AI-Based Demand Forecasting at Andhra Pradesh DISCOMs

Short-term and Long-term Load Forecasting: Methods, Accuracy, and the Road ahead

Workshop on Strengthening Load Research & Demand Forecasting · AIDA – Prayas (Energy Group)
New Delhi · 24 June 2026

Agenda

OVERVIEW

AP forecasts across two time-horizons

Rapid RE growth, weather sensitivity, large agricultural load, EVs and open access are reshaping both the size and the shape of demand. AP runs two AI forecasting systems, tuned to very different decisions.

SHORT-TERM · OPERATIONAL

Next block → Week ahead

Horizon: Intraday, Day-ahead, Week-ahead (15-min blocks)

Drives: Scheduling, Power-exchange bids, DSM control

Engine: Multi-model system (Statistical + ML + Econometric)

Frequency: Re-forecast continuously through the operating day

LONG-TERM · PLANNING

1 year → ~15 years (to FY2040)

Horizon: Monthly to Annual, ~15-year trajectory

Drives: Power procurement, Capacity & Network planning, RPO

Engine: Two-stage AI (Driver projection → Neural demand model)

Frequency: Refreshed annually and stress-tested by scenario

SECTION 01

Short-Term Forecasting

Forecasting the next blocks, days and week to run operations and the market

Short-term forecasts run from the next 15-minute block to a week ahead

All horizons run at 15-minute resolution (5-minute ready) and feed directly into scheduling, power-exchange bidding and deviation (DSM) management.

INTRADAY

Rolling revisions

Re-forecast through the day (about every 1.5 hours) as actuals and RE generation update

DAY-AHEAD

96 blocks, by 09:00

Full next-day curve submitted each morning to drive scheduling and day-ahead market bids

WEEK-AHEAD

96 blocks × 7 days

Seven rolling days ahead for unit commitment, maintenance and advance procurement

SHORT-TERM · INPUTS

Five categories of inputs feed the short-term engine

Weather

Temperature, humidity, wind, rainfall, cloud

via automated weather APIs

Weather zones

State split into regional clusters

refreshed monthly

Calendar & events

Day-of-week, festivals, holidays, special events

distinct demand signatures

Agricultural load

Crop & irrigation schedules, feeder rostering

large, seasonal swings

Grid operations

Outages, open-access draws, DR, EV load

from SCADA / SLDC feeds

Inputs ingested automatically from weather-data APIs and SCADA / SLDC feeds; variables selected per season to avoid multicollinearity.

The engine blends Statistical, ML and Econometric models, weighted by recent accuracy

No single model wins every day.

Calm, stable weather

Time-series models

SARIMA · Holt-Winters · ARFIMA

Perform best under stable weather and form the reliable baseline

Changeable weather

Machine-learning models

Neural networks · Gradient boosting

Variation introduced by weather conditions makes ANNs perform much better than the likes of SARIMA

Extreme or sudden swings

Combination + Fuzzy rules

Dynamic blend · Bottom-up build-up

A combination of models is used to work around extremely high variability

KEY IDEA

Dynamic weighting engine

Each forecast cycle, models are re-scored on their error over a rolling window; the best performers carry more weight.

Data Processing: from data to dashboard in six automated steps

1 Data ingestion

SCADA / SLDC feeds, weather APIs and calendar inputs, validated automatically

2 Drivers & adjustments

Heating/cooling degree-days, holidays, agri schedules, outages applied

3 Multi-model engine

Statistical, ML and econometric models run in parallel on the same data

4 Dynamic ensemble

Models re-weighted each cycle by recent error; the system self-learns

5 Forecast outputs

Block-wise intraday, day-ahead and week-ahead curves published

6 Performance monitoring

MAPE and DSM deviation tracked; systematic errors trigger model updates

Short-term forecasts track actuals within ~2.5% on a typical day

~2.5%

Average day-ahead error (MAPE) on an illustrative deployment day

>97%

Forecast accuracy sustained

96

Blocks per day scored on Absolute % Error: block, day, month, season

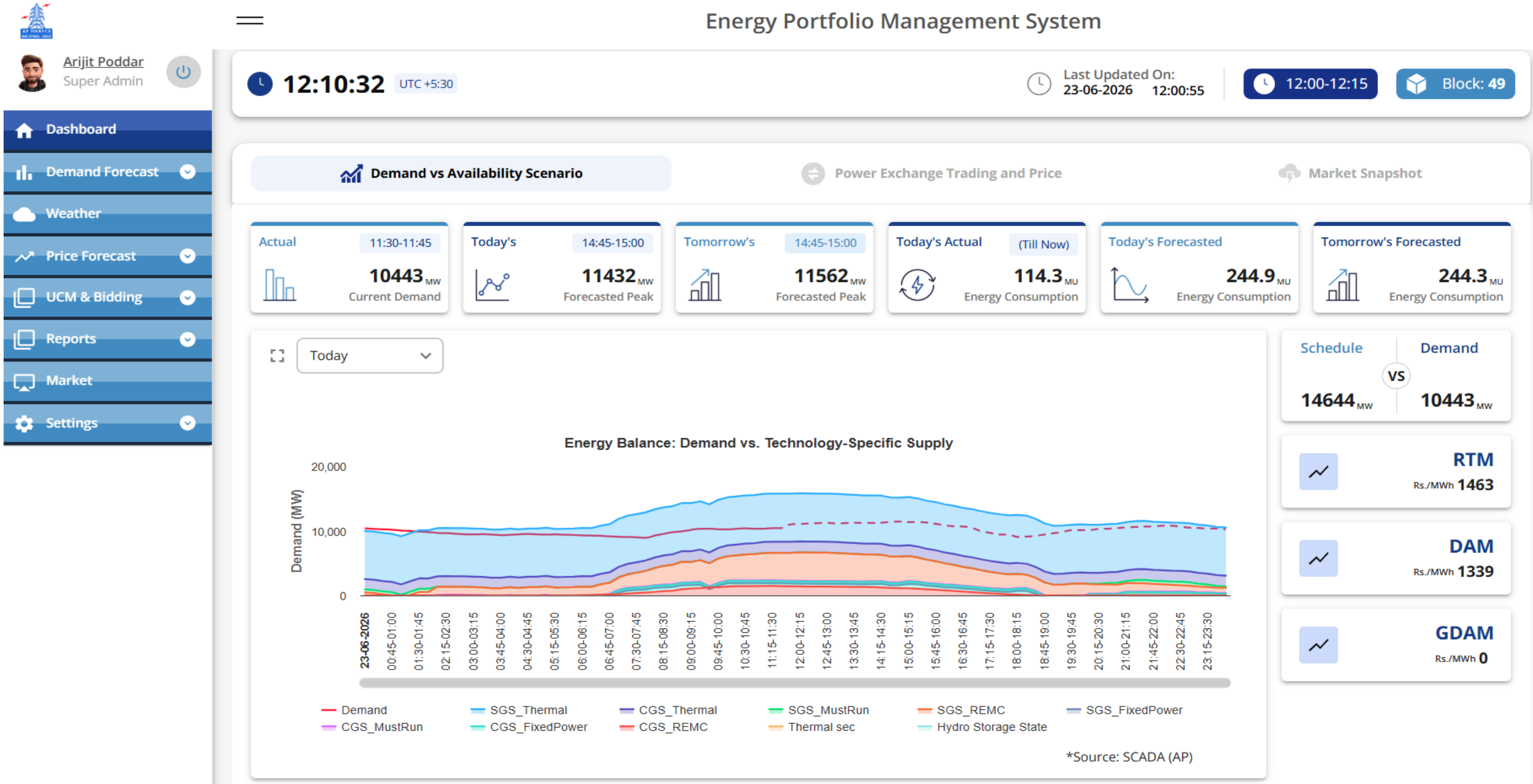
How accuracy is measured and improved

- Absolute % Error tracked at block, daily, monthly and seasonal levels across all three horizons.
- DSM deviation blocks (15-min blocks breaching the regulatory threshold) tracked as a co-equal objective — error carries a direct financial cost.
- Monthly performance reviews identify systematic errors and trigger model re-training and re-weighting.

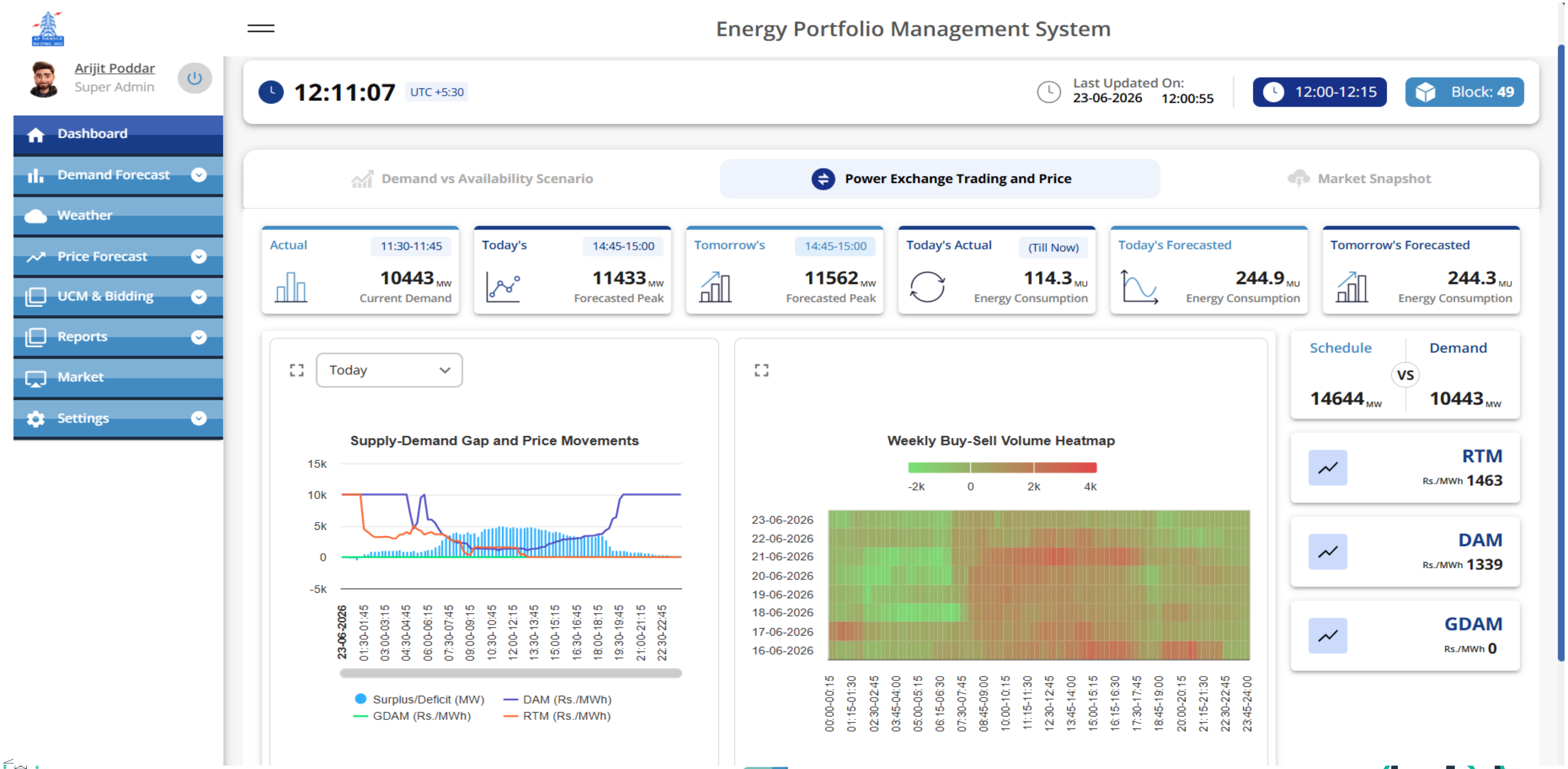
Indicative figures from forecasting-tool deployments; actual accuracy varies by horizon, season and weather conditions — to be validated against AP's own back-testing.

EPMS MODULES

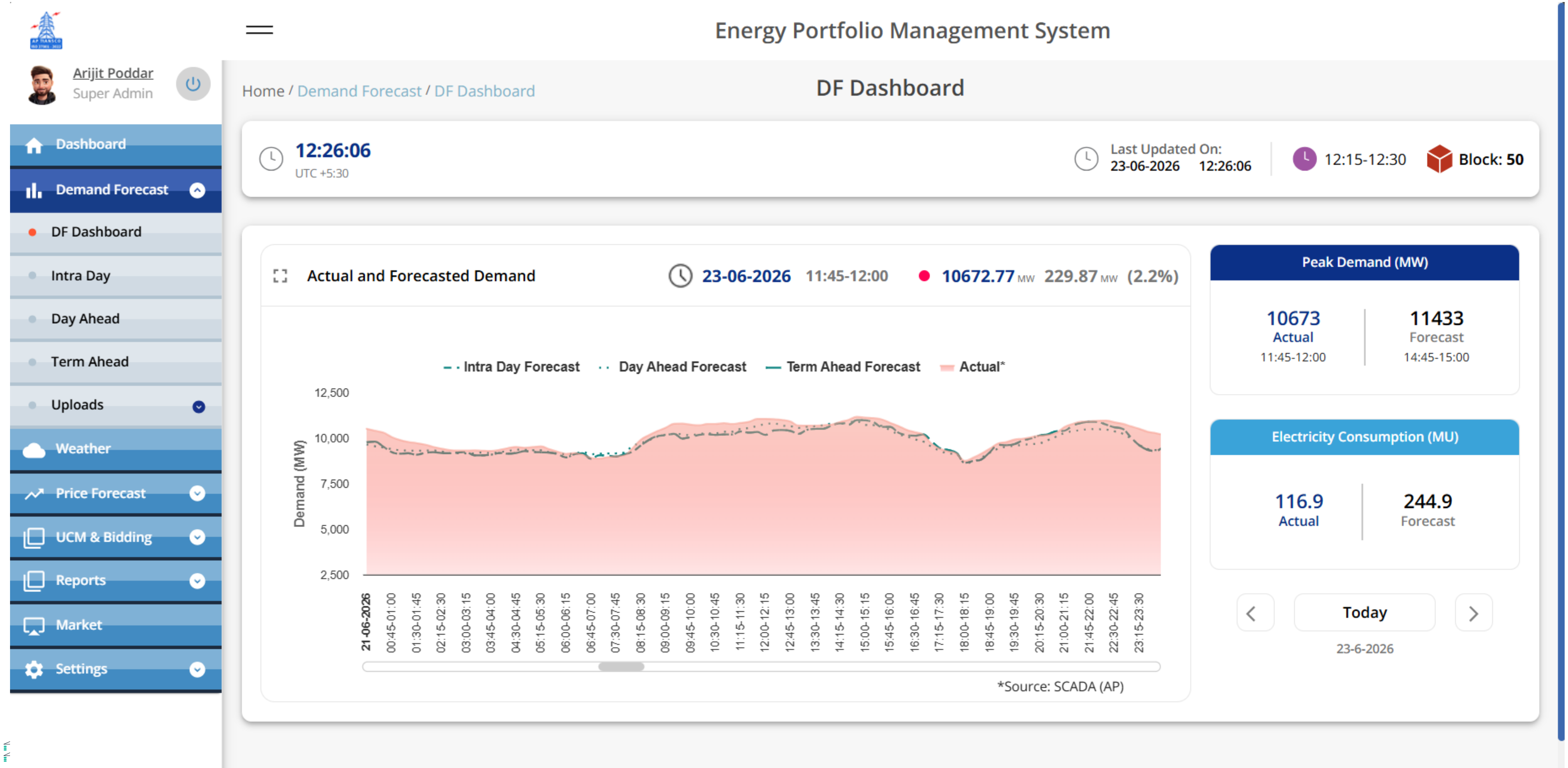
EPMS Dashboard/ Landing Page



EPMS Dashboard/ Landing Page



EPMS – Demand Forecast Module



EPMS – Price Forecast Module

Energy Portfolio Management System

Arijit Poddar
Super Admin

- Dashboard
- Demand Forecast
- Weather
- Price Forecast
  - PF Dashboard
  - RTM
  - DAM
  - GDAM
- UCM & Bidding
- Reports
- Market
- Settings

Home / Price Forecast / PF Dashboard

PF Dashboard

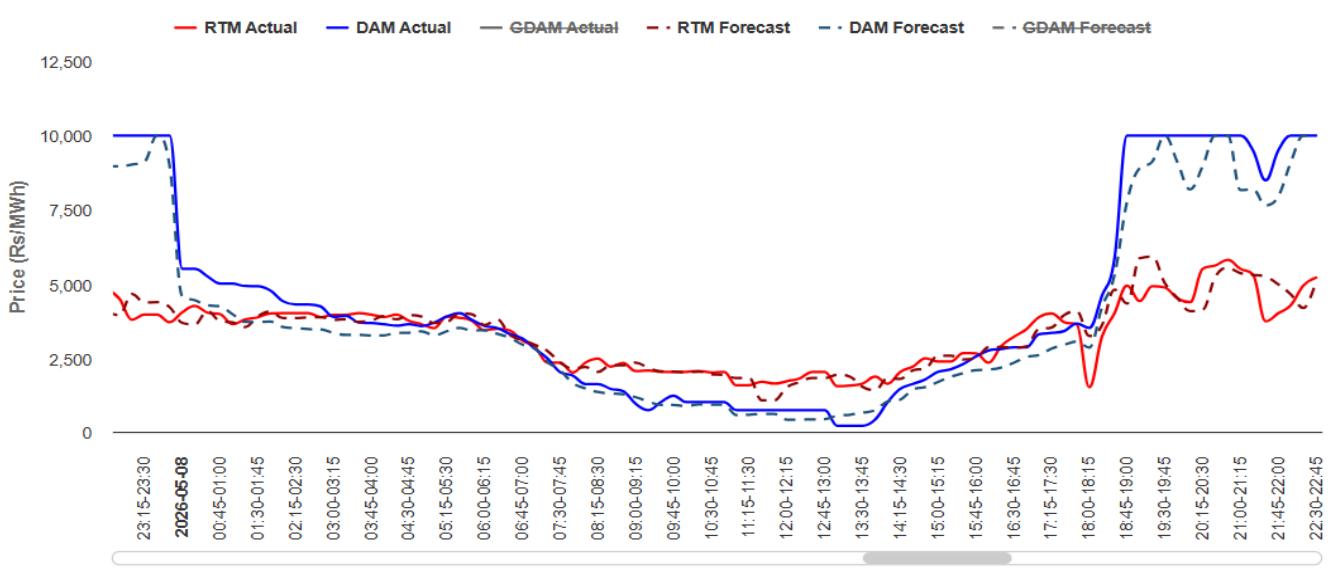
12:34:21
UTC +5:30

Last Updated On:
23-06-2026 12:16:47

12:30-12:45 Block: 51

Actual and Forecasted Price

Start Date 05/10/2026



Source: IEX

Current Block Status

Market	MCP (Rs./MWh)	MCV (MW)
DAM	1339	10036
RTM	495	9502
GDAM	0	0

Today's Summary (Rs. /MWh)

Market	Max	Min	Avg.
DAM	10000	1096	5611
RTM	10000	399	3504
GDAM	0	0	0

EPMS – Unit Commitment Model (UCM) Module

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Super Admin

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- UCM & Bidding
  - Intra Day
  - Day Ahead
- Reports
- Market
- Settings

Home / UCM / Dayahead

Day Ahead

Availability | Demand, Contingency & Price Selector | Scheduling | Bids | Last Updated On: 23-06-2026 09:36:56

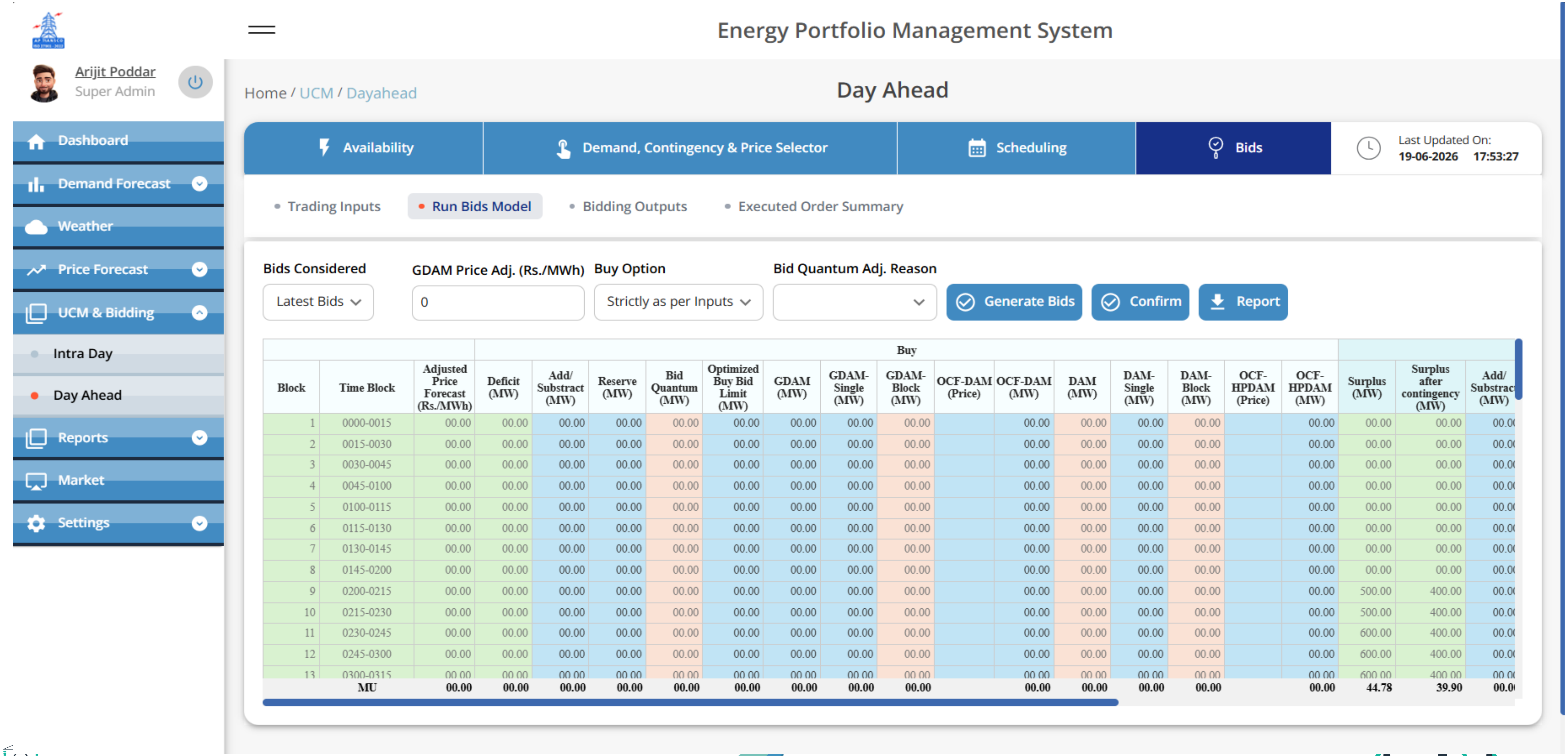
Demand Considered: Last Saved Demand

Reference Price Considered: Last Reference Price

View Graph | Confirm

TB	Time Desc	Forecast (MW)	Demand Adjustment (MW)	Final Demand (MW)	Total Avl. Excl. St. Hydro (MW)	Srisailam (MW)	State Hydel (MW)	Shortfall (-) / Surplus (+) (MW)	Contingency (MW)	Exchange Buy Limit (MW)	Exchange Sell Limit (MW)	Price Forecast (Rs./MWh)	Price Adjustment (Rs./MWh)	Deficit Price (Rs./MWh)
1	00:00-00:15	10380.00	00.00	10380.00	9962.34	00.00	400.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
2	00:15-00:30	10300.00	00.00	10300.00	9851.84	00.00	450.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
3	00:30-00:45	10234.00	00.00	10234.00	9943.44	00.00	300.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
4	00:45-01:00	10166.00	00.00	10166.00	9807.67	00.00	350.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
5	01:00-01:15	10027.00	00.00	10027.00	9461.43	00.00	550.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
6	01:15-01:30	9977.00	00.00	9977.00	9402.33	00.00	550.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
7	01:30-01:45	9887.00	00.00	9887.00	9344.85	00.00	500.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
8	01:45-02:00	9802.00	00.00	9802.00	9230.08	00.00	550.00	00.00	00.00	00.00	00.00	00.00	00.00	10000.
9	02:00-02:15	9678.00	00.00	9678.00	10148.05	00.00	00.00	500.00	100.00	00.00	00.00	00.00	00.00	10000.
10	02:15-02:30	9625.00	00.00	9625.00	10131.14	00.00	00.00	500.00	100.00	00.00	00.00	00.00	00.00	10000.
11	02:30-02:45	9551.00	00.00	9551.00	10117.32	00.00	00.00	600.00	200.00	00.00	00.00	00.00	00.00	10000.
12	02:45-03:00	9451.00	00.00	9451.00	10015.03	00.00	00.00	600.00	200.00	00.00	00.00	00.00	00.00	10000.
13	03:00-03:15	9450.00	00.00	9450.00	10059.37	00.00	00.00	600.00	200.00	00.00	00.00	00.00	00.00	10000.
14	03:15-03:30	9468.00	00.00	9468.00	10117.93	00.00	00.00	600.00	200.00	00.00	00.00	00.00	00.00	10000.
	MU	**246.76**	**00.00**	**246.76**	**289.12**	**00.00**	**02.46**	**44.78**	**04.88**	**00.00**	**00.00**			

EPMS – Bid Management Module



		Buy																		
Block	Time Block	Adjusted Price Forecast (Rs./MWh)	Deficit (MW)	Add/ Substract (MW)	Reserve (MW)	Bid Quantum (MW)	Optimized Buy Bid Limit (MW)	GDAM (MW)	GDAM-Single (MW)	GDAM-Block (MW)	OCF-DAM (Price)	OCF-DAM (MW)	DAM (MW)	DAM-Single (MW)	DAM-Block (MW)	OCF-HPDAM (Price)	OCF-HPDAM (MW)	Surplus (MW)	Surplus after contingency (MW)	Add/ Substract (MW)
1	0000-0015	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
2	0015-0030	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
3	0030-0045	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
4	0045-0100	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
5	0100-0115	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
6	0115-0130	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
7	0130-0145	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
8	0145-0200	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.0
9	0200-0215	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	500.00	400.00	00.0
10	0215-0230	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	500.00	400.00	00.0
11	0230-0245	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	600.00	400.00	00.0
12	0245-0300	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	600.00	400.00	00.0
13	0300-0315	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	600.00	400.00	00.0
	MU	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00	00.00		00.00	00.00	00.00	00.00		00.00	44.78	39.90	00.0

Implementation Outcomes: Realized and Expected

Expected Outcomes	Outcomes Realized AoD
Reduced power procurement costs	**Operational Efficiency** Fully automated reducing manual work; especially for day ahead bidding decisions
Informed power procurement planning	**Prediction Accuracy** Significantly improved prediction accuracy having a direct impact on procurement costs
Improved demand management	
Improved grid reliability	
Enhanced consumer services	
Agile response to market volatilities	
Grid integration of Renewable Energy	

SECTION 02

Long-Term Forecasting

Planning electricity demand over a 15-year horizon, to FY2040

Long-term demand is built in two stages: Drivers first, then the Load curve

The system first projects each demand driver into the future, then the second stage uses these projections as inputs to turn them into the load curve covering the next ~15 years

STAGE 1 · Project the drivers

A separate AI model projects each driver from its own history

Sector GSDP
15 economic sectors

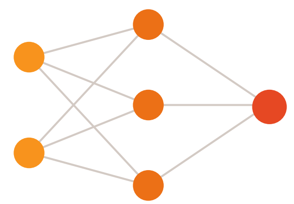
Population
to ~54 million

EV uptake
registrations → load

Rooftop solar
behind-the-meter

Weather: ERA-5 reanalysis
temperature, humidity, rain, solar · 37 sub-regions

STAGE 2 · Build the load curve



Neural-network demand model (MLP)
trained on drivers + actual demand history

Adjustments:

+ T&D losses + rooftop-solar offset + EV charging

Output: demand at 15-minute blocks, FY2026 → FY2040, aggregated to hour / day / month / year

Two stages = drivers that can be defended, demand to plan around

Each driver is projected from its own data, then validated before use

Driver	Source	Projection basis / trajectory
Sector GSDP (15 sectors)	DES, Govt of Andhra Pradesh	13 yrs (FY12–FY24), constant prices; AI projection per sector
Population	MoHFW, Govt of India	Official series to 2036, ML beyond; to ~54 million
Transmission loss	AP Transco	Held at ~2.5% across the horizon
Distribution loss	DISCOMs (APEPDCL/APCPDCL/APSPDCL)	Improving from 7.1% to ~6.3% by 2040
Rooftop solar	Capacity plan + solar irradiance	80 MW → 1,280 MW behind-the-meter
EV uptake	MoRTH registrations + NITI Aayog	0.20 → 2.78 million EVs by 2040
Weather	ERA-5 reanalysis (ECMWF)	2018–24 hourly, 37 sub-regions of the state

AP long-term AI demand-forecast methodology: last 12 months of each series held back as a validation set before models are used

A neural-network model turns drivers and weather into a 15-minute load curve

THE MODEL

Multi-Layer Perceptron neural network (layers of 400–190–80), ReLU activation, Adam optimiser, with early stopping; PCA + MinMax scaling on all inputs.

BUILT TO EXTRAPOLATE

Training data augmented with scaled examples so the model predicts beyond historical ranges; the COVID year (2020) is excluded to avoid distorted patterns.

THEN ADJUSTED

After the base forecast, the model adds T&D losses, nets off rooftop-solar generation and adds EV charging demand.

WHAT IT OUTPUTS

Demand at 15-minute blocks, aggregated to hour / day / month / year, and split by feeder class (urban, industrial, rural, agricultural).

LONG-TERM · ACCURACY

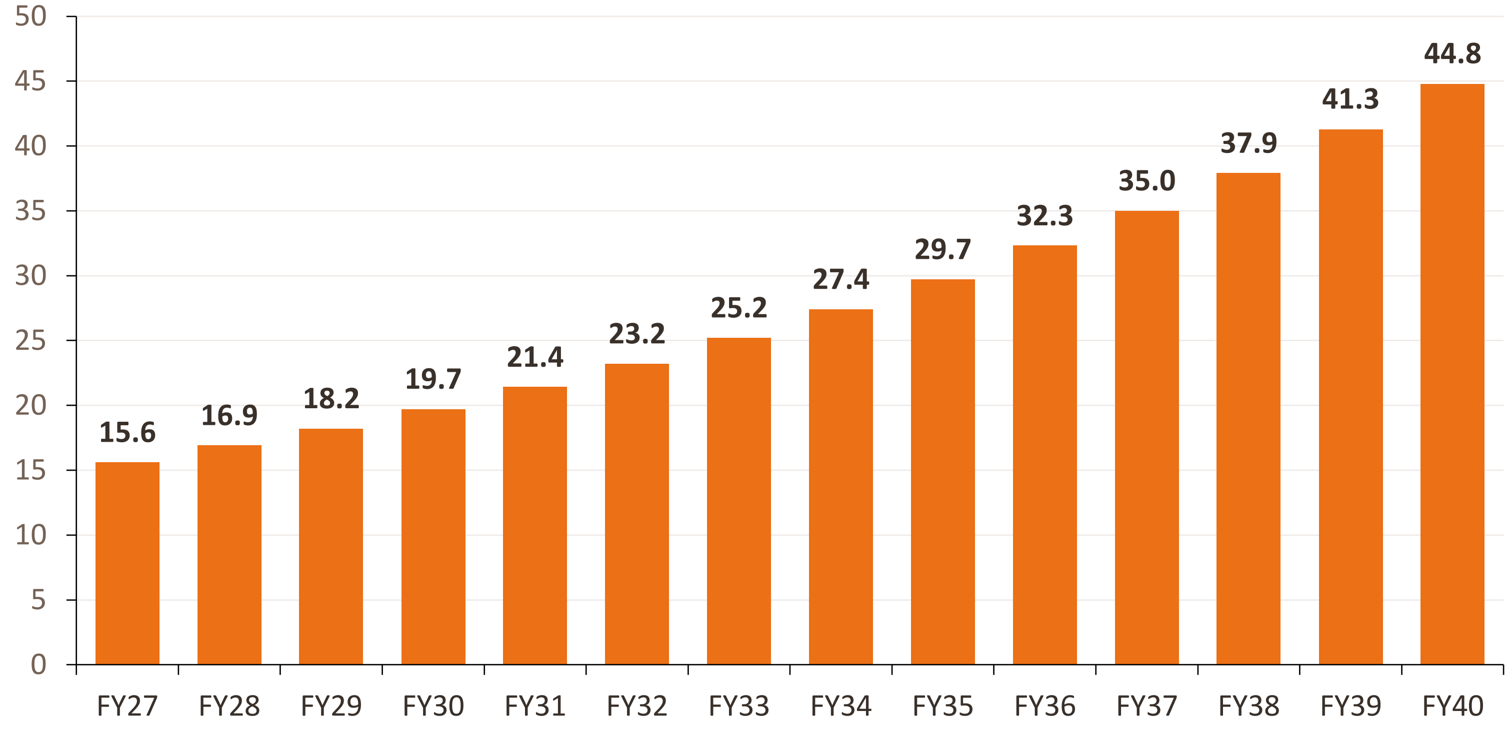
On historical inputs the model holds ~5.6% block MAPE and 0.44% cumulative error

Two tests: On actual weather/drivers (model quality), and on projected drivers (a true forward forecast).
Peaks and cumulative energy; what planning cares about most, are predicted most accurately.

Metric	On actual inputs	On projected drivers
Block-level MAPE	5.56%	9.41%
Cumulative demand error	0.44%	1.04%
Annual all-day peak MAPE	5.72%	1.98%
Annual evening-peak MAPE	0.40%	1.13%
RMSE	557 MW	926 MW
MAE	428 MW	715 MW

AP long-term AI demand-forecast model performance metrics: Lower is better; cumulative energy error stays near 1% even on fully projected inputs.

AP's peak demand is projected to nearly triple by FY2040, to ~44.8 GW



15.6 → 44.8 GW

Peak demand, FY2027 → FY2040 (~2.9×)

90k → 254k MU

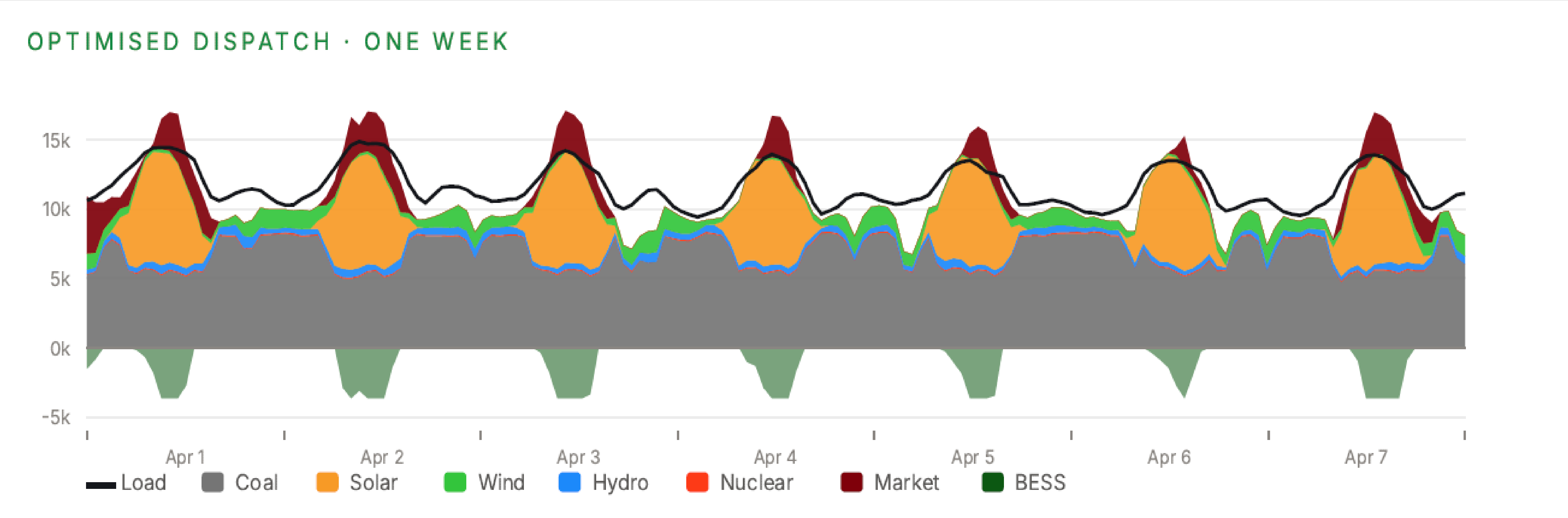
Annual energy demand over the same period

~8% / yr

Compound growth; March is the system peak month

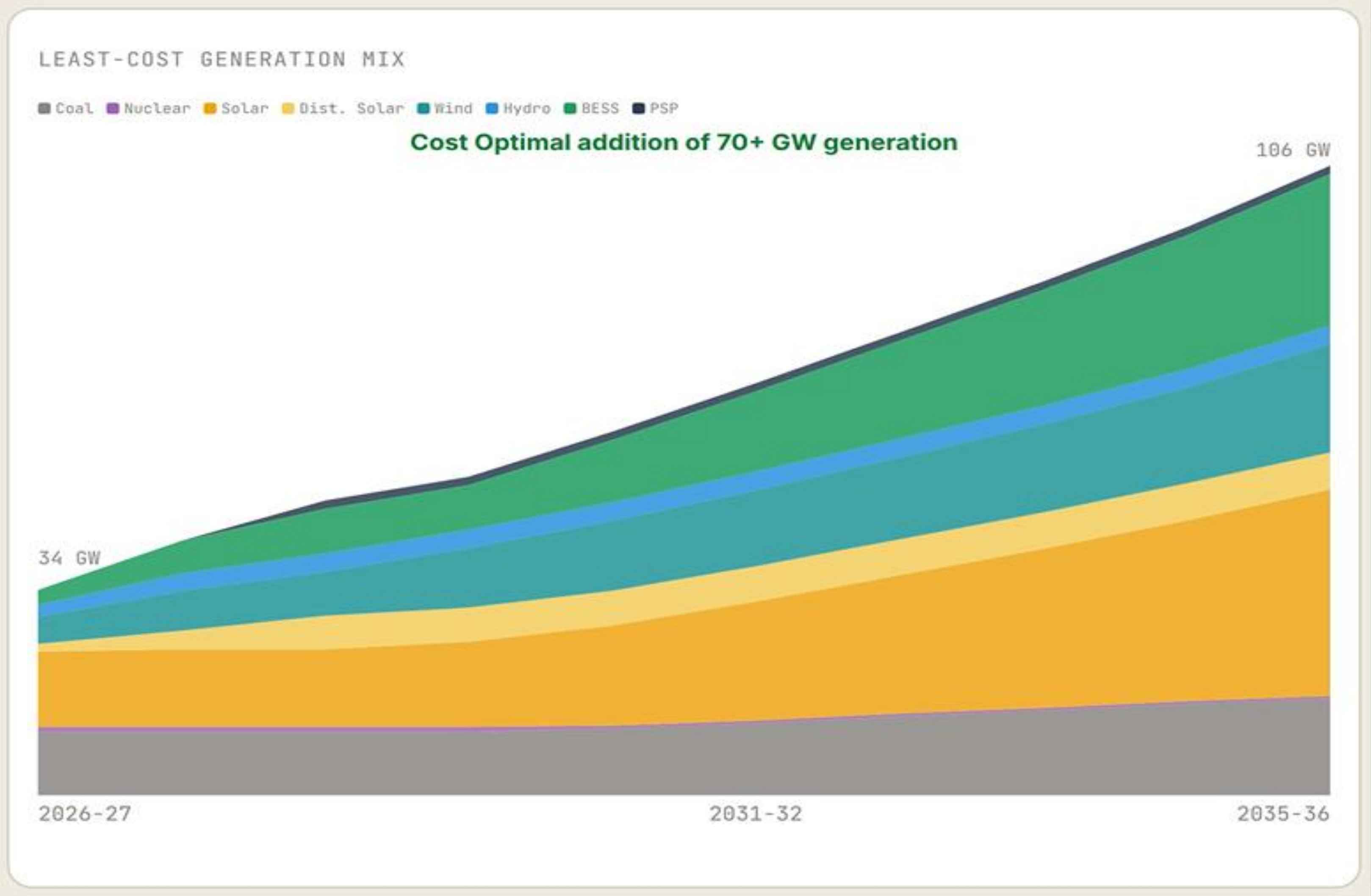
GRIDBRICKS OUTPUTS

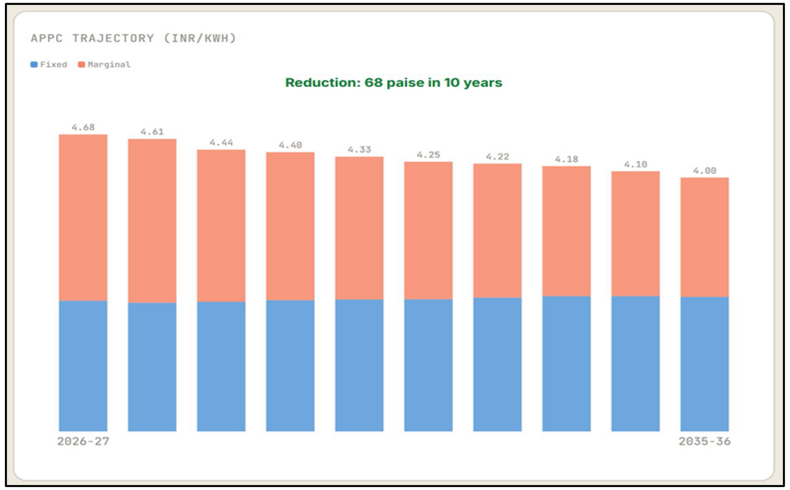
Optimised Dispatch : One Week (illustrative)

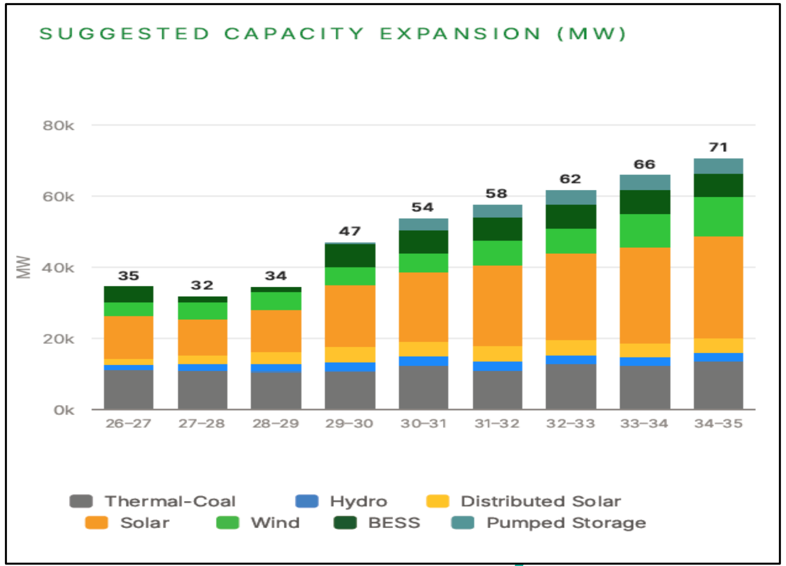


GRIDBRICKS OUTPUTS

Suggested Mix (illustrative)







Major outcomes and insights

Retain thermal capacity

- The Model predicted the need to retain thermal capacity
- The **state procures ~ 11 GW of Thermal Capacity** from state GENCOs, IPPs & CGS stations. However, **increasing demand from newly planned Industries, data centers etc**., adding to the base load combined with aged thermal plants close to retirement increases requirement of **round the clock reliable power supply**. Hence need for new Thermal Power Plants

Much higher BESS capacity

- The Model predicted a much higher need for BESS than expected. The state now has focused on ramping up the BESS capacity to meet the expected demand
- Addition of **large solar capacities to the energy mix through contracts** like SECI 7000 MW, and deployment of **Distributed renewables through PM KUSUM and PM Surya Ghar** schemes is expected to increase afternoon surplus, while increased demand during evening **leading to peak load deficits**, which can be met through addition of storage to the system. PSP taking longer to execute and **reduced prices of BESS make it a favorable** choice to add to the energy mix

SECTION 03

Challenges & the Road Ahead

What makes accurate forecasting challenging and how to strengthen it

Short-term accuracy is constrained by Weather and RE forecast quality

Weather forecast quality

Day-ahead accuracy depends on third-party weather forecasts; gaps and errors degrade both load and RE estimates.

RE forecast error — esp. wind

High error % in developer-supplied wind (and solar) forecasts makes net-demand and supply estimation difficult.

Sudden weather shifts

Models trained on history under-predict when conditions swing sharply from the norm; most acute in day-ahead.

Data latency & granularity

Timely feeder/SCADA, open-access and EV signals are needed to revise intraday forecasts fast enough to act.

Long-term accuracy hinges on clean Econometric inputs and Industry behavior

Econometric input availability

Reliable sector / industrial GDP growth rates are hard to source and project; yet demand is highly sensitive to them.

Changing industrial usage

Greater reliance on open access and captive RE means grid demand no longer tracks economic activity; new industries are mis-sized.

Structural disruptors

EV uptake, rooftop solar, storage and efficiency shift both the size and the shape of the future load curve.

Policy & climate uncertainty

Tariff and subsidy changes, monsoon timing and climate trends widen the long-range forecast band.

Strengthening forecasting: new sources, better inputs, tighter feedback, shared learning

New Sources — Smart meter data from Consumers, DTs, Feeders adds another layer, strengthening existing models, potentially giving rise to stronger new ones.

Raise weather & RE forecast quality — Independent RE forecasting, accountability for developer forecast error, and ensembling of multiple weather sources.

Deepen the data foundation — Feeder-level load research, smart-meter and open-access/captive visibility, and EV-charging telemetry.

Institutionalize feedback — Continuous error tracking (MAPE, DSM blocks), scheduled model re-training, and scenario-based long-term planning.

Build econometric partnerships — Formal data-sharing with DES and industry for sector GDP and the large-load / new-industry pipeline.

Share learning across DISCOMs — Common metrics and methods through forums like AIDA for faster collective improvement.

Thank You

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