Strengthening Load Research and Forecasting Capabilities of Discoms

A Multi-Stage Framework for Electricity Demand Forecasting

AIDA
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प्रयास
Prayas (Energy Group)

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About Prayas

Prayas (Initiatives in Health, Energy, Learning and Parenthood) is a non-Governmental, non-profit organization based in Pune, India. Members of Prayas are professionals working to protect and promote public interest in general, and interests of the disadvantaged sections of the society, in particular. Prayas (Energy Group) works on theoretical, conceptual, regulatory and policy issues in the energy and electricity sectors. Our activities cover research and engagement in policy and regulatory matters, as well as training, awareness, and support to civil society groups. Prayas (Energy Group) has contributed to policy development in the energy sector as part of several official committees constituted by Ministries, Regulatory Commissions and the Planning Commission / NITI Aayog. Prayas is registered as SIRO (Scientific and Industrial Research Organization) with Department of Scientific and Industrial Research, Ministry of Science and Technology, Government of India.

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About AIDA

All India Discoms Association (AIDA) is a not-for-profit collaboration platform representing a wide spectrum of electricity distribution entities of India. Its members are state government owned Distribution Companies, private sector Discoms, Electricity Departments of Union Territories and Franchisees.

AIDA serves as the unified voice of all electricity distribution entities in the country serving 345 million electricity consumers. Its core objectives include fostering collaboration among members, advocating for progressive policy and regulatory reforms, and driving holistic development across the power distribution sector.

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Foreword

India's electricity demand is growing rapidly. For Electricity Distribution Companies, understanding these changes in the demand and planning for them in advance is becoming increasingly important. In this environment, accurate demand forecasting is no longer just a regulatory routine; it is a necessity for the survival of our Discoms.

Traditionally, utilities have relied on basic methods, like extending past sales trends or projecting a single annual peak demand number. These old approaches do not show how demand changes hour by hour or season by season. This lack of detail often leads to expensive power purchases and local grid overloads. Fortunately, widespread digital reforms and smart metering now give Discoms access to massive amounts of data. The main challenge today is building the skills needed to use this data for better planning leading to least cost capacity expansion.

The guideline, jointly prepared by Prayas (Energy Group) and the All India Discom Association (AIDA), offers a practical roadmap. It breaks the forecasting process down into three clear steps that utilities can implement using data they already own:

- **Stage 1: Discom-Level Aggregate Forecasting –** Focuses on overall trends, seasonal changes, and how weather affects peak demand using historical load curves.
- **Stage 2: Spatial and Feeder-Level Forecasting –** Looks at specific areas within the network to see exactly where demand is growing, which consumers are contributing to this growth, this data can help utilities better plan for load growth and local grid upgrades
- **Stage 3: Consumer-Level Forecasting –** Uses smart meter data and consumer surveys to understand how appliance usage, electric cooking, and EV charging drive electricity use. It also shows how bottom-up tools like the PIER model can help simulate future demand scenarios.

Rather than working in isolation, these three stages connect broad energy trends with everyday grid realities.

I thank the teams at Prayas and AIDA for putting together this highly useful guide. I strongly encourage Discoms to adopt this framework to improve utility planning and build a more reliable power grid.

Shri. Alok Kumar

Director General,
All India Discoms Association (AIDA)

Executive Summary

Long-term electricity demand and load forecasting is becoming increasingly important for India's distribution sector. Rising cooling demand, growth in electric mobility, increasing adoption of distributed energy resources, and changing patterns of electricity consumption are creating new challenges for distribution companies (Discoms). Accurate load forecasts are essential not only for power procurement planning but also for network development, demand-side management, renewable energy integration, peak management and ensuring reliable and affordable electricity supply. At the same time, significant investments are being made in digitalisation of the distribution sector through smart metering and other reforms, creating opportunities to strengthen the analytical foundations of utility planning.

Despite these advancements, load forecasting practices in many DISCOMs remain constrained by limited institutional capacity, underutilization of available data, and a predominant focus on short-term forecasting, occasionally supported by AI/ML-based tools. Although most utilities develop long-term demand forecasts to meet regulatory and planning requirements, these exercises often lack a systematic approach that incorporates spatial analysis, end-use assessments, and evolving drivers of electricity demand. Consequently, planning and investment decisions are frequently made without fully harnessing the expanding pool of consumer, feeder, and system-level data now available across the power sector.

This guideline proposes a practical three-stage framework for electricity demand forecasting that can be progressively adopted by Discoms using data that is already available within most utilities. The first stage focuses on aggregate Discom-level forecasting through analysis of historical load curves, growth trends, seasonal patterns, and weather sensitivity. The second stage introduces spatial and feeder-level forecasting to identify geographic concentrations of demand growth, which can support better spatial load growth, consumer category wise change in pattern and help in improve network planning and investment decisions. The third stage suggests forecasting consumer demand by leveraging smart meter data, load research surveys, and end-use modelling to understand the underlying drivers of electricity consumption, including cooling demand, electric vehicles, distributed RE generation, and changing appliance ownership patterns.

Together, these three stages provide a layered and integrated approach to load forecasting that links system-wide demand trajectories with local network realities and consumer behaviour. The framework can enable Discoms to move beyond single-point demand projections towards more robust, data-driven, and scenario-based load forecasting practices. By institutionalising load research and progressively enhancing analytical capabilities, Discoms can improve the quality of planning and investment decisions, better manage emerging demand uncertainties, and build a more reliable, efficient, and consumer-responsive electricity system.

Contents

1. Introduction

India's electricity sector is experiencing a period of rapid transformation characterized by changes in demand, supply, and grid operations. Over the past decade, electricity consumption has grown steadily due to urbanization, rising incomes, increased appliance ownership, and increase in electrification of industrial and commercial uses. At the same time, rapid expansion of air-conditioning use, increase in distributed renewable energy sources, and increasing weather variability are fundamentally reshaping electricity demand patterns.

Within this changing environment, accurate demand forecasting has become one of the most critical activities for electricity distribution companies (discoms). These forecasts are used in operational and planning decisions, including power procurement planning, network expansion, tariff design, and demand-side management programs. Variation between forecast and actual demand can lead to over-procurement or expensive procurement of power and infrastructure shortages which impacts supply quality and reliability.

Historically, many discoms have relied primarily on relatively simple forecasting techniques based on historical energy sales or aggregate demand trends. These approaches typically extrapolate past growth rates to estimate future demand. While such methods may be adequate in relatively stable demand environments, they are increasingly insufficient in today's electricity systems where demand drivers are rapidly evolving.

Several factors are contributing to increasing uncertainty in electricity demand patterns. One of the most significant factors is the rapid growth in cooling demand. Rising temperatures, urban heat island effect, and higher household incomes are accelerating the adoption of air conditioners, making cooling a major contributor to peak electricity demand in many regions of India. At the same time, electricity demand is increasingly being defined by geography and location. Urban expansion across cities is creating pockets of demand growth that are often not captured in aggregate forecasts. As a result, discoms need forecasting approaches that can help understand these patterns and plan for demand according to when and where it is required.

In addition, technological changes such as captive solar installations, use of energy-efficient equipment, and electric vehicles are impacting the consumption patterns at the consumer level. These developments need to be incorporated into the forecasting rather than relying solely on historical trends.

Given these evolving challenges, there is a need for discoms to develop systematic load research and forecasting capabilities that combine multiple sources of data and analytical approaches. This report proposes a **three-stage analytical framework** for strengthening load research and forecasting capabilities within discoms. The framework is designed to progressively improve the forecasting level, beginning with aggregate system-level forecasting and move towards more granular forecasts with spatial and consumer-type detail.

Insights from discussions with DISCOMs under the AIDA engagement

As part of the PEG AIDA engagement, discussions were held with several (7) discoms to understand current load forecasting practices and the availability of relevant data.

These discussions indicated that most discoms currently focus primarily on short-term demand forecasting, such as day-ahead or week-ahead projections used for short-term power procurement and operational planning. Forecasts are often based on recent demand trends and operational experience. Forecasting over longer horizons is typically limited to simple projections of annual demand and peak load.

However, officials acknowledged that medium- and long-term demand forecasting would be valuable for planning network expansion, estimating future peak demand, and designing demand-side management programs.

Encouragingly, many utilities indicated that a large share of the data required for improved forecasting such as historical load curves, feeder-level demand data, consumer information, and weather data is available within the organisation, although it is not always systematically used for forecasting.

Overall, the discussions suggested strong interest among discoms for the need for a more structured load research and forecasting methodology, particularly if the proposed approaches can be implemented using data that they already have.

Key observations

- Forecasting is currently focused on short-term operational needs
- Long-term forecasts are often limited to single annual demand and peak estimates
- Utilities expressed interest in improving forecasting methods

2. Overview of the Three-Stage Forecasting Framework

The forecasting framework proposed in this report outlines a step-by-step approach to improving demand forecasting by gradually using more detailed data and insights at different levels of electricity consumption. The framework is organized into three stages, each adding a denser data layer to develop more understanding of electricity demand patterns.

Stage	Output	Relevance
Stage 1	Discom-level load curve forecasting	Understanding aggregate demand patterns
Stage 2	Spatial and feeder-level forecasting	Identifying geographic/spatial demand growth
Stage 3	Consumer and end-use modelling	Understanding consumer level drivers of demand

Each stage addresses a distinct dimension of demand forecasting.
Stage 1 focuses on **system-level demand trends**, examining historical load curves to understand daily, seasonal, and long-term demand patterns.

Stage 2 introduces **spatial analysis**, examining how electricity demand varies across feeders and geographic regions within the discom service area.

Stage 3 focuses on **consumer and end-use drivers**, analysing how appliance ownership, technology adoption, and socioeconomic factors influence electricity consumption.

Together, these stages create a layered forecasting approach in which each level provides additional insight into the drivers of electricity demand.

3. Stage 1: Discom-Level Aggregate Load Forecasting

3.1. Purpose of Stage 1

The first stage of the forecasting framework focuses on analysing electricity demand at the aggregate discom level. The primary objective is to develop a clear understanding of historical aggregate demand patterns and establish a reliable baseline for future electricity demand projections. By examining historical system-level load data, discoms can identify long-term growth trends, seasonal demand variations, and relationships between electricity demand and external drivers such as weather.

System-level load curves contain a lot of information about how electricity demand evolves across hours, days, and seasons. Careful analysis of these curves can allow discoms to identify different characteristics of demand such as peak demand periods, seasonal demand variations, and system ramping requirements.

Stage 1 aims to provide an approach to medium- to long-term load forecasting of electricity demand using aggregate demand data. The methodology provides an approach which can be adopted using datasets commonly available within discoms. The approach combines statistical models with time-series analysis of load curves to enable discoms to improve their demand estimates.

Why single annual demand projections are not sufficient

Many utilities prepare long-term demand forecasts as single projections of annual energy consumption and peak demand. While useful as broad indicators, these estimates do not capture the full complexity of electricity demand.

Electricity use varies significantly across hours, days, and seasons, and key characteristics such as peak periods, ramping needs, and seasonal demand shifts cannot be determined from annual numbers alone. Demand growth may also occur unevenly across sectors, feeders, substations, or geographic areas, especially in rapidly growing cities.

Analysing load curves, seasonal patterns, sectoral and spatial demand variations can therefore provide more useful insights for planning power procurement, network expansion, and demand-side programs.

3.2. Data Requirements

Stage 1 analysis relies primarily on historical datasets that are typically available within discom data systems. These datasets provide the necessary information to analyze demand patterns across different temporal scales. For example, 15-minute load data can enable discoms to identify peak demand periods, ramping characteristics, and intra-day variations in electricity consumption. When combined with weather and calendar information, these datasets can provide more information on drivers of electricity demand.

Data – 10 years	Description
System Load Curves	15 /30 minute or hourly interval annual load data
Monthly Energy Sales	Electricity sales data disaggregated by consumer category
Weather Data	Meteorological variables such as temperature, humidity, and seasonal indicators
Calendar Data	Information on weekdays, weekends, holidays, and special events

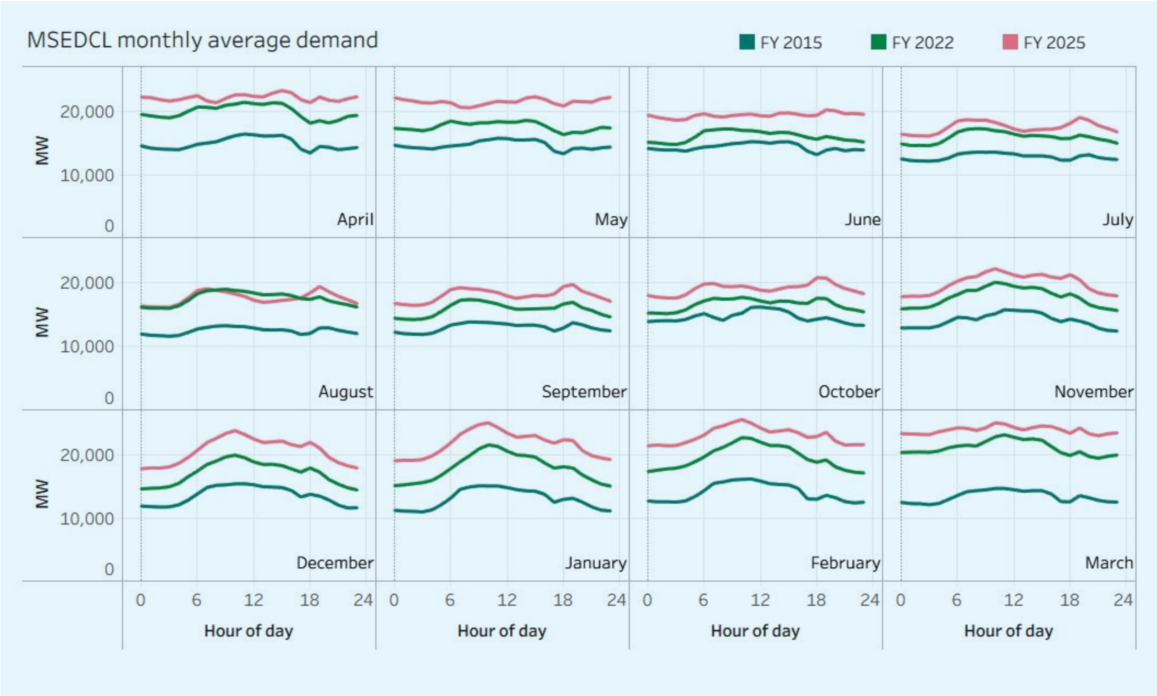

Figure 1: Average Monthly Demand for MSEDCL. Data source : Maharashtra SLDC Daily Reports

3.3. Methodology

The methodology for Stage 1 focuses on different techniques to analyse historical demand data and use them for demand projections. These include load curve analysis, trend estimation, growth rate calculations, time-series decomposition, and weather sensitivity analysis. Each method provides a different perspective on demand, and together they enable more robust forecasting.

3.3.1. Load Curve Analysis

The first step in Stage 1 forecasting would involve analysing historical system load curves to understand temporal patterns in electricity consumption. Annual load curves represent electricity demand measured at regular intervals typically every 15 minutes and provide a detailed picture of how demand varies throughout the day and across seasons.

Daily load curves reveal characteristic demand patterns such as morning and evening peaks associated different consumer consumption patterns. In many discoms, electricity demand rises during the morning hours as commercial activity begins, remains elevated during the afternoon, and peaks again during the evening when residential consumption increases.

Weekly load patterns also provide important insights. Electricity demand often differs significantly between weekdays and weekends due to variations in industrial and commercial activity. Recognizing these patterns helps discoms distinguish between demand trends and routine change in cycles.

Seasonal load curves reveal longer-term patterns associated with climatic conditions. In many parts of India, electricity demand increases substantially during summer months due to cooling requirements. Similarly, in states with significant agriculture pumping demand, demand is higher during the winter-summer crop season. These seasonal variations are particularly important for understanding peak demand conditions and planning system capacity.

By examining load curves across multiple time horizons - hourly, daily, weekly, and seasonal - discoms can identify fundamental demand characteristics that provide information for future demand projections.

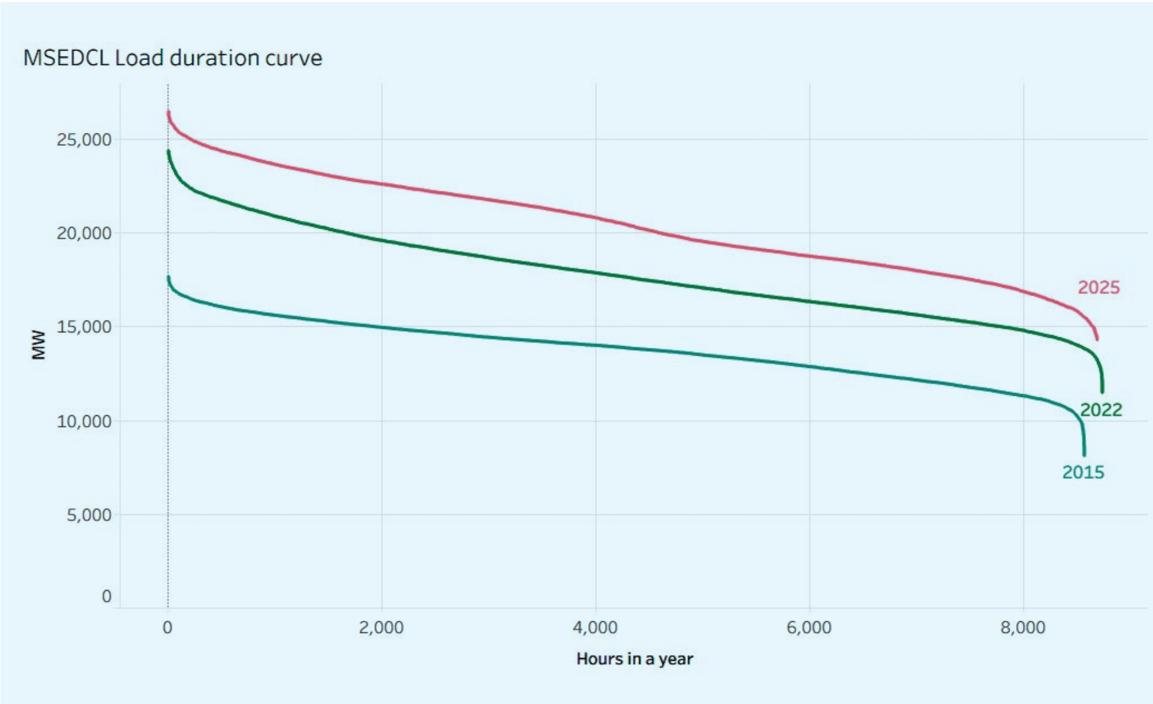

Figure 2 : Load Duration Curve for MSEDCL. Data Source : Maharashtra SLDC Daily Reports

3.3.2. Linear Trend Analysis

Once historical load patterns have been examined, the next step involves estimating long-term demand growth using trend analysis. Linear trend analysis is one of the simplest and most widely used techniques for long-term electricity demand forecasting.

This method involves fitting a regression line to the annual average demand data (such as annual peak demand or total annual load curve with 15-minute or hourly granularity). Using annual data helps capture structural growth trends while smoothing out short-term variability driven by weather or operational factors. The regression line can then be extended into the future to project demand over the forecast horizon.

Because the methodology is simple and easy to interpret, the resultant projections can be easily validated using historical data. The slope of the fitted trend line represents the average absolute increase in demand over time (e.g., MW per year or MU per year). This distinguishes linear trend analysis from the Compound Annual Growth Rate (CAGR) approach, which captures a constant percentage growth rate. While CAGR assumes exponential growth, linear trend analysis assumes a constant incremental increase, making it more appropriate in contexts where demand growth is steady but not compounding.

The estimated slope can also be used to develop preliminary demand scenarios. By adjusting the slope, alternative growth trajectories such as high-growth, moderate-growth, and low-growth scenarios can be constructed. These scenarios provide an initial assessment of potential system requirements under different economic or policy conditions.

3.3.3. Compound Annual Growth Rate (CAGR) Analysis

Another commonly used metric for evaluating long-term demand growth is the Compound Annual Growth Rate (CAGR). CAGR represents the smoothed average annual growth rate of a variable over a specified time period.

In electricity demand forecasting, CAGR can be calculated using historical data on annual energy consumption or peak demand over a multi-year period. The metric is derived using the following general relationship:

$$CAGR = (Vf/Vi)\ \hat{}(1/n) - 1$$

where (Vf) represents the final value of demand, (Vi) represents the initial value, and (n) represents the number of years in the observation period.

CAGR can provide a stable estimate of long-term demand growth by smoothing out short-term fluctuations. Discoms can use CAGR calculated over the previous five to ten years to project future energy consumption or peak demand over the forecasting horizon. CAGR can also allow discoms to compare demand growth across different consumer categories or geographic regions. For example, residential demand may exhibit higher growth rates than industrial demand in rapidly urbanizing areas.

3.3.4. Seasonal Decomposition of Load Curves

While trend analysis and CAGR provide insights into long-term demand growth, electricity demand also shows strong cyclical and seasonal patterns that must be incorporated into forecasting.

Commonly used method is Seasonal-Trend Decomposition using Loess[1] (STL). STL is a method that breaks electricity demand data into long-term growth, seasonal patterns, and random variation. This can help discoms better understand and forecast load behaviour. This approach is particularly effective for electricity demand analysis because it can handle complex seasonal patterns and irregular data.

Another widely used approach is the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. SARIMA extends standard ARIMA models[2] by incorporating seasonal components that capture periodic patterns such as daily or annual demand cycles.

1. Loess -Locally Estimated Scatterplot Smoothing.
2. https://www.ibm.com/think/topics/arima-model.

ARIMA models are designed to capture temporal dependencies in a time series using three components:

- Autoregressive (AR): captures the relationship between current demand and its past values
- Integrated (I): accounts for trends by differencing the data to make it stationary
- Moving Average (MA): captures the influence of past forecast errors

In essence, ARIMA models explain current electricity demand as a function of its historical values and past deviations, making them well-suited for medium-term forecasting where temporal correlations are strong.

SARIMA, which extends ARIMA adds seasonal AR, I, and MA components. These seasonal terms allow the model to capture periodic patterns such as:

- daily cycles (in hourly or 15-minute data),
- weekly cycles (weekday vs. weekend effects), and
- annual cycles (summer vs. winter demand variations).

When external drivers are important, SARIMA can be further extended to SARIMAX, which incorporates exogenous variables such as temperature, humidity, or economic activity. This is particularly relevant for projecting electricity demand, as the role of weather is becoming critical.

By applying decomposition techniques to historical load curves, discoms can get representative load profiles for different seasons for example, summer weekdays, winter weekends, or monsoon periods. These representative load curves can then be scaled using projected growth rates derived from trend or CAGR analysis.

This approach ensures that future demand projections retain temporal pattens rather than depending solely on annual energy estimates.

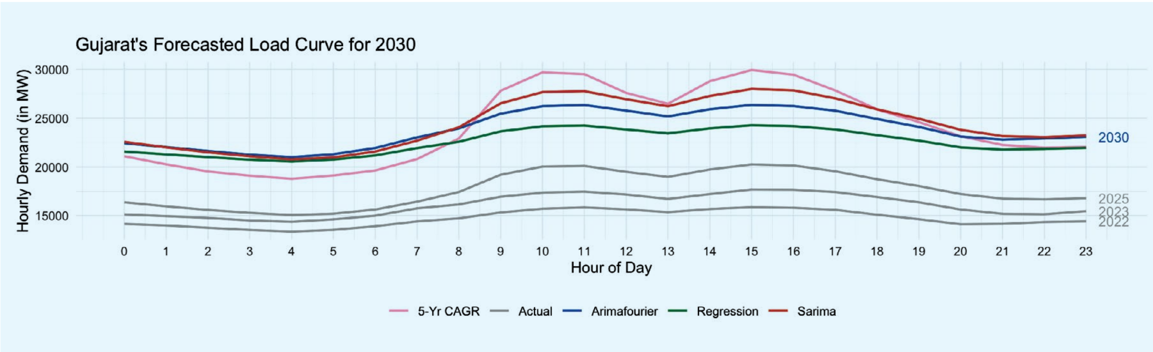

Figure 3 : Shows sample load forecasted for Gujarat using 5 year CAGR, Arima Fourier, Regression and Sarima techniques. Data source : For past years Ihttps://iced.niti.gov.in/

Forecasting Methodology for Gujarat's 2030 Load Curve

The projected hourly load curve for 2030 has been developed using historical hourly demand data from FY2022 to FY2025 (8,760 observations per year). Multiple forecasting approaches were employed to capture the underlying demand trends, seasonal variations, and weather-driven effects. The forecast results from three modelling techniques ; SARIMA, ARIMA with Fourier terms, and Regression are presented alongside a simple 5-year CAGR projection for comparison.

SARIMA (Seasonal Autoregressive Integrated Moving Average)

SARIMA is an extension of the ARIMA framework that explicitly accounts for recurring seasonal patterns in time-series data. Electricity demand exhibits strong seasonal behaviour driven by weather conditions, economic activity, and consumer usage patterns. The SARIMA model captures these recurring trends and generates a forecast that preserves the historical daily and annual demand profile while projecting future growth. In the figure, SARIMA produces the highest forecast among the statistical models and captures pronounced daytime demand peaks.

ARIMA with Fourier Terms

ARIMA with Fourier terms enhances conventional ARIMA modelling by incorporating Fourier series components to represent complex and multiple seasonal cycles. This approach is particularly useful for electricity demand data, where demand patterns repeat across both daily and annual time periods. By modelling these periodic fluctuations more flexibly, the ARIMA-Fourier model produces a smoother demand profile while retaining the characteristic morning and evening peaks observed in the historical data.

Regression-Based Forecast

The regression model combines historical demand with explanatory variables such as temperature and time-related factors to estimate future electricity consumption. Unlike purely statistical time-series models, regression explicitly captures the relationship between load and external drivers of demand. As shown in the figure, the regression forecast follows the overall shape of the historical load curve but projects a relatively more conservative growth trajectory compared to the ARIMA-based models.

5-Year CAGR Projection

For benchmarking purposes, a simple 5-year Compound Annual Growth Rate (CAGR) approach has also been applied. This method extrapolates future demand based on historical growth rates without explicitly accounting for seasonal dynamics or weather effects. Consequently, while the CAGR projection provides an indication of the upper-bound growth trajectory, it tends to produce sharper peaks and greater variability than the model-based forecasts.

Comparison of Forecast Results

All three advanced forecasting approaches indicate substantial growth in Gujarat's electricity demand by 2030 compared to FY2022–FY2025 levels, while preserving the characteristic daily load shape. The SARIMA and ARIMA-Fourier models project higher demand levels, particularly during peak daytime hours, whereas the regression model yields a more moderate estimate. Together, these forecasts provide a range of plausible demand scenarios that can support long-term resource planning, infrastructure investment, and demand-side management strategies.

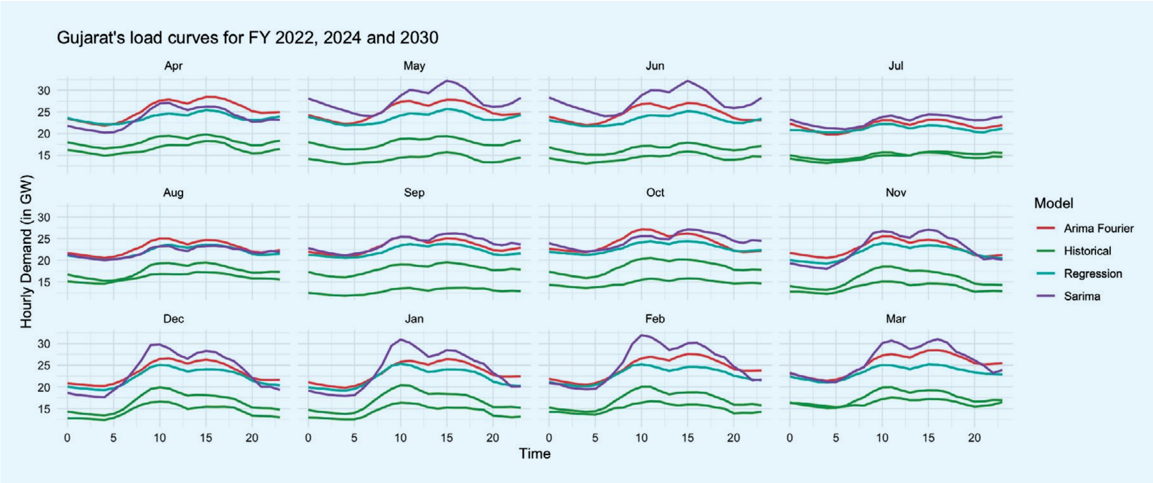

Figure 4 : Example ; Monthly Load Forecast Curve for Gujarat for FY 2030

3.3.5. Weather Sensitivity Analysis

Weather plays a significant role in shaping electricity demand, particularly in regions where cooling or heating loads significantly impact peak demand. As air-conditioning penetration increases across India, electricity demand changes will be linked closely with temperature variations.

Weather sensitivity analysis aims to assess the correlation between electricity demand and meteorological variables such as temperature and humidity. This can be done by estimating the temperature elasticity, which measures the change in electricity demand associated with a one-degree change in temperature. Historical load data can be combined with meteorological observations i.e. future projections of weather variables to estimate this correlation using statistical regression techniques.

The correlation between temperature and electricity demand may be nonlinear in some cases. For example, electricity demand may remain relatively stable within moderate temperature increase but show sharp increase once temperatures exceed certain thresholds. Similarly depending on the consumer mix the aggregate load curve may or may not capture these shifts. Using different regression methods, the correlation between electricity and temperature can be measures using elasticity values for different temperature ranges.

Another weather metric that can be used is Cooling Degree Days (CDD). CDD measures cumulative deviations of temperature above a specified comfort threshold and provides an indicator of cooling demand. Similarly, Heating Degree Days (HDD) measure deviations below a heating threshold, although heating demand is relatively limited in most regions of India.

Hence, incorporating weather sensitivity into forecasting can allow discoms to estimate the impact of temperature variations on electricity demand. Such analysis is becoming increasingly important as occurrence of extreme climatic events is expected to increase across many parts of India.

Typical Examples

Linear Trend Analysis:

Using annual peak demand data from 2015 to 2025, a discom can use linear regression and find that peak demand is increasing by approximately 150 MW per year. This trend is can then be extended to estimate peak demand over the next five years under a particular scenario.

CAGR Analysis:

If total annual electricity consumption for discom increased from 10,000 MU to 14,000 MU over 7 years, the CAGR is calculated and used as a benchmark growth rate to project future consumption under a steady-growth assumption.

Seasonal Decomposition / SARIMA:

A discom can apply STL decomposition on hourly load data and identify recurring summer peaks and weekend dips. A SARIMA model can then be used to forecast monthly demand while preserving these seasonal patterns.

Weather Sensitivity Analysis:

By correlating daily peak demand with temperature data, a discom can find that demand increases by a few hundred MW for every 1°C rise above 32°C. This relationship can then be used to estimate demand under different temperature scenarios, including extreme heat conditions.

These examples are indicative and can be adapted based on data availability, analytical capacity, and specific objectives of the discom. Including such practical applications can help bridge the gap between conceptual methods and implementation.

3.4. Integration of the methods

Each of the methods described above have some limitations in terms of their accuracy and details that they can provide. However, a combination of these methods can provide more information and hence a better estimate of the forecasted values.

The Trend analysis and CAGR can provide estimates for long-term demand growth, whereas seasonal decomposition provides a better temporal behaviour of load curves, such that forecasts show daily, weekly and seasonal patterns. Further, weather sensitivity analysis can provide scenarios for projections to account for temperature-driven demand variability.

4. Stage 2: Spatial and Feeder-Level Demand Forecasting

4.1. Benefits of Spatial Forecasting

While aggregate demand forecasting provides an understanding of overall electricity consumption trends within a discom's service area, it does not capture how demand evolves across different regions/ areas within the distribution network. For example, demand growth is often concentrated in specific geographic areas owing to urban growth, industrial development or change in demographics. Similarly, semi-urban areas may show change in demand resulting from reduced agricultural consumption patterns to more residential and commercial loads. It is important to map these changes at the local levels to plan for demand and network expansion accordingly.

Forecasting the demand and load at a spatial level can play a critical role in better estimation and distribution planning. Analysing demand patterns at the feeder, circle or substation level can help discoms identify emerging demand clusters, trends in consumption, identify critical capacity constraints which can help in planning for the demand growth and infrastructure investments more efficiently.

Consequently, Stage 2 of the forecasting framework focuses on strengthening spatial demand estimation by combining feeder-level load analysis with geographic and socio-economic data.

4.2. Data Requirements

Spatial forecasting requires a broader set of datasets than aggregate demand analysis because it must capture both technical information and geographic demand drivers. High-resolution feeder data can be typically obtained from SCADA systems or feeder meters.

Combining load data with geographic and socio-economic indicators can also enable discoms to develop spatially differentiated demand forecasts, for example different forecasts for urban vs. rural, industrial clusters vs. commercial etc.

Data Source	Description
System Load Curves	15 /30 minute or hourly interval annual load data
Circle /Feeder Load Data	Historical (5 years) 15 min electricity demand measured at individual distribution feeders or Circle
GIS Network Maps	GIS location and mapping of feeders, substations, and distribution infrastructure
Consumer Connection Data	Number and type of consumer connections served by each feeder
Land-Use Data	Information on urban/rural zones and industrial clusters[3]

3. This data can be obtained through State Remote Sensing Applications Center and Town/City Planning Departments.

Weather Data	Meteorological variables such as temperature, humidity, and seasonal indicators[4]
Socioeconomic Data	Population growth, economic activity, infrastructure development indicators and policies introduced at State/Sectoral Level[5]

4.3. Methodology for Stage 2

The methodology for spatial and feeder-level demand forecasting involves several analytical steps, including feeder load profiling, spatial mapping of electricity demand, feeder-level forecasting, and integration with distribution planning.

4.3.1 Feeder Load Profiling

The first step in Stage 2 forecasting involves analysing historical load patterns at the feeder, circle, or substation level. This begins by developing load curves using at least five years of historical demand data for each feeder, circle, or substation.

Load profiling helps discoms understand the specific characteristics of demand served in different parts of the network. For example, feeders serving predominantly residential areas may show strong evening peaks, while industrial feeders often have relatively stable daytime loads. Commercial areas may display clear differences between weekday and weekend demand.

By examining load curves across different times of the day, week, and across seasons, utilities can identify trends in peak demand, overall energy consumption, and variations in load patterns. This analysis can also highlight feeders or substations experiencing sustained growth in peak demand or noticeable changes in load shape, which may indicate shifts in consumer mix or electricity usage patterns.

Based on these patterns, feeders can be broadly classified as residential, commercial, industrial, or mixed-use. Such classification allows Discoms to group feeders with similar demand characteristics, making forecasting and planning more systematic and manageable.

4.3.2 Spatial Mapping of Electricity Demand

After analysing feeder-level, circle or substation level load patterns, the next step can include mapping electricity demand geographically using Geographic Information Systems (GIS).

GIS tools allow discoms to combine feeder load data with spatial information such as urban areas, population density, and industrial clusters. For example, if new road networks or housing projects are emerging in areas, or if industrial zones are planned can help determine electricity demand growth drivers.

4.3.3 Feeder Clustering and Load Segmentation

Given that discoms may operate hundreds or thousands of feeders, it is often impractical to model each feeder individually. To address this challenge, clustering techniques can be used to group feeders with similar load characteristics.

4. The Indian Meteorological Department and State Disaster Management Authorities can provide this data.
5. Directorate of Economics and Statistics and State Departments (Energy, Urban Development, Industry) can provide information on the same.

Clustering algorithms can be used to analyse load profiles and categorize feeders into groups based on similarities in demand patterns. For example, feeders with comparable daily load shapes, seasonal variation, or growth rates may be grouped into the same cluster. Some of the common clustering techniques include K-means clustering, Hierarchical clustering or Self-organizing maps (SOM). Once clusters have been identified, discoms can develop representative load profiles for each cluster and apply differentiated growth assumptions based on observed trends. This can help in providing consumer /area specific demand forecasts.

4.3.4 Feeder-Level Forecast Models

Once feeder clusters or representative feeders are identified, discoms can use existing forecasting methods to estimate future demand at the feeder level. Different factors that influence electricity demand, such as past growth trends in feeder demand, change in number of consumers, urban development, change in economic activity or increase in distributed energy sources can be included in the methods.

Simple regression methods can be used to understand how these factors affect electricity demand. For example, an increase in consumer connections usually leads to higher electricity consumption, but it is also dependent on the type of connections and connected load, the correlation between these variables can be used as regressors in the method.

In addition to statistical methods, other machine learning models can also be used for feeder-level forecasting. These models have techniques which can also help capture more complex relationships between demand and influencing factors. Hence a combination of statistical methods with machine learning can help in building more reliable forecasts.

4.3.5 Data Pre-processing

Feeder-level forecasting relies on high-resolution data that may often contain missing values, anomalies, or inconsistencies. Therefore, data pre-processing is an essential step in the forecasting process.

Data aggregation:15-minute load data may be aggregated into hourly, daily, or monthly intervals to capture broader demand trends.

Missing data corrections: Techniques such as interpolation, seasonal decomposition, or machine learning models may be used to estimate missing values.

Outlier detection: Statistical methods can be used identify abnormal load values caused by measurement errors or exceptional events.

4.3.6 Advanced Forecasting Models

While feeder-level forecasting helps understand how demand is distributed across the network, capturing future demand accurately also requires models that can identify complex patterns in electricity consumption over time.

One commonly used approach is time-series modeling. Methods such as ARIMA and SARIMA analyse historical load data to identify trends and recurring seasonal patterns. These models help explain how past demand influences future demand and are useful for forecasting when demand follows relatively stable historical patterns.

Another method which is being widely for across the globe is machine learning. Different machine learning models can be used to capture the nonlinear relationship between electricity demand and variables impacting it. There are several readily available tools like Prophet which can be used to forecast demand using a combination of time series and regression techniques. These models can be further developed using deep learning algorithms such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) which can learn complex temporal patterns in electricity demand and are particularly useful when high-resolution data such as hourly or 15-minute load data is available. However, the effectiveness of these methods depends on the availability of reliable historical data. Their predictions are most useful in situations where there are no major structural changes in the system and when the models are appropriately tuned.

4.3.7 Scenario Modelling

Long-term demand forecasting always involves uncertainty, especially when information on the factors driving changes in consumption patterns is limited or evolving. There are different sources of uncertainty including changes in economic growth, speed and pattern of urbanisation, population and household changes, growth in industrial and commercial activity, adoption of new technologies such as electric vehicles, rooftop solar and energy-efficient appliances, and shifts in consumer behaviour which can impact electricity demand. Policy changes, tariff structures, and incentives can also significantly alter demand trends. In addition, weather variability and rising cooling needs add further uncertainty to future electricity demand.

To manage uncertainties, discoms need to focus on scenario-based analysis for forecasting. This means preparing different demand projections based on different assumptions. For example, one scenario may assume higher economic growth and faster urban expansion, while another may consider rapid uptake of electric vehicles and rooftop solar, and yet another may assume slower economic activity and limited technology adoption. This helps in understanding a range of possible outcomes instead of relying on a single forecast.

Another useful approach is probabilistic forecasting, which does not give one fixed number but a range of possible demand values. Techniques like Monte Carlo simulation can be used to test how demand changes when multiple uncertain factors vary together.

4.4 Integration with Distribution Planning

The outputs of feeder-level forecasting can also be used for better distribution network planning. By identifying feeders/circles that will be expecting a rapid demand growth, discoms can prioritize infrastructure upgrades in those areas. Ultimately, integrating feeder-level demand forecasting into distribution planning can also help improve system reliability, reduces congestion, and also support long-term infrastructure optimization.

5. Stage 3: Consumer-Level Forecasting

5.1 Need for Consumer-Level Load Forecasting

While aggregate and feeder-level forecasting provide important insights into overall demand growth and spatial distribution of electricity consumption, they do not fully explain the underlying drivers that shape electricity demand. Many emerging electricity loads particularly space cooling, electric vehicles, data centres, and distributed energy resources are significantly dependent on consumer behaviour, appliance ownership and usage patterns. Hence it is important to also assess how end use of electricity impacts current demand patterns and how it could influence future demand.

The third stage of the proposed framework therefore focuses on consumer-level demand forecasting. By moving beyond purely historical demand patterns and incorporating structural demand drivers, discoms can better anticipate future changes in load shapes and peak demand.

The increasing deployment of Advanced Metering Infrastructures (AMI) across discoms is creating a new opportunity to undertake such analysis. Smart meters have the ability to record 30 min consumption data often at 15-minute intervals which allows discoms to observe detailed load profiles at the individual consumer level. When anonymized and aggregated appropriately, these datasets can reveal typical load patterns for different consumer segments and provide insights into how demand varies across income groups, housing types, and climate conditions.

In addition to smart meter data, load research surveys play a critical role in consumer-level modelling. These surveys collect information on appliance ownership, usage frequency, building characteristics, and consumer preferences on residential electricity use. Similar information can be collected regarding commercial and industrial electricity use. Such information is essential for constructing bottom-up demand models that estimate electricity consumption based on appliance-level energy use and other end-use energy applications.

5.1.1 Contours of Load Research Survey

To conduct load research surveys effectively, it is important to use a structured and representative sampling approach. The survey should aim to cover different types of consumers such as residential, commercial, and industrial and account for variations across income groups, locations (urban and rural), and housing types. Both primary data collection and existing secondary data can be used for this purpose.

Primary surveys are required for gathering detailed information on appliance ownership, how and when appliances are used (including seasonal differences), and user behaviour such as temperature settings or usage preferences. These surveys can be carried out through household visits, phone interviews, or digital tools, depending on what is feasible. For a smaller group of consumers, short-term appliance-level monitoring (using plug-level meters or data loggers) can also be done to validate the information collected through surveys.

Where smart meter data is available, it can be used alongside survey data to provide more detailed insights into consumption patterns. This helps in validating typical load shapes and understanding variations across different consumer groups.

The survey should be designed to ensure that the sample is large and diverse enough to represent the broader consumer base. It is also useful to conduct such surveys periodically (for example, every 3-5 years) to capture changes in appliance use, technology adoption, and consumption behaviour over time.

5.2 Data Requirements for Consumer-Level Forecasting

Effective consumer-level load forecasting requires different types of data to help discoms know electricity demand across consumer segments and how it changes over time.

Data	Description
Smart Meter Data (AMI)	Consumption data, typically recorded at 30-minute interval
DT Meter Data (AMI)	Load data, recorded at 30 min /1 hour granularity
Load Research Surveys	Detailed surveys capturing ownership and energy usage patterns and energy consumption behaviour across consumer categories
Electric Vehicle Data	Information on EV ownership, charging behaviour, and charging infrastructure
Distributed Generation Data	Data on rooftop solar installations and behind-the-meter energy resources
Policy information	National or state government targets, policies to encourage or discourage different types of end-uses

5.3 Methodology for Stage 3

Consumer-level load forecasting can be implemented using a multi-step approach that uses statistical analysis, behavioural data, and bottom-up data integration. The sections below provide a detailed description.

5.3.1 Consumer Segmentation

The first step in consumer-level modelling involves classifying consumers into distinct segments based on demographic, socio-economic, and electricity consumption characteristics.

Segmentation allows discoms to analyse electricity demand patterns for different types of consumers rather than relying on aggregate averages. Consumers may be grouped according to factors such as income levels, housing type (apartments, independent houses, rural dwellings), geographic location, or historical consumption levels.

For example, high-income urban households may show higher penetration of air conditioning and other energy-intensive appliances, while rural households may have lower electricity consumption this appliance usage patten can be identified by the load shape. Similarly, commercial establishments and small businesses may show different load patterns influenced by working hours and activity.

By grouping consumers into representative categories, discoms can develop segment-specific demand estimates that capture the unique consumption characteristics of each group. These segmented models can then be used to provide more accurate forecasts.

5.3.2 End-Use Load Modelling

End-use load modelling can help discoms understand electricity demand at the consumer level as it can estimate electricity demand segregated by different appliances, their efficiency rating etc. Typical end uses studied in load research include air conditioning, lighting, refrigeration, water heating, pumping, cooking appliances, irrigation, different industrial processes, and electric vehicle charging. Total household electricity use can be estimated by adding the consumption of each appliance type. Similarly, HT and LT industry consumption can be estimated by aggregating demand from different industries present in the discom's area and their likely future trajectory.

For example, electricity demand from air conditioners depends on how many households own them, how many use them, how efficient the units are, and how long do the households use them in different weather conditions.

This approach can help discoms understand how changes such as rising incomes, better appliance efficiency, or new technologies like EV charging may affect future electricity demand. To inform energy policy and research in a rapidly evolving sector, Prayas (Energy Group) has built an open-source, generic, customisable, free-to-use and feature-rich demand-oriented energy systems modelling platform called Rumi. Using the Rumi framework, PEG built the PIER (Perspectives on Indian Energy based on Rumi) energy model of India. In PIER, India is modelled as 5 regions and 25 'states', with a model horizon year FY2030-31. Such open-source models can be used to model bottom-up demand estimation.

The PIER (Perspectives on Indian Energy based on Rumi) model provides a highly granular, bottom-up approach to electricity demand estimation, specifically within its residential and industrial modules.

Advanced End-Use Modeling via PIER/Rumi

- Geographic and Consumer Granularity: PIER models India across 5 regions and 25 states, disaggregating the residential sector into 250 distinct consumer types based on state, urban/rural location, and five expenditure quintiles.
- Temporal Precision: The model uses a sophisticated time-slice approach. Each year is divided into 12 months (seasons), with each month represented by a typical day of 24 hours, resulting in 288 time-slices per year to capture shifting peak loads and ramping needs.
- Specific Service Demand Drivers:
    - Space Cooling: Hours of use for fans, coolers, and air conditioners are calculated using temperature projections and specific "trigger" temperatures tailored for urban vs. rural settings.
    - Appliance Breakup: Demand is modelled by specific technology (e.g., Direct Cool vs. Frost Free refrigerators) and efficiency ratings (BEE Star Ratings), allowing discoms to simulate the impact of mandatory efficiency standards on total load.
    - Modern Cooking: Electric cooking loads are modelled with specific load profiles (e.g., 2 hours in the morning and evening) to understand their impact on peak demand.
- Scenario-Based Planning: PIER also allows for modelling alternative futures, using high growth and BAU scenarios, to account for uncertainties in economic growth and technology adoption.

5.3.3 Behavioural Analysis

Electricity demand is influenced not only by the number and efficiency of appliances but also by how people use them. Factors such as temperature settings, usage habits, and responses to electricity prices can affect consumption.

Discoms can study these patterns using smart meter data, consumer surveys, and pilot programs on time-of-use tariffs or demand response. For example, smart meter data can show how households use air conditioners or how businesses change consumption during peak tariff periods.

Understanding these behavioural patterns helps discoms design demand-side programs and assess the impact of policies such as efficiency standards, tariff changes, or incentives for EV charging.

5.4 Advanced Data Analytics for Consumer-Level Forecasting

Consumer-level forecasting can be improved by using detailed data and better analysis methods. With the availability of smart meter data and load surveys, discoms can better understand what drives electricity use. These methods help identify patterns in the datasets and show how factors like weather, income, and appliance ownership affect demand. They can also help capture relationships that may not be reflected in aggregate data analysis.

In addition, detailed smart meter data can be used to break down overall electricity use into different end-uses, such as cooling, lighting, or appliances. This can help discoms better understand how consumers use electricity and improve demand estimates for different consumer groups. While this may require specialized tools and expertise, such services are also offered by external agencies.

6. An Integrated Approach to Load Forecasting

The three stages of the forecasting framework aggregate load forecasting, spatial feeder-level forecasting, and consumer-level load forecasting are designed to complement each other rather than function as independent analytical exercises.

The integrated approach ensures that insights from each stage inform and strengthen the other stages. Aggregate load forecasting provides the overall demand trajectory, feeder-level analysis translates this into location-specific requirements, and consumer-level insights explain the underlying drivers of change. Together, these stages enable discoms to move beyond uniform assumptions and develop more grounded and actionable forecasts.

At the same time, each of these approaches can also be applied independently, depending on the availability and granularity of data. In contexts where only limited or aggregated data is available, discoms may rely primarily on aggregate forecasting, while more detailed datasets enable feeder-level or consumer-level analysis. This flexibility allows discoms to adopt a forecasting approach that is both practical and suited to their data environment.

Overall, this improves the quality of electricity procurement planning, network investment decisions, and demand-side management strategies by aligning them with both system-level trends and local realities.

7. Conclusion

In conclusion, adopting a structured, multi-level forecasting framework can allow discoms to better forecast future demand in an increasingly complex and dynamic environment. As electricity consumption patterns evolve due to urbanisation, economic growth, and the adoption of new technologies, relying only on short term forecasting is no longer sufficient. By combining aggregate trends, spatial insights, and consumer-level understanding, discoms can develop more reliable and transparent forecasts. This not only supports better planning and investment decisions but also enhances the ability to respond to emerging uncertainties and ensure a reliable and efficient power system.

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