery energy storage systems influence load profiles by shifting consumption through charging and discharging cycles, which can be influenced via incentives and utility operational goals.

- **Key behavior drivers:** Battery behavior is primarily influenced by economic incentives (such as time-of-use rates), reliability needs (such as its use for back-up power), and opportunities for participating in electricity markets and and virtual power plants (VPPs) programs.
- **Modeling approaches:** Models typically assume that batteries will optimize their dispatch to maximize economic returns or enhance reliability, depending on their use case.

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[4] https://pvwatts.nrel.gov/

  - Residential systems are generally modeled as optimizing for self-consumption and energy arbitrage.
  - Commercial systems are typically modeled with an emphasis on peak shaving and energy arbitrage.
- **Key challenges:**
  - Forecasting battery systems is complicated by the lack of standardized modeling practices and assumptions across the industry, along with highly variable participation in regional markets and distribution system programs.
  - Categorizing battery systems as part of the load or as dispatchable generation is a key challenge. This distinction requires forecasting how much storage will be operated for customer-driven economics versus utility or market dispatch.

Building Electrification

Building electrification increases electricity demand, particularly for space heating and cooling (often measured as the number of heating degree days or cooling degree days) and shifts seasonal peak load patterns.

- **Key behavior drivers:** The primary drivers of building electrification include the adoption rate of heat pumps, regional climate conditions that determine heating and cooling needs, and policy incentives that support fuel-switching.
- **Modeling approaches:**
  - Most models use reference heat pump technologies that are driven by outdoor temperature profiles.
  - Heating and cooling loads are assumed to activate when temperatures cross specific thresholds.
  - Scenarios may include or exclude back-up electric resistance heating, which is critical in cold climates and significantly impacts demand during extreme weather events.
  - Heat pump adoption modeling requires understanding building stock characteristics. ISOs like the New York Independent System Operator use the National Renewable Energy Laboratory's ResStock and ComStock datasets, while utilities rely on market research, vendor data, and local partnerships.
- **Key challenges:**
  - Data standardization remains a challenge, as jurisdictions lack consistent reporting on key adoption parameters (e.g., back-up heating system sizing).
  - Back-up heating assumptions significantly impact peak winter demand forecasts. The majority of U.S. non-electric energy consumption is for space heating, making accurate electrification forecasts essential (ESIG, 2024).
  - Regional variability in heat pump adoption rates and efficiency improvements can make this challenging to model. Building electrification is expected to drive winter peak demand growth, particularly in East Coast ISO regions, where morning winter peaks may surpass summer peaks between 2030 and 2035.

Transportation Electrification

Transportation electrification, primarily through EVs, is adding flexible and growing demand to the grid, altering daily and seasonal load patterns depending on where, when, and how charging occurs.

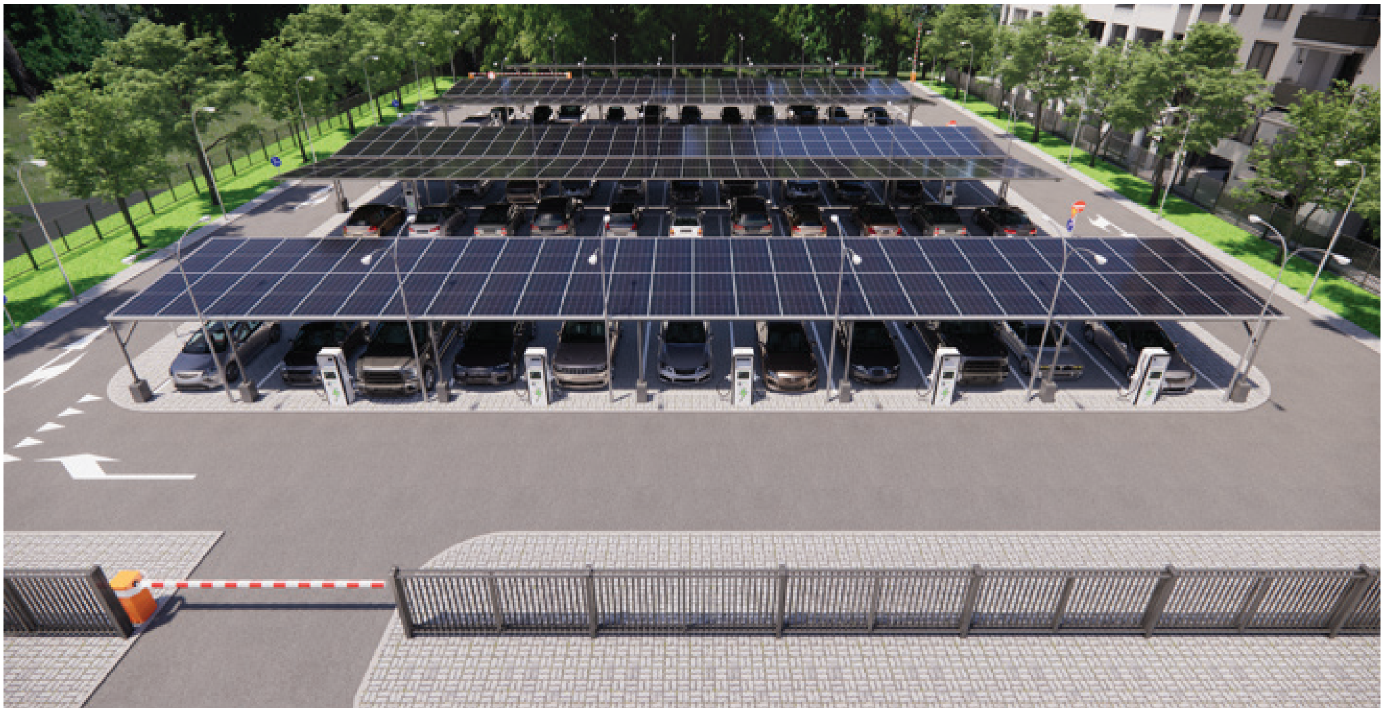
- **Key drivers:** The main drivers include EV adoption rates, travel and commuting behavior, the availability and type of charging infrastructure, and EV drivers' responsiveness to price signals and managed charging programs.
- **Modeling approaches:**
  - Charging demand is typically modeled using assumptions about EV technologies, travel patterns, and user charging behavior.
  - Models incorporate responsiveness to time-varying electricity rates, managed charging programs, and demand-side controls to simulate flexible load potential.
  - Models should differentiate between home, workplace, and public fast charging to reflect distinct usage patterns and grid impacts.
- **Key challenges:**
  - EVs function as "mobile DERs," making it difficult to forecast their charging behavior and grid impact, especially compared to stationary resources.

  - Uncertainty in future EV adoption rates and charging behavior introduces forecasting challenges. Unlike solar or battery storage, historical adoption data for EVs have not traditionally been tracked by utility load forecasting departments.
  - The industry has not yet aligned on a consistent set of modeling assumptions for transportation electrification, leading to divergent forecasts (ESIG, 2023a).
  - High-power fast charging stations could create localized grid constraints if their locations are not properly planned.
  - Forecasting EV charging loads depends on linking transportation adoption and behavior models with electric load models, which are traditionally modeled separately and by different actors.
  - Although chargers are stationary, vehicle mobility determines where and when charging occurs, demanding fine-grained, spatially explicit forecasting.
  - As EV adoption grows among residents in multi-family housing, charging behavior may shift toward workplace and public locations. This introduces additional uncertainty into load forecasting, particularly around spatial impacts and timing of charging.
  - Future electricity rate structures will play a critical role in shaping EV charging behavior. For example, continued use of overnight discount rates may amplify winter morning peaks. Forecasting needs to consider alternative rate scenarios and their influence on load profiles.

Energy Efficiency

Energy efficiency reduces total electricity consumption and can lower system peak demand, moderating long-term load growth forecasts.

- **Key drivers:** The primary drivers of energy efficiency include appliance and equipment standards, state and local building codes, utility-run efficiency programs, lighting upgrades, and changes in consumer behavior.
- **Modeling approaches:**
  - System-level forecasts often include energy efficiency by customer class using forecasted savings from utility programs or policy targets.
  - SAE models are frequently used and capture historical trends in equipment efficiency, appliance saturation, and usage patterns.
  - Energy savings estimates are distributed to substation/feeder levels for distribution planning via a top-down allocation.



- **Key challenges:**
  - Forecasting energy efficiency savings can conflict with SAE base load models, which already include some historical efficiency improvements, creating a risk of double-counting.
  - Variability in efficiency program adoption and savings assumptions introduces forecast uncertainty.
  - Peak demand reductions from energy efficiency may not scale proportionally to energy savings, requiring careful modeling of load shape impacts to avoid overestimating capacity benefits.

Demand Flexibility

Demand flexibility reduces or shifts peak demand, providing grid reliability and operational flexibility via coordinated devices, utility programs, and pricing mechanisms.

- **Key drivers:** The effectiveness of demand flexibility is driven by customer participation in demand response programs, responsiveness to price signals, behavioral norms, and grid operational conditions.
- **Modeling approaches:**
  - Some system-level forecasts apply explicit adjustments for demand flexibility by using historical demand response peak reduction performance to estimate future impacts.
  - Increasingly, time-of-use rates and dynamic pricing schemes are incorporated into load forecasts to capture shifts in customer behavior and energy usage patterns.
  - Historical demand-response peak load reductions are used to adjust system-level forecasts to estimate future impacts.
- **Challenges and considerations:**
  - In many utility and market contexts, demand response is modeled outside of the load forecast as a dispatchable resource, similar to storage. This creates challenges for coordination between load forecasting and resource adequacy planning, especially when demand response effects are not captured in historical load trends.
  - Because demand response customers can opt out, demand flexibility is not consistently reliable for distribution-level planning and is often excluded from those models.
  - Demand flexibility resources are typically aligned with system-level peak events and may not coincide with distribution system constraints, thus limiting their local planning value. Distribution planning models lack robust demand response integration, as they often represent demand response as a fixed MW value instead of incorporating dispatch patterns and coincidence factors.
  - As variable renewable generation increases, future demand flexibility will need to shift from infrequent peak shaving to more frequent, time-sensitive load shifting, potentially at daily or even intra-day intervals.
  - Electrification is introducing dual seasonal peaks (winter and summer), and pricing mechanisms may shift flexible loads from traditional summer afternoon peaks to winter mornings or summer evenings, which will require more holistic and adaptive forecasting approaches.

Accurately modeling DER behavior is essential, but aligning these projections with broader system-level load forecasts remains a challenge. Differences in forecasting methodologies, assumptions, and resolutions can create discrepancies between system and local planning efforts. The next section explores how different load and DER forecasts can be reconciled to ensure consistency across planning processes and improving grid reliability.

Accurately modeling DER behavior is essential, but aligning these projections with broader system-level load forecasts remains a challenge. Differences in forecasting methodologies, assumptions, and resolutions can create discrepancies between system and local planning efforts.

Reconciliation of Different Load and DER Forecasts

Once DER adoption and behavior forecasts are developed, load projections produced for different use cases and granularity levels need to be reconciled to ensure consistency across planning processes. Differences in methodologies, assumptions, and resolutions can create significant discrepancies between system-wide and local forecasts, creating misalignment in the decision-making on resource needs, infrastructure expansion needs, and customer programs and rates design. To improve alignment between system and local distribution forecasts, planners must address three key challenges:

- **Forecast components:** What base load assumptions and exogenous load and DER factors are included in system and local forecasts?
- **Forecast reconciliation:** How do non-coincident local peaks relate to system-wide coincident peak demand, and how do contribution factors impact forecast accuracy?
- **Forecast allocation:** How are system-level load and DER forecasts distributed to higher-resolution grid areas, such as transmission nodes and distribution substations, and what are the risks of misallocation?

Figure 11 (p. 42) shows how system forecasts, which are typically allocated to transmission nodes using historical distribution contribution factors, may not fully align with the sum of local distribution forecasts, for a few reasons:

- Local forecasts incorporate granular insights such as known customer interconnection requests, which are often absent in top-down system-level allocations to transmission and distribution nodes.
- Local forecasts take more conservative approaches to load and DER assumptions since there is less geographic diversity in a small portion of the grid to average and smooth out load profiles.

This section explores forecast reconciliation and allocation challenges in detail, and outlines ways to improve alignment across use cases.

Coincidence and Contribution Factors

When reconciling load and DER forecasts at different resolution levels and for different use cases it is important to distinguish between coincident and non-coincident peak demand.

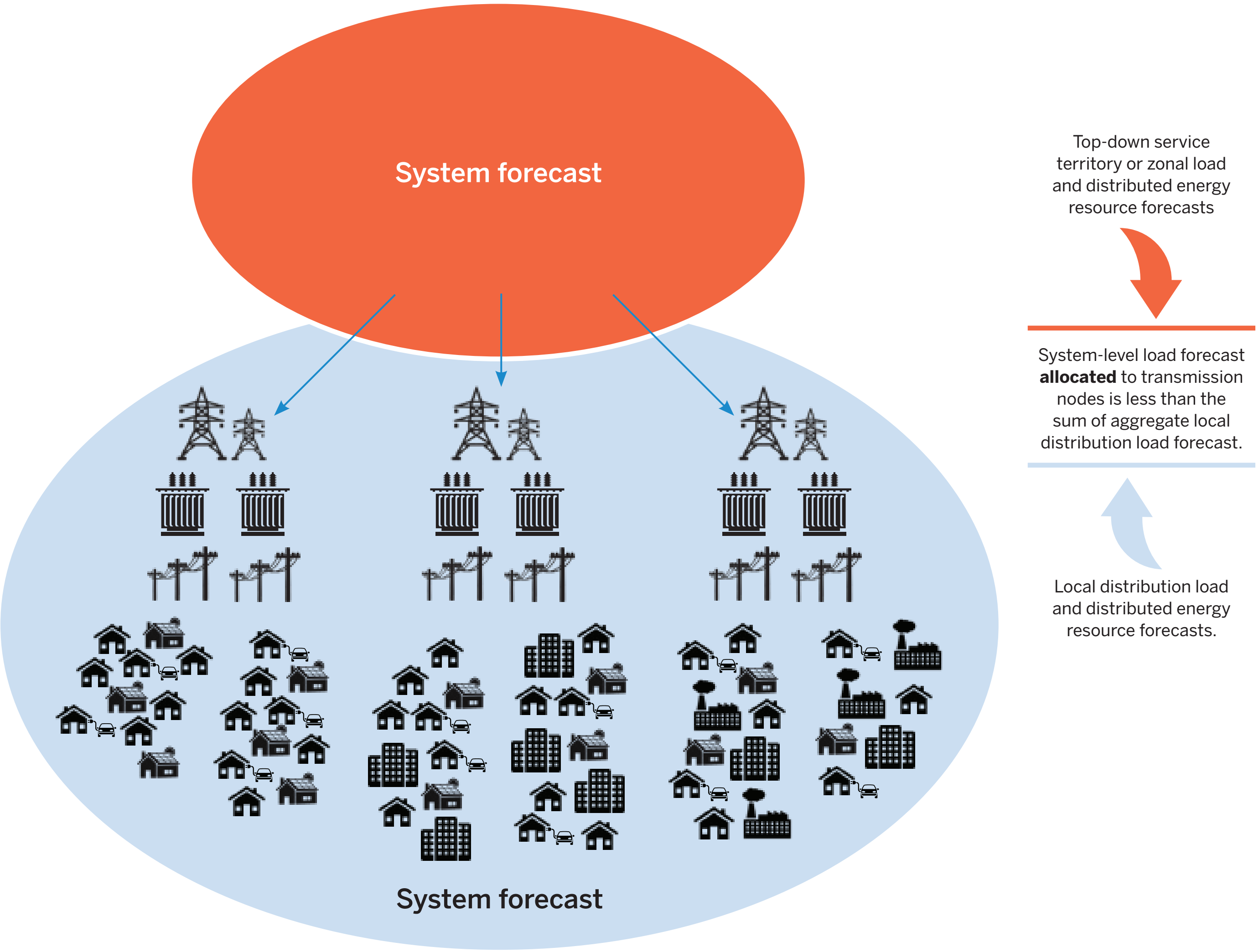
- **Coincident peak demand** refers to the maximum aggregate load of a system (however defined) at a single point in time.
- **Non-coincident peak demand** refers to the maximum loads experienced by individual subsystems, which may occur at different times.

For example, a utility's coincident peak demand, which is used for transmission and resource planning, occurs at a single system-wide peak, while non-coincident peaks at distribution substations are used for local planning and may occur at different times. The sum of non-coincident peaks is always greater than or equal to the system's coincident peak, because not all local peaks align with the system-wide peak. When planning for grid infrastructure such as substations and feeders, planners focus on the highest demand at a specific location, rather than the aggregate demand across the service area or region.

A **coincidence factor**, or the ratio of a system's coincident peak demand to the sum of non-coincident peaks, reflects the extent to which local distribution system peaks align with the system-wide peak. If all local substations peak

FIGURE 11

Illustration of Top-Down System-Level Load and DER Forecast Versus Aggregate Local Distribution Load and DER Forecasts



Source: Energy Systems Integration Group.

at the same time as the system, the coincidence factor is 1, but if local peaks occur at different times, the coincidence factor is less than 1 (i.e., there is less unity). The coincidence factor is used to reduce the sum of the non-coincident peak load forecast of the local distribution area to estimate the peak load of the aggregate distribution area at the time of the coincident system peak load.

However, coincidence factors may need to be adjusted over time to account for the impact of exogenous demand-side modifiers. Since most load and DER forecasts do not provide an 8,760 time series, planners often rely on historical coincidence factors to compare local substation loads and DER non-coincident peaks to system peaks. These coincidence factors are assumed to stay constant over the forecast horizon, which fails to capture the impact that exogenous demand-side modifiers like DERs can have on local load shapes and shifting the day and time of future peaks.

The **contribution factor** is the ratio of the energy or peak load of a subsystem to the system energy or peak load. It is given in "per unit" of the subsystem energy or maximum demand and is used to allocate a system energy or peak load forecast to a subsystem. Like the coincidence factor,

traditional contribution factors are based on historical load records, assumed to be constant over the forecast horizon, and used to allocate long-term load and DER forecasts. If DER adoption significantly alters local demand, assuming a fixed contribution factor over the forecast horizon can lead to inaccuracies.

If annual hourly time-series forecasts replace annual energy and peak load values, planners can directly compare non-coincident and coincident peak loads and determine contribution factors for each subsystem. This approach better captures shifts in local and system peak timing due to changes in load patterns and DER adoption over each year in the forecast horizon.

Allocation of Top-Down Forecasts

At the zonal or utility service territory levels, load forecasts are typically based on state-level technology adoption outlooks, state policies, or regulatory targets. A key challenge is that the methods used to allocate forecasts developed at the state, zonal, or utility service territory level load to transmission buses can introduce errors.

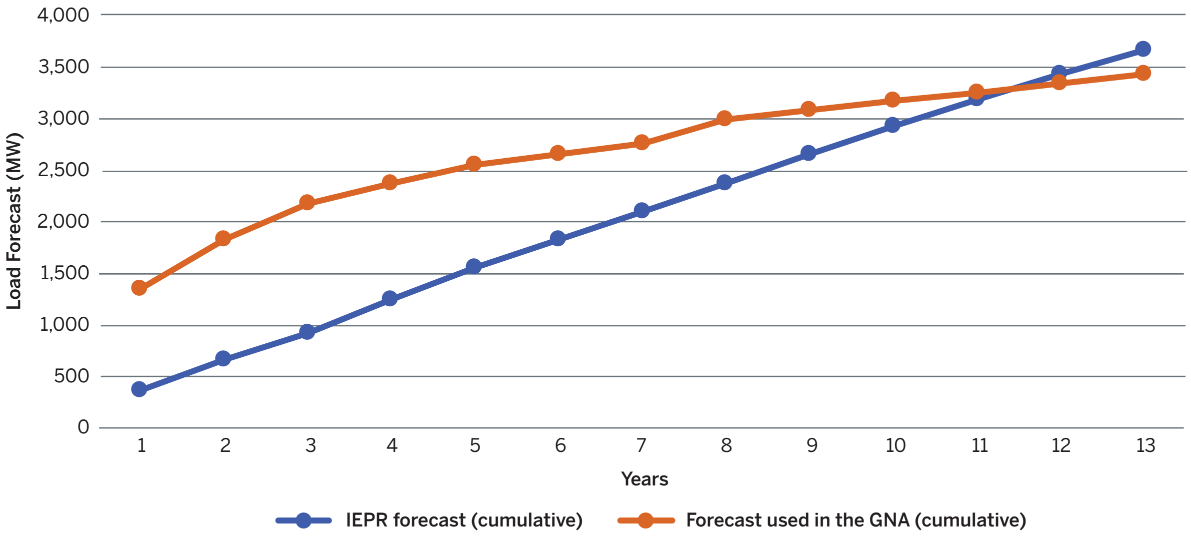
One issue that can arise is if a top-down system-level net load forecast from an ISO, regional planning entity, or utility includes future solar, and it is allocated down to a transmission node using historical energy or peak load contribution factors, this would produce unrealistic results. For example, a densely populated urban area may have a high contribution factor relative to the system load but limited rooftop and land space for solar installations, resulting in a forecast overestimating local solar capacity on that node. Similarly, a top-down allocation of EVs that fails to account for the uneven geographical distribution of EV adoption may miss hot spots of local load growth pockets.

For these reasons system-level allocations to transmission nodes can overlook local load growth pockets and result in substantial differences in net load forecasts when compared to distribution net load forecasts rolled up to transmission nodes. Industry is increasingly concerned over system-level DER forecasts not matching

System-level allocations to transmission nodes can overlook local load growth pockets and result in substantial differences in net load forecasts when compared to distribution net load forecasts rolled up to transmission nodes.

FIGURE 12

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



California system-level load-only forecast (no DERs or electrification) (*Integrated Energy Policy Report* (IEPR); https://www.energy.ca.gov/data-reports/reports/integrated-energy-policy-report-iepr) for the three investor-owned utilities’ service territories (blue), compared to bottom-up local load-only forecast from the distribution utilities (using known new loads and economic forecast) used in the utilities’ Grid Needs Assessment distribution annual plans.

Source: Resource Innovations (2022).

distribution forecasts, and the mismatch is becoming more apparent when comparing forecasts at transmission nodes for transmission planning. For distribution load and DER forecasts to effectively support transmission planning, they must be long-term and robust. If distribution planning forecasts do not include formal economic growth or fail to capture bottom-up geospatial DER impacts, they cannot be reliably used for long-term transmission planning. Collaboration is needed within utility departments and between utilities, ISOs, and regional planning entities to better allocate system level or zonal level forecasts to transmission nodes using geospatial disaggregation methods.

While most utilities still use a top-down system-level forecast from an internal utility load forecasting department or ISO forecasts allocated to transmission nodes for transmission planning, some utilities have seen the need to:

- **Update or adjust the transmission node load and DER forecast in high growth areas** using the distribution planning load and DER forecast where loading could be underestimated
- **Aggregate distribution load and DER forecast to transmission nodes** for transmission planning instead of using the ISO or utility system-level top-down load forecast

Figure 12 illustrates the mismatch between (1) a top-down system load-only forecast (no DERs or electrification loads) in California, and (2) an aggregated local distribution planning forecast incorporating economic growth and known new customer business loads. The short-term aggregated distribution load forecast is substantially higher than the top-down load forecast, though the two cumulative forecasts converge in the later years. This discrepancy questions whether the distribution planning department might be over-estimating demand and, as such, over-building the grid infrastructure needs, or the system level forecast might be under-predicting load growth, which would result in resource capacity shortages and transmission infrastructure bottlenecks.

Key Takeaways

This report provides an analysis of long-term load and DER forecasting challenges, methodologies, and emerging practices. As the energy landscape evolves, forecasters must balance accuracy, complexity, and usability to meet the needs of different stakeholders. The key takeaways from this ESIG Long-Term Load and DER Forecasting Taskforce report are summarized below.

A Shift Toward 8,760 Time-Series Forecasting Can Significantly Improve Temporal Forecasting Accuracy

Traditional top-down allocation methods face increasing challenges. While system-level long-term forecasts are commonly used for distribution and transmission planning, they must be disaggregated and allocated to transmission- or distribution-level infrastructure to reflect local conditions. Traditional methods, which allocate load and DER growth based on proportional scaling of energy consumption, peak demand, or customer count, often fail to capture emerging geospatial adoption patterns.

A shift toward 8,760 time-series forecasting, which models hourly load profiles rather than disaggregating annual peak and energy values, can significantly improve forecasting accuracy by natively modeling hourly usage patterns at the asset level. This approach enables a more precise assessment of how DERs, electrification, and climate trends influence system and local load patterns. These more granular methods are becoming essential for accurate grid and transmission planning.

> **As the energy landscape evolves, forecasters must balance accuracy, complexity, and usability to meet the needs of different stakeholders.**

Greater Geographic Granularity Can Address Several Forecasting Challenges

DER adoption is not geospatially uniform across the distribution system, and concentrated adoption in specific geographies is common. These concentrations can require upgrades to the distribution system that are most efficiently built if planned well in advance along with the introduction of mitigating technologies (e.g., grid edge equipment and controls).

For example, high concentrations of EV charging demand (fast chargers or medium/heavy-duty fleets) can trigger substantial distribution system upgrade requirements, and high concentrations of data centers on the transmission system can not only require transmission system upgrades but also trigger changes in practices used by system operators. Employing granular geospatial forecasting can equip transmission and distribution planners to better anticipate and address these types of challenges.

Emerging Adoption and Behavior Trends Require New Forecasting Approaches

Traditional load forecasting, which primarily relies on historical load patterns, is becoming less effective due to growing demand from new sectors, electrification, and DER adoption that are difficult to understand using historical data. These new trends require load forecasting methods that account for the underlying drivers of new sector demands and technology adoption. To improve accuracy, forecasts are increasingly capturing load at the end-use level and explicitly model technology adoption that reflects consumer preferences and adoption drivers.

Scenario Planning Is Essential for Capturing Uncertainty

While this report outlines key long-term forecasting considerations, it does not argue for a single "best" approach that forecasters ought to implement for their jurisdictions. There is no one-size-fits-all methodology, and forecasters must carefully select the method that is best for their jurisdiction. For example, in many regions, energy policy, utility programs, and customer adoption of new energy technologies are driving the rapid uptake of EVs and building electrification technologies, enrollment in demand flexibility, and the increasing pace of large load additions. These trends are prompting many regulators, utilities, and ISOs to implement more sophisticated and detailed load forecasting methods that are more geospatially and temporally granular, but these trends are not uniform.

In the face of rapidly evolving changes to energy demand, technology adoption, and policy frameworks, scenario-based forecasting approaches better equip planners to assess a range of possible futures and provide opportunities for greater coordination of scenarios across planning entities to improve system-wide preparedness.

Coordination Across Forecasting Entities Is Increasingly Critical Through Integrated Planning Approaches

Long-term load forecasting is typically part of annual planning processes and performed by multiple entities within the same region, and sometimes by multiple departments within the same entity. These processes can often result in multiple forecasts being produced for multiple use cases for the same—or overlapping—regions. While these forecasts may share some commonalities, most often they are based on different core assumptions, inputs, methods, and models. This is an inefficient outcome that leads to stakeholder confusion and increases the likelihood of errors being introduced into planning analyses and decision-making.

As rapid load growth and DER adoption alter the operational characteristics of the grid and the planning it requires, integrated planning approaches offer a framework for evaluating diverse energy resources, their benefits to the grid and its participants and users, and the resources' ability to reliably serve load. As a result of integrated planning, there is a greater need for coordination and data-sharing on long-term load forecasting across grid planning entities and within planning departments to align long-term load forecasting requirements.

As rapid load growth and DER adoption alter the operational characteristics of the grid and the planning it requires, integrated planning offers a framework for evaluating diverse energy resources, their benefits to the grid and its participants and users, and the resources' ability to reliably serve load.

Incorporating Climate Change Models into Forecasting Remains Complex

Most existing load-to-weather models are based on historical data, which may not fully capture climate change impacts. Enhancing forecasting methodologies with updated climate models is necessary to ensure resilience against evolving weather patterns.

Reconciliation Between Top-Down and Bottom-Up Forecasts Is Complex

Reconciling top-down and bottom-up forecasts remains a challenge in grid planning across system and local levels. Differences in assumptions, methodologies, and allocation methods can cause significant misalignments. Key challenges include aligning base assumptions and improving allocation of system-level forecasts to transmission nodes and finer grid resolutions. Without careful reconciliation, top-down forecasts may underrepresent localized growth and DER impacts, while bottom-up forecasts may overestimate needs, leading to either infrastructure overbuilds or capacity shortfalls.

Known New Customer Loads Must Be Carefully Integrated into Forecasts

Methodologies for long-term base load forecasting have traditionally centered on extrapolating historical load data based on observed weather, projected demographics, and economic factors, resulting in annual growth rates of annual electricity demand applied to historical load. Increasingly, local grid planners also use information from medium to large customers seeking new customer interconnection at the distribution level, while system planners increasingly use data provided by large load customers to account for data center developments and large manufacturing that will be added as exogenous factors to the base load forecast. A key challenge is reconciling these inputs and avoiding double-counting of the load growth derived from the economic indicators (gross domestic product, population, etc.) used to determine the annual base load growth rates from the known new customer load growth data collected by utilities.

Transportation Electrification Presents Similar Reconciliation Challenges

Without proper integration, transportation electrification forecasts may overlap with baseline load growth projections or known new customer loads, leading to potential overestimations. This possibility is especially real with fleet and heavy-duty-vehicle charging sites, which can add significant localized demand.

Future Price Signals May Influence Load Forecasting

Forecasters and stakeholders need to consider the impact that future price signals could have on forecasted load usage and consumption patterns. The implementation of future programs or technologies that change existing consumption behavior via price signals is an active area of ongoing policy development and program implementation—these include dynamic electricity rates, demand-response incentives, flexible load programs, and local flexibility markets. Where relevant, stakeholders can incorporate the future potential impact of price signals on load forecasts by including them in the scenario analyses, thus enhancing long-term forecasting accuracy and grid management strategies.

In conclusion, while the challenges of long-term load and DER forecasting are complex and ever-evolving, they present exciting opportunities for innovation and improvement. As energy systems integrate new technologies, demand patterns, and policies, more advanced, geospatially and temporally granular forecasting methods are crucial for ensuring grid reliability and effective planning. By adopting a flexible, scenario-based approach and fostering better coordination across entities, forecasters can better navigate the uncertainties of future energy demand. By embracing these advancements and improving stakeholder coordination, energy planners can pave the way for a more resilient and efficient grid, prepared to meet the demands of tomorrow's energy landscape.

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Long-Term Load and DER Forecasting

A Report by the Energy Systems Integration Group's Long-Term Load and DER Forecasting Task Force

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This report is available at https://www.esig.energy/long-term-load-and-der-forecasting/.

To learn more about ESIG's work on this topic, please send an email to info@esig.energy.

The Energy Systems Integration Group is a nonprofit organization that marshals the expertise of the electricity industry's technical community to support grid transformation and energy systems integration and operation. More information is available at https://www.esig.energy.

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