Greening Puducherry's Grid

Renewable Integration & Demand Flexibility Roadmap To 2030

January, 2026

Acknowledgment

This report was initiated by Auroville Consulting

About Auroville Consulting
Drawing on expertise in ecological and socially responsible development, Auroville Consulting works to foster a prosperous ecosystem that supports all life on the planet. The organisation collaborates with academic, private, and public sector partners in India and internationally to advance sustainable urban and industrial policies, promote environmentally friendly technologies, and nurture future leaders. Founded in 2010, Auroville Consulting is a unit of the non-profit Auroville Foundation.

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Executive Summary

Puducherry's electricity demand will grow to 39.87 GWh by 2029-30, driven by industrial (37% growth) and domestic sectors amid India's 500 GW non-fossil target and RPO mandates. Integrating high shares of variable renewables like solar and wind creates grid stress from mismatched peaks, steep evening ramps (up to 346 MW/hour), curtailment (up to 1.22% in wind-dominant scenarios), and market reliance (up to 3.35%). A wind-dominant renewable mix (WD scenario, 54-60% wind share) emerges as optimal, minimizing costs (₹4,869 crore total), emissions (0.09 tCO_2/MWh), and BESS needs (2-3% share) compared to solar-dominant cases.

Key Findings

Demand-side flexibility via redesigned Time-of-Use (ToU) tariffs (e.g., WD ToU2: 25% peak surcharge, 15% off-peak rebate, solar-sponge midday discount) and Active Demand Response (ADR) for industries cuts gross peaks to 613 MW, net peaks to 398 MW, and max ramps to 307 MW while phasing out low-PLF (<40%) coal units. These measures reduce total system costs by up to ₹60 crore (to ₹4,809 crore in ADR3), supply costs to ₹12.11/kWh (from ₹12.97/kWh baseline), RE curtailment by 56%, and market imports by 78% versus business-as-usual. Emission intensity drops to 0.084 tCO_2/MWh in advanced ADR, with flatter net-load profiles enabling 63% RE penetration and less storage cycling.

Policy Actions

- Diversify RE procurement: Prioritize wind (50-75% share) from multiple regions alongside rooftop solar to smooth ramps and cut coal/gas reliance.
- Revamp Time of Use tariffs: Expand to all consumers with solar-aligned rebates (10:00-16:00) and peak prices (6:00 – 7:00 and 17:00 – 23:00) to shift loads, lowering costs and curtailment.
- Introduce Active Demand Response programs: Contract industries for interruptible loads during critical hours, reducing peaks by up to 6 MW and enabling power generation and transmission asset deferral.
- Strategic BESS deployment: Site at distribution network level and at substations/RE pooling stations (785-796 MW needed) to handle evening ramps; incentivize behind-the-meter storage.
- Implementing these unlocks a resilient, low-cost grid with more than 60% energy from renewables, establishing Puducherry as a clean energy hub for green industries and sustainable tourism.

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Abbreviations

Abbreviation	Description
APR	Annual Performance Review
ARR	Aggregate Revenue Requirement
BESS	Battery Energy Storage System
CC	Capacity Credit
CEA	Central Electricity Authority
CEM	Capacity Expansion Model
CF	Capacity Factor
CUF	Capacity Utilization Factor
DAM	Day-Ahead Market
DoD	Depth of Discharge
DSF	Demand Side Flexibility
e_initial	Initial state of charge (MWh)
e_max_pu	Maximum state of charge as a percentage of e_nom
e_min_pu	Minimum state of charge as a percentage of e_nom
e_nom	Energy capacity in MWh (nominal energy content of storage)
ESS	Energy Storage Systems
EUE	Expected Unserved Energy
F&V	Fixed and Variable (costs)
IEA	International Energy Agency
IEX	Indian Energy Exchange
IRENA	International Renewable Energy Agency
LCOE	Levelised Cost of Energy
LCOS	Levelised Cost of Storage
LOLE	Loss of Load Expectation
LOLH	Loss of Load Hours
LOLP	Loss of Load Probability
MU	Million Units (million kilowatt-hours of electrical energy)
MW	Mega-Watts (unit of power)
NENS	Normalized Energy Not Served
NTPC	National Thermal Power Corporation
p_max_pu	Maximum output for each snapshot per unit of p_nom
p_min_pu	Minimum output for each snapshot per unit of p_nom
p_nom	Power capacity in MW (nominal power rating of an asset in PyPSA)
p_nom_max	Maximum nominal capacity (upper bound on p_nom)
p_nom_min	Minimum nominal capacity (lower bound on p_nom)
p_set	Active power set point (MW)
P/E	Power to Energy ratio (MW to MWh ratio for storage sizing)
PAF	Plant Availability Factor
PCM	Production Cost Modelling
PLF	Plant Load Factor
PSH	Pumped Storage Hydro
RM	Reserve Margin
RPO	Renewable Purchase Obligation
RTM	Real-Time Market
RTS	Rooftop Solar
SoC	State of Charge
T&D	Transmission and Distribution
TC	Transmission costs
TFC	Transmission fixed costs
VRE	Variable Renewable Energy

01

60%
Of Puducherry's electricity in FY 2024–25 is from coal-based power plants

39.87 GWh
Is the estimated electricity demand in FY 2029-30

Introduction

India's commitment to achieving net-zero emissions by 2070 and expanding renewable energy capacity sets the stage for Puducherry's transition, where rising electricity demand, seasonal consumption patterns, and the integration of variable renewable sources necessitate demand flexibility solutions and energy storage solutions.

India has set an ambitious target to install 500 GW of non-fossil fuel energy capacity and meet 50% of its energy requirements through renewable sources by 2030 (Government of India, 2022). This national commitment provides a strong foundation for regional energy transitions, including Puducherry's shift toward a more sustainable power mix.

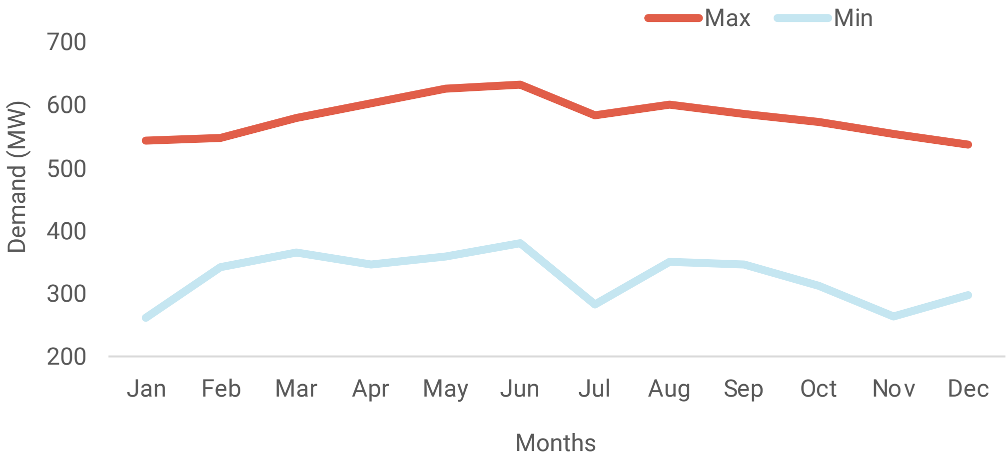
As of FY 2024–25, 60% of Puducherry's electricity was sourced from coal-based power plants (JERC, 2024), highlighting the need for a strategic transition toward cleaner energy sources. Puducherry is now at a crucial juncture in its energy transition, aligning with India's broader goal of achieving 50% cumulative installed capacity from non-fossil fuel-based energy resources by 2030 (Ministry of Power, Government of India, 2023).

To support this transition, the Government of India has been actively promoting renewable energy adoption through various policy measures. One such initiative is the Renewable Purchase Obligation (RPO), which mandates states to procure a specific share of their electricity from renewable sources. As per the latest RPO order, the trajectory for states has been defined from 2022-23 to 2029-30, ensuring a structured approach to increasing the share of wind, hydro, and other renewable power sources in the energy mix (Ministry of Power, Government of India, 2023).

Puducherry's electricity demand across various sectors is projected to grow by 2029-30, with total consumption increasing from 3,187.92 MU in 2023-24 to 3,685.87 MU in 2029-30. The highest growth is expected in HT industries, where demand is anticipated to rise from 1,122.75 MU in 2023-24 to 1,464.21 MU in 2029-30. Similarly, domestic sector consumption is projected to increase from 1,014.55 MU to 1,327.33 MU, while commercial sector demand is expected to grow from 246.66 MU to 317.21 MU. These projections align with the EPS 20 survey (CEA 2022).

The rising energy demand, along with the integration of variable and weather-dependent renewable sources like solar and wind, leads to fluctuations in power generation that often do not match consumption patterns. As a result, the grid must be equipped to handle sudden supply shortages while also managing surplus generation during periods of peak renewable output. Additionally, the incorporation of technologies such as Battery Energy Storage Systems (BESS) further complicates grid operations and load management. The inherent variability of renewable energy, combined with the need for precise coordination of BESS charging and discharging, presents significant challenges for grid stability.

Figure 1 Monthly min and maximum demand variations for Puducherry 2029-30.



Puducherry experiences both seasonal and diurnal variations in electricity demand, influenced by temperature fluctuations and renewable energy generation patterns. During summer (April–June), high temperatures drive electricity consumption, particularly for cooling loads like air conditioning and refrigeration, causing demand to fluctuate between 345.35 MW and 631.32 MW, with peaks in May and June. In contrast, the Northeast Monsoon season (October–December) brings heavy rainfall, reducing daytime cooling demand and lowering minimum demand to around 263.28 MW, while evening consumption remains steady, keeping overall demand within the range of 263.28 MW to 573.56 MW.

Beyond seasonal variations, diurnal shifts significantly influence electricity demand-supply dynamics. Demand typically declines during late-night and early morning hours when most households and businesses reduce activity. A secondary dip often occurs in the late afternoon, before the evening peak. The highest demand is observed during the daytime due to commercial, industrial, and residential activities, with another surge in the evening as households and businesses rely more on lighting, cooling, and indoor appliances.

On the supply side, renewable energy generation follows its own diurnal cycle. Solar power generation peaks at midday but declines sharply in the evening, often misaligned with the highest demand hours. Wind energy, on the other hand, can be more variable, with some regions experiencing stronger winds at night. These fluctuations highlight the need for greater grid flexibility, demand-side management, and energy storage solutions to balance supply and demand efficiently.

This report aims to (i) identify the flexibility needs for Puducherry's grid management in 2030 and (ii) estimate the grid benefits of demand flexibility options, such as time-varying tariffs and active demand response interventions. By exploring potential flexibility mechanisms across demand, the report provides a comprehensive framework for integrating 50% renewable energy efficiently. Through these insights, the roadmap supports informed decision-making in Puducherry's power sector, ensuring a reliable, sustainable energy future while meeting the territory's growing electricity demand.

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Power System Flexibility

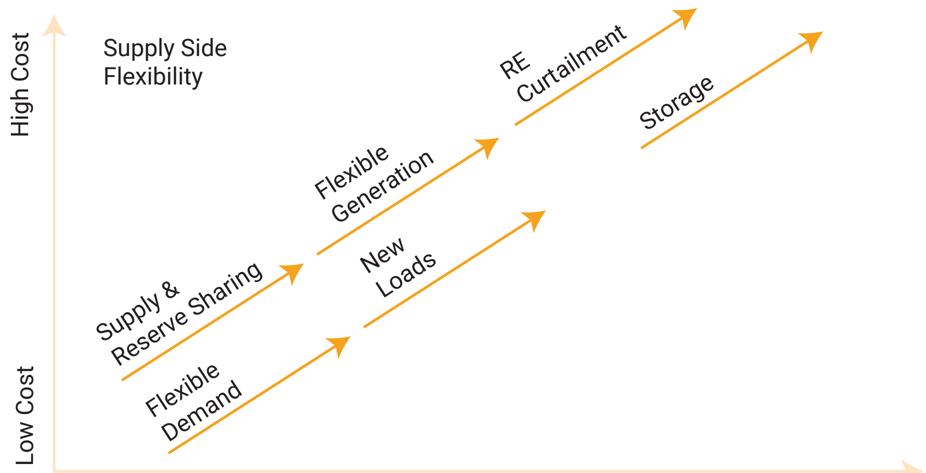
Power system flexibility, encompassing supply-side, demand-side, storage, and market-based mechanisms, is essential for maintaining grid stability amid increasing renewable energy integration, with demand-side flexibility emerging as a cost-effective and scalable solution to optimize energy use, reduce reliance on fossil fuels, and enhance grid resilience.

Power system flexibility is the cornerstone of a stable and reliable electricity grid, particularly in the context of integrating high shares of renewable energy. Power system flexibility has been widely studied from various perspectives, each addressing different challenges in maintaining grid stability and reliability. One of the primary areas of focus is generation flexibility, also known as supply-side flexibility, which refers to the ability of power plants to ramp up or down efficiently in response to fluctuations in demand or renewable energy generation.

Another critical aspect is demand-side flexibility (DSF), which leverages the capability of consumers to modify their electricity usage based on grid conditions. This approach reduces reliance on traditional flexibility sources and possibly enables a more responsive and cost-effective energy system. In addition to supply and demand adjustments, energy storage systems provide an essential flexibility mechanism by storing excess energy during periods of low demand and discharging it when the grid requires additional support. Technologies such as batteries, pumped hydro, and thermal storage play a significant role in balancing short-term and long-term energy variations.

Finally, market and transmission-based flexibility comes into play by optimizing power flows across regions and ensuring that electricity is delivered efficiently while preventing network congestion. These different aspects of flexibility collectively enhance the adaptability of the power system, enabling it to meet the challenges posed by an evolving energy landscape.

Figure 2 Flexibility supply curve



Adapted from: Nickell [2008]

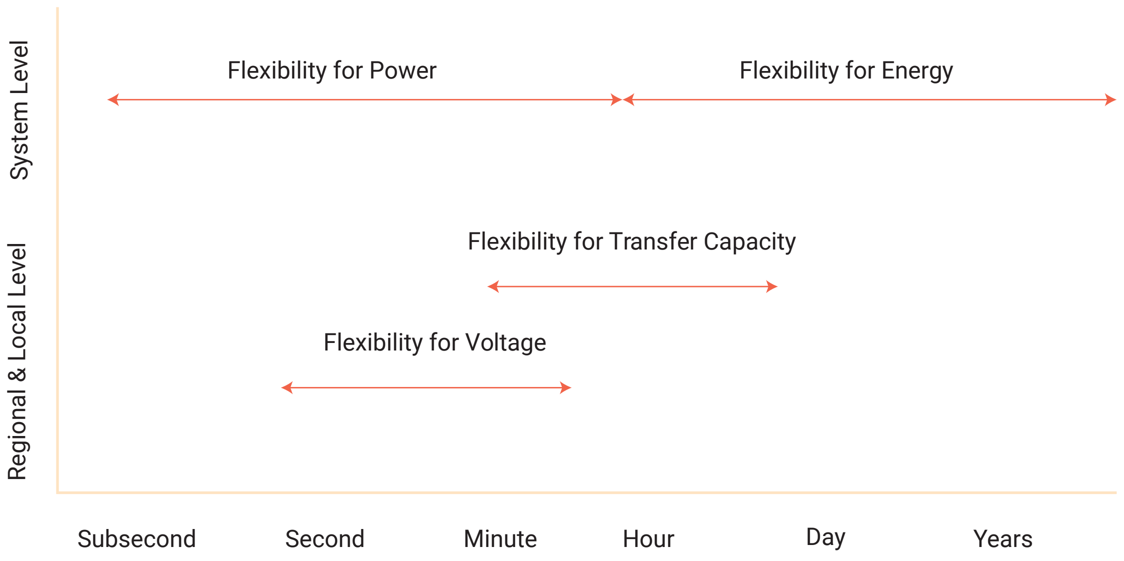
One of the key mechanisms to enhance DSF is through Time-of-Use (TOU) tariffs, which encourage consumers to shift their electricity usage to off-peak hours when renewable generation is abundant. TOU pricing structures create financial incentives for consumers to modify their energy consumption, thereby reducing peak demand stress on the grid and enhancing the utilization of renewable energy.

Additionally, demand response programs provide another crucial avenue for leveraging DSF. These programs enable utilities or grid operators to request temporary load reductions or modulations from consumers during peak periods or times of grid instability. Automated demand response systems, smart meters, and real-time pricing mechanisms allow consumers to respond dynamically to grid conditions, thereby improving grid reliability and reducing dependence on fossil-fuel-based peaking plants.

Implementing these strategies in Puducherry can help mitigate challenges associated with integrating high shares of variable renewable energy (VRE) while promoting a more sustainable and cost-effective energy system. By fostering active consumer participation and utilizing advanced demand management technologies, DSF can play a transformative role in shaping a resilient and adaptive power system for the region.

Compared to traditional flexibility solutions, DSF offers several advantages. Unlike generation flexibility, which requires significant capital investment in fast-ramping power plants, DSF leverages existing infrastructure, making it more cost-effective. It also provides a faster and more scalable response, whereas traditional supply-side flexibility takes minutes or hours, and improves renewable energy integration by aligning electricity consumption with periods of high renewable generation, thereby reducing the need for curtailment and reliance on fossil-fuel-based backup generation. Additionally, it reduces the need for expensive grid investments by alleviating congestion and delaying costly transmission and distribution upgrades. DSF prevents curtailment of renewables by shifting demand to periods of excess renewable generation, ensuring efficient utilization of solar and wind power. These advantages make demand-side flexibility a critical tool in achieving a resilient, low-cost, and renewable-integrated power system.

Figure 3 Flexibility supply curve



Adapted from: IEA [2019]

03

Methodology

The methodology adopted in this study integrates demand forecasting, capacity expansion planning, economic dispatch simulation, identification of stress periods, and demand-side flexibility assessment through Time-of-Use (ToU) pricing and corresponding demand response strategies. By following a sequential and data-driven approach, the model captures the impact of policy, technical, and economic constraints across different layers of the power system, providing insights into how demand flexibility can be a key tool to enhance system efficiency and reliability.

Figure 4 Flow chart

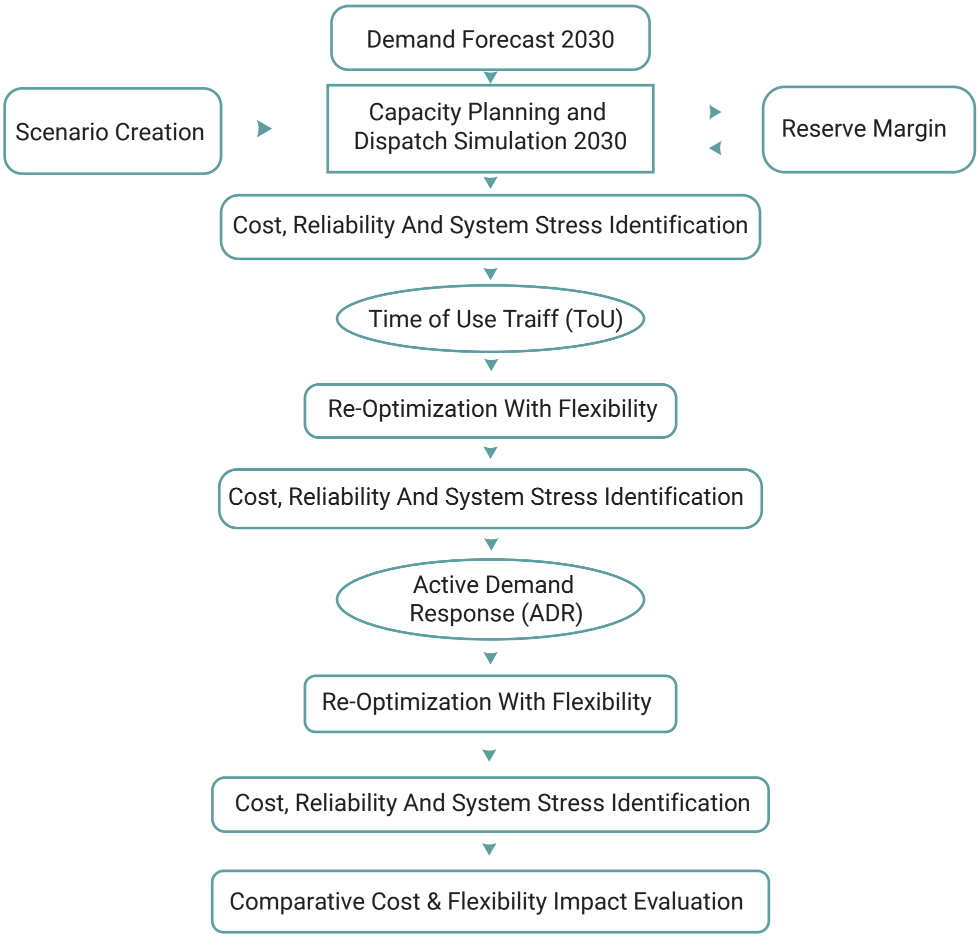
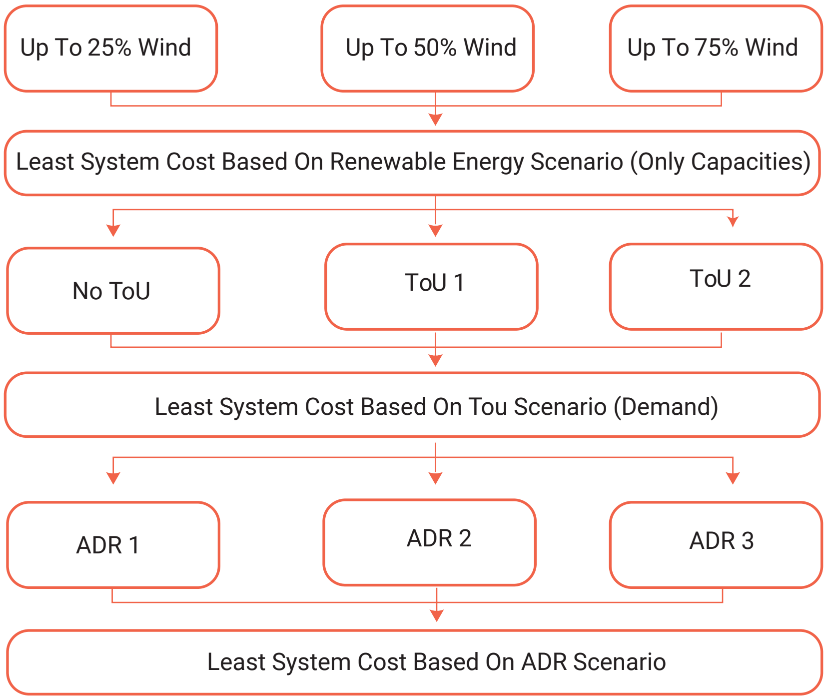


Figure 5 illustrates the stepwise scenario evolution adopted to assess the impact of demand flexibility on system costs. The analysis progresses from renewable energy scenario assessment to the application of Time-of-Use (ToU) pricing and, subsequently, Active Demand Response (ADR) interventions. At each stage, system costs are evaluated to understand the incremental contribution of demand-side flexibility measures. The lowest-cost outcomes across the scenario pathways highlight the role of demand flexibility in improving overall system performance.

Figure 5 Scenario evolution for demand flexibility assessment



3.1 Demand Forecasting

The first component of the modelling framework involves forecasting electricity demand for the year FY 2029–30 using a Random Forest Regression Model trained on historical hourly demand data (in MW) from FY 2018–24, excluding the COVID-19 affected year FY 2020–21. The Random Forest Regression Model was chosen for its capability to capture non-linear relationships and temporal variations, and the final forecast represents hourly electricity demand at the state periphery (excluding transmission losses), forming the basis for subsequent capacity expansion and production cost modelling.

Before training the Random Forest Regression Model, demand data was pre-processed to reflect gross demand by adding back net-metered rooftop solar (RTS) generation, which is not visible to the grid due to its behind-the-meter nature. This adjustment ensures that the model captures actual electricity consumption patterns instead of net grid demand. The demand profile is captured through patterns learned by the model and supplemented by a gradual year-wise scaling to reflect realistic medium-term growth. For more information, refer to Appendix 1.

3.2 Integrated Capacity Expansion Model & Production Cost Model

This step employs an integrated, iterative modelling framework that combines long-term capacity planning with detailed hourly dispatch simulations to determine a cost-effective and reliable generation-storage portfolio for the year FY 2029-30.

To operationalize the integrated capacity expansion and production cost modelling framework, we employ the Python for Power System Analysis (PyPSA) platform. PyPSA is an open-source modelling tool designed for simulating large-scale power systems and enables the co-optimisation of generation and storage investments alongside dispatch decisions under technical and economic constraints. The HiGHS solver is utilized for solving the underlying linear and mixed-integer programming problems due to its computational efficiency and scalability. The modelling is performed at an hourly temporal resolution for the entire year (8,760 hours), allowing for a detailed representation of intra-day and seasonal variations in load, renewable generation, and storage dynamics. Cost and performance assumptions for generation technologies — including annualised fixed costs, variable O&M costs, minimum stable load, ramp rates, and efficiency factors — are derived from national benchmarks such as CEA reports (CEA Technology Catalogue, 2020), tariff orders (FY 2018-19 to FY 2023-24).

The process begins with an assumed Planning Reserve Margin (PRM) of 10%, which provides an initial buffer over peak demand to ensure system adequacy. The hourly demand projections, prepared in the earlier step using a Random Forest regression model, serve as primary inputs to this capacity expansion and dispatch modelling framework.

Recognising the uncertainty regarding the future mix of renewable energy technologies, three distinct scenarios were developed based on varying wind energy penetration levels. While Renewable Purchase Obligation (RPO) targets specify the total renewable energy share, they do not mandate specific contributions from solar or wind. Therefore, to evaluate system behaviour under different resource mixes, the following scenarios were modelled:

Table 1 RE scenarios

Scenarios	Share of wind energy on total energy
Scenario 1: Solar Dominant (S_D)	Up to 25%
Scenario 2: Wind Dominant (W_D)	Up to 75%
Scenario 3: Balanced	Up to 50%

For each scenario, separate capacity expansion and corresponding hourly economic dispatch simulations were performed. This enables assessment of system adequacy, total system cost, flexibility requirements, and the occurrence of system stress points across different wind and solar penetration levels. For more information regarding the mathematical governing equation, refer to Appendix 2.

Battery Energy Storage Systems (BESS) are modelled using technology-specific parameters, including round-trip efficiency, standing losses, depth of discharge (DoD), deployment year and fixed costs.

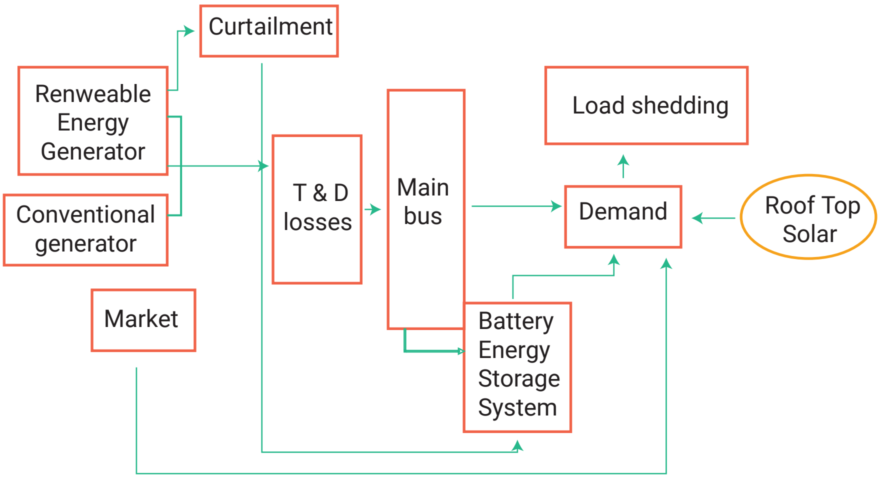
Renewable energy curtailment is allowed only when system demand is fully met, and available storage capacity is fully charged. Any excess renewable generation that cannot be absorbed or stored is curtailed to maintain system balance. A curtailment penalty of ₹15,000/MWh is applied.

Hourly Day-Ahead Market (DAM) volumes and prices are forecast using a Random Forest–based multivariate regression model trained on historical Indian Energy Exchange (IEX) DAM data for the period 2019–2023, excluding the COVID-affected year (FY 2020–21). The model follows a lag-based autoregressive structure, using market outcomes from the previous 24 hours as input features, with all variables normalised using min–max scaling prior to training. Forecasting for FY 2029–30 is carried out using a recursive approach, wherein predicted values are iteratively fed back into the model to generate 8,760 hourly forecasts. The forecasted outputs are subsequently rescaled to original units, and market prices are adjusted and capped at ₹14,000/MWh to reflect realistic market bounds. The resulting hourly DAM availability is then integrated into the production cost model, with market purchases constrained to a maximum of 10% of the projected annual peak demand. Further details are provided in Appendix 2.

Load shedding is introduced in the model when the total available supply from generators, battery storage systems, and market purchases is insufficient to meet the hourly demand. The penalty for unserved energy (load shedding) is set at the 99th percentile of historical Day-Ahead Market (DAM) prices to reflect the high economic cost of unmet demand. For cost assumptions, refer to Appendix 2.

Figure 6 provides a conceptual overview of the PyPSA-based system representation; the actual model implementation follows PyPSA’s standard bus–component formulation.

Figure 6 Modelling base network



Reliability standards are evaluated using key metrics, including Loss of Load Probability (LoLP) and Expected Energy Not Served (EENS), with threshold targets aligned with industry benchmarks (e.g., LoLP ≤ 0.0027). If the reliability standards are not met, the PRM is incrementally increased, and the capacity planning and dispatch process is repeated. For more information regarding input assumptions, refer to Appendix 2.

This iterative loop continues until a generation-storage mix meets reliability requirements, with cost-effectiveness assessed based on total system cost and average cost of supply. The final outputs include technology-wise installed capacities, system dispatch costs, and key performance indicators, providing a comprehensive view of future system adequacy and operational feasibility. From these results, the renewable energy scenario that meets reliability criteria and delivers the lowest total system cost is selected as the base system configuration for subsequent stages of the analysis.

3.3 Stress Points Identification

System stress periods are identified by analysing hourly net load profiles and comparing them with the gross load profile for each scenario. This analysis highlights operating conditions where system flexibility is constrained. The following key stress points are identified:

- Load shedding events
- High renewable energy curtailment
- Steep and sustained ramping requirements
- High marginal cost events

Periods with steep ramping requirements are identified where rapid changes in net load occurs due to variations in renewable generation relative to demand. These conditions indicate increased reliance on system flexibility from conventional generators and battery storage.

High renewable curtailment is observed during hours when renewable generation exceeds gross demand and available storage capacity is fully utilised. Load shedding events are flagged when total available supply is insufficient to meet, especially during low renewable contribution hours or sudden reduction in renewable generation. Hours with high marginal costs are identified as indicative of expensive dispatch conditions, usually due to high reliance on peaking thermal units.

By identifying these stress events, the analysis enables targeted application of demand-side flexibility strategies. This ensures that price-based load shifting and demand response are targeted to periods of greatest need, thereby optimising system costs and improving reliability.

3.4 Selection of Demand Response Strategies

To address system stress periods—such as load shedding, renewable curtailment, steep ramping, and high marginal cost hours—Time-of-Use (ToU) tariffs and Interruptible DR strategies have been applied. ToU helps shift demand away from peak and high-cost hours, improving ramping profiles and solar utilization. Interruptible DR enables direct curtailment of industrial loads during critical hours. These strategies were chosen based on their relevance to industrial consumers, ease of integration within the modelling framework, and the availability of supporting data. Other DR mechanisms were not considered due to limited implementation and data gaps in the Indian context.

3.5 Designing Time-of-Use (ToU) Tariffs

To improve grid flexibility and optimise renewable energy integration in Puducherry, ToU tariffs were developed based on an analysis of system stress and surplus periods identified through detailed dispatch simulations. The primary objective is to realign electricity consumption patterns by providing price signals to consumers, encouraging demand shifting from high-cost evening peaks to solar-abundant midday periods.

The tariff design approach draws upon Auroville Consulting's ToU tariff modelling study for Tamil Nadu (AVC, 2023), where periods of system stress and surplus were statistically clustered to structure differentiated tariff slabs. For a detailed description of the methodology and assumptions, refer to this report.

The ToU-induced demand adjustments are implemented using a rule-based elasticity model applied to hourly demand data. This approach modifies the load profile in response to predefined tariff signals while preserving overall energy balance, and provides the adjusted demand inputs for subsequent capacity expansion and production cost simulations.

The ToU tariff structures are defined separately in a later chapter and are applied after identifying the least-system-cost renewable energy scenario from the initial capacity expansion and production cost analysis across the three RE scenarios. Once the base RE scenario is selected, the ToU tariffs are used to modify the demand profile. The capacity expansion model and production cost model are then re-run using the ToU-adjusted demand, allowing installed capacities and dispatch outcomes to adjust in response to the revised load shape. Each ToU structure is evaluated independently to assess impacts on key performance indicators, including total system cost, cost of supply, peak demand reduction, renewable energy utilisation, and ramp-rate smoothing.

3.6 Demand Response Modelling

DR modelling is undertaken after identifying the least-system-cost Time-of-Use (ToU) tariff scenario. Based on the hourly dispatch outputs of this selected ToU case, DR is applied to the industrial (HT) sector, which represents a significant and controllable share of total system demand. The objective is to mitigate peak system stress by temporarily reducing industrial load during critical hours and redistributing it to lower-stress periods.

DR is implemented using a rule-based, interruptible demand response framework. Interventions are triggered during predefined evening peak hours (19:00–22:00) when the gross system load exceeds a minimum threshold, ensuring that demand response is activated only under high-stress conditions. During these peak hours, a specified fraction of industrial demand is curtailed and redistributed evenly across adjacent recovery hours, preserving overall energy balance while reshaping the load profile.

Multiple DR scenarios are evaluated by varying the proportion of industrial demand shifted, representing increasing levels of demand-side flexibility. The resulting DR-adjusted demand profiles are subsequently used as inputs to the capacity expansion and production cost models to assess impacts on total system cost, cost of supply, peak demand reduction, renewable energy utilisation, and operational flexibility.

04

23%
Growth in electricity demand from FY22-23 to FY29-30

631MW
Is the estimated peak load in FY29-30

455MW
Is the average annual demand in FY29-30

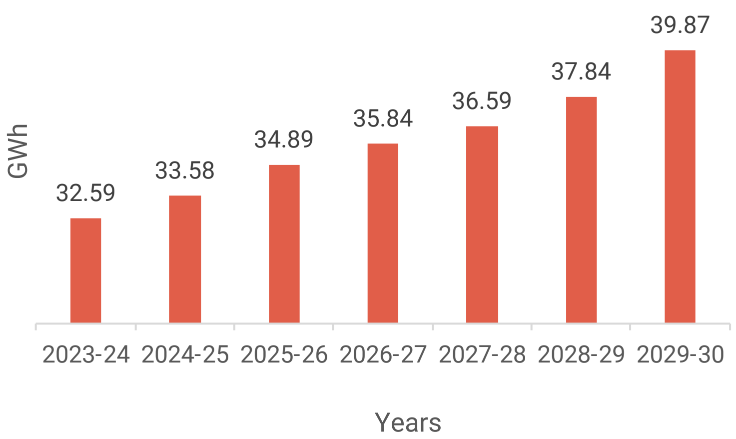
Demand & Generation Forecasting

4.1 Demand Forecasting

By FY 2029–30, Puducherry's electricity demand rises steadily, with evening peaks driven in part by growing electric vehicle (EV) and air conditioning (AC) loads and only brief periods of high system stress.

Figure 7 depicts a continuous rise in annual electricity demand in the Union Territory of Puducherry, with projections increasing from about 32.59 GWh in FY 2023–24 to 39.87 GWh in FY 2029–30. This represents a 23% overall growth in demand over the period, reflecting the territory's expanding energy requirements as electrification and development progress.

Figure 7 : Estimated annual demand



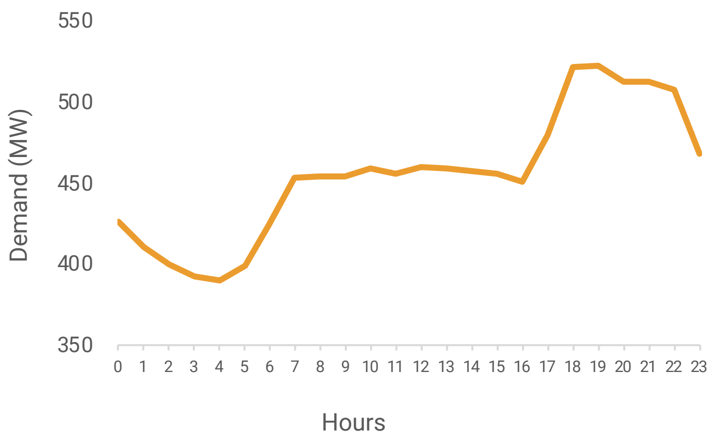
To comprehensively understand annual electricity consumption patterns and system requirements, it is essential to analyse demand on an hourly basis throughout the year. The 8,760-hour electricity demand forecast for FY 2029–30 captures consumption behaviour based on historical demand patterns, including the effect of ToU tariffs that were in place during the training years. No additional policy interventions or demand-side measures are assumed. This forms the basis for analysing key load characteristics—such as peak demand levels, frequency of high-load hours, seasonal and diurnal variation—providing a benchmark against which future flexibility strategies can be assessed.

Table 2 summarises key load characteristics for the FY 2029–30 demand profile. The estimated annual peak demand is 631.32 MW, while average demand is 455.17 MW, resulting in a robust load factor of 0.72. Demand exceeds 600 MW in just 60 hours over the year, highlighting a predominantly stable system with infrequent periods of high stress. This profile suggests efficient utilisation of generation resources and limited instances where demand approaches peak capacity.

Table 2 Load distribution and instances for the FY 2029-30 BAU scenario

Characteristics	Value
Annual Peak Demand (MW)	631.32
Average Demand (MW)	455.17
Frequency (>600MW)	60
Load Factor	0.72

Figure 8 Average hourly demand profile FY 2029-30



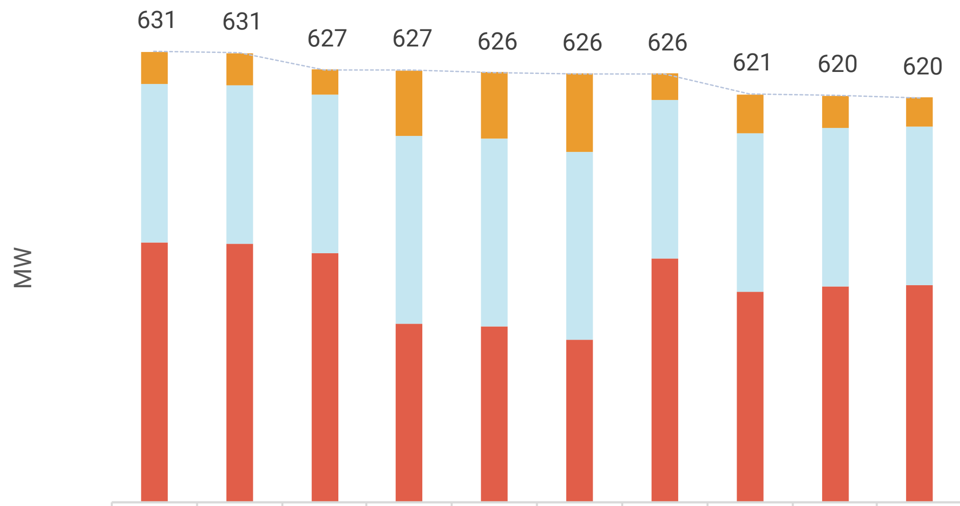
A breakdown of the demand frequency shows that the system operates within the 500–600 MW range for 1,961 hours, 400–500 MW for 5,138 hours, and 300–400 MW for 1,520 hours. Only 81 hours in the year fall below 300 MW, suggesting that extremely low-demand conditions are relatively rare. Overall, the demand remains concentrated in the load zone of 400–500 MW with 59% of instances.

Table 3 Load frequency distribution for the FY 2029-30 BAU scenario

Gross Load Range (MW)	Number of Hours	% of hours
> 600 MW	60	1%
500-600 MW	1,961	22%
400-500 MW	5,138	59%
300-400 MW	1,520	17%
< 300 MW	81	1%

Isolating the top 10 gross load instances projected for the year 2030 reveals that all of them occur during the evening hours between 21:00 and 22:00, primarily in the summer months of May and June. Combined EV and AC loads account for up to 12% of these identified peak load instances.

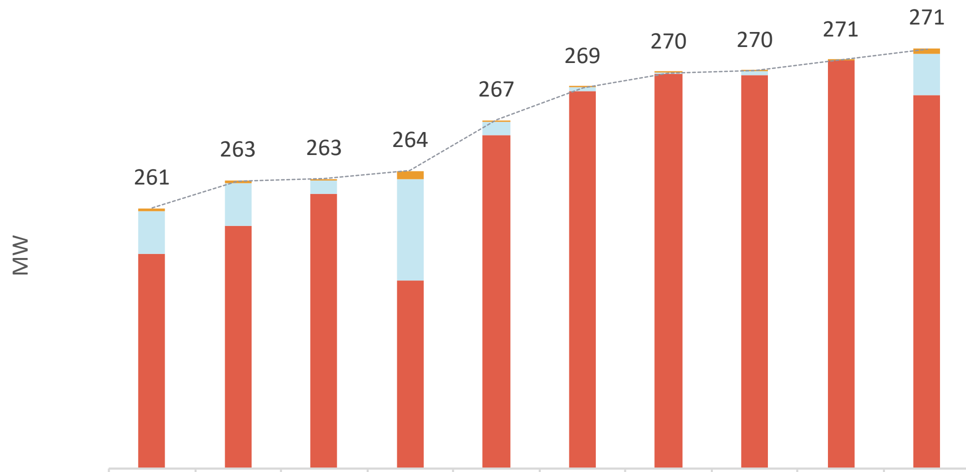
Figure 9 : Top 10 gross load peak instances



	Jun 22:00	Jun 22:00	May 22:00	Jun 21:00	Jun 21:00	Jun 21:00	May 22:00	Jun 22:00	Jun 22:00	May 22:00
AC load	8	8	6	16	16	19	6	10	8	7
EV load	39	39	39	46	46	46	39	39	39	39
Base load	584	584	581	564	563	560	580	572	573	574
Total	631	631	627	627	626	626	626	621	620	620

Conversely, the top 10 lowest valley gross load instances are observed in the winter months, especially in November and December, occurring during late-night and early-morning hours from 01:00 to 05:00

Figure 10 Top 10 gross load valley instances



	Jan 04:00	Jan 04:00	Nov 03:00	Jan 05:00	Jan 03:00	Nov 02:00	Jan 01:00	Jan 02:00	Jan 01:00	Nov 04:00
AC load	0.19	0.17	0.09	0.54	0.05	0.02	0.00	0.01	0.00	0.31
EV load	2.65	2.65	0.86	6.36	0.86	0.22	0.04	0.22	0.04	2.65
Base load	259	260	262	257	266	269	270	270	271	268
Total	261	263	263	264	267	269	270	270	271	271

Electricity demand projections for FY 2029–30 show clear seasonal variations across quarters, illustrating how weather and user patterns influence system needs throughout the year. These trends reveal periods of persistent load growth, system stress, and opportunities for targeted flexibility in planning. The table below summarises quarterly average, peak, and valley demand values.

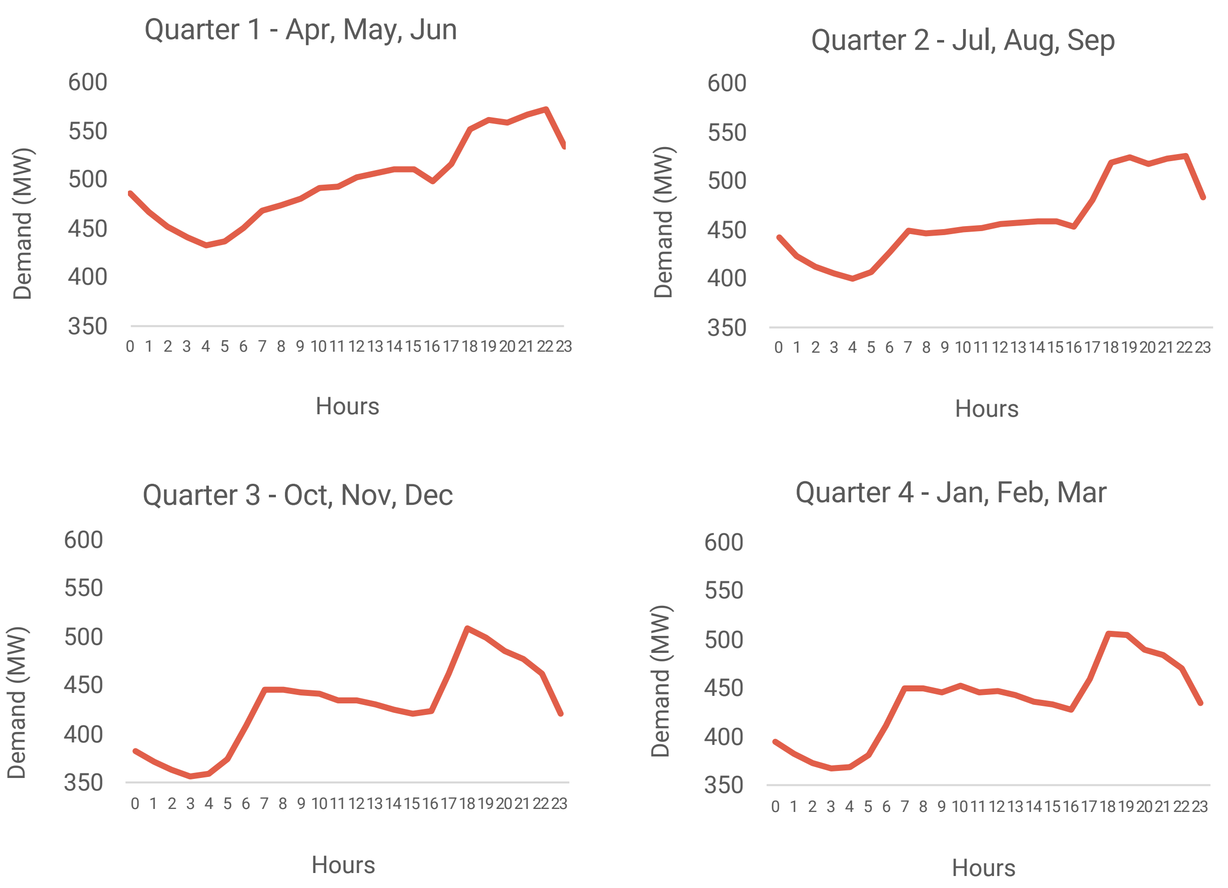
Table 4 Key characteristics by quarter for the 2029-30 BAU scenario

Quarter	Average Demand (MW)	Peak (MW)	Valley (MW)	Avg. Load Factor
Q1 (April to June)	498.07	631.32	345.35	0.79
Q2 (July to September)	459.02	601.00	282.97	0.76
Q3 (October to December)	428.10	573.56	263.28	0.75
Q4 (January to March)	435.53	579.18	261.39	0.75

Quarter 1 (April–June) records the highest peak and valley values, with demand rising to approximately 631.32 MW and the lowest at 345.35 MW. The increase is largely due to heavy cooling requirements during the summer. Demand decreases moderately in Quarters 2 and 3. Quarter 4 sees a mild recovery in evening demand compared to Quarter 3, but it remains slightly below Q1 levels.

Throughout the year, the load factor remains steady between 0.75 and 0.79, suggesting only moderate variation between average and peak demand. This indicates that the demand profile is neither extremely peaky nor flat. A drop in average and peak demand during Q3, likely due to reduced cooling needs in the monsoon months, is followed by a slight increase in Q4. Overall, these quarterly shifts point to pronounced seasonal changes in electricity demand intensity.

Figure 11 : Diurnal variation of quarterly average demands



4.2 Solar and Wind Generation Forecast

Integrated solar and wind generation balances supply, reduces ramping needs, and improves grid flexibility and reliability.

Analysis reveals the temporal complementarity between solar and wind generation. Solar output follows a typical diurnal pattern, rising from early morning, peaking between noon, and declining to zero by evening. Wind generation tends to provide moderate availability during the night and early morning hours, which helps meet demand when solar power is not available. These distinct generation profiles highlight the benefits of combining solar and wind resources to lower ramping needs and enhance overall system flexibility.

Figure 12 Average daily generation profile of wind and solar

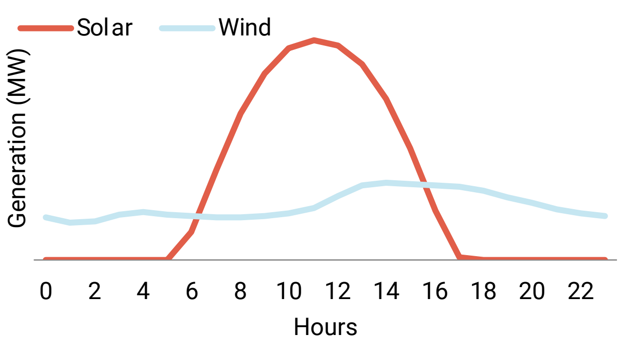


Figure 13 below illustrates how the average daily generation profiles of wind and solar resources change substantially across quarters, reflecting clear seasonal patterns. Solar output consistently peaks during noon in each quarter, with the highest production observed during the longer summer days in Quarter 1, and reduced output during winter in Quarter 4 due to shorter daylight hours. Wind generation, in contrast, displays relatively stable production throughout the day and night, but with subtle variations in amplitude across quarters. Wind output tends to be stronger during the early morning and night, providing essential generation during non-solar periods. Collectively, these seasonal generation profiles highlight the importance of integrating both wind and solar resources to balance supply throughout the year and enhance grid flexibility

Figure 13 Average daily generation profile of wind and solar by quarter

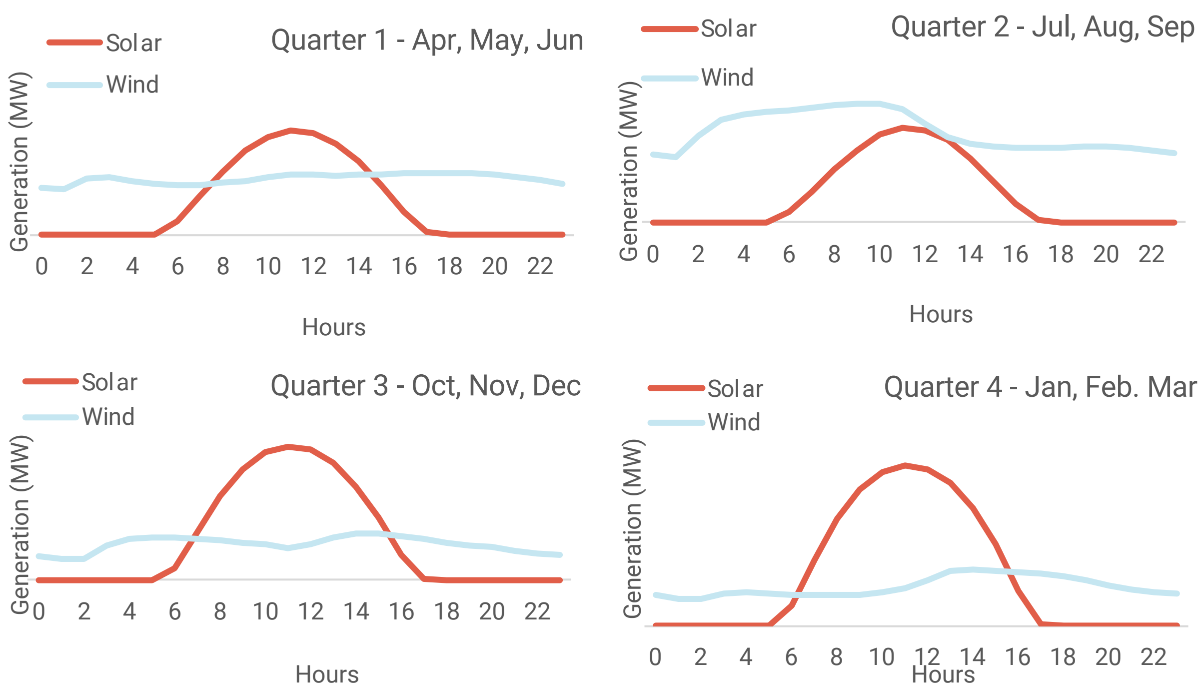
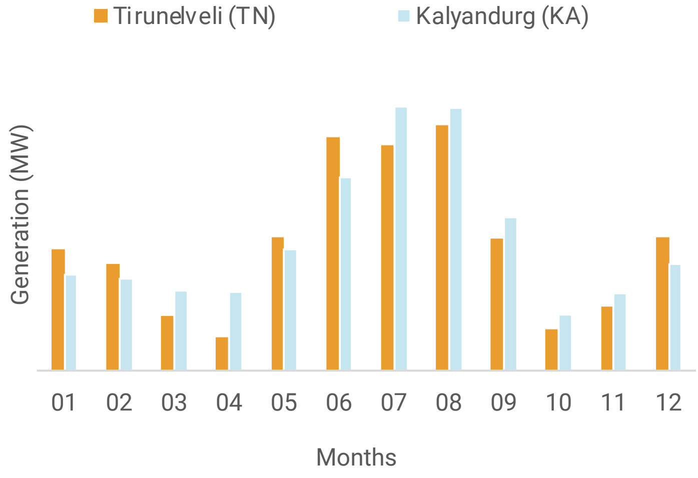


Figure 14 displays the annual wind generation profiles for two distinct geographical locations: Tirunelveli in Tamil Nadu and Kalyandurg in Karnataka. The data reveals that wind turbines in Kalyandurg produce a more stable and consistently higher output, especially during the monsoon season, compared to Tirunelveli. For modelling purposes, wind generation capacity is assumed to be equally shared between the two sites. Presenting these profiles emphasizes the value of geographical diversity among generator locations, which enhances overall system resilience by providing complementary generation patterns. Such diversity can help mitigate local weather variabilities, reduce supply risks, and improve grid reliability.

Figure 14 Wind generation profiles for Kalyanduyr and Tirunelveli



05

12.97 ₹/kWh
The wind-dominant scenario shows the lowest cost of supply

75%
Carbon emission intensity(t/CO_2/ MWh) can be achieved.

Up to 65%
Solar and wind energy can be expected in the energy mix

Renewable Energy Scenario Modelling

This section presents the system-level modelling results for FY 2029–30, based on three previously defined renewable energy scenarios. The analysis evaluates key operational parameters using both the monthly peak demand days and the monthly average values for each corresponding hourly time stamp across different generators. This dual approach captures the system's behaviour during critical peak periods and provides a representative picture of typical daily dispatch patterns aggregated over the year. Together, these perspectives offer insight into how the power system operates under varying renewable energy shares. Metrics such as generation mix, battery dispatch, curtailment, system costs, and ramping stress are assessed for each scenario. The outcomes from this analysis form the basis for understanding the operational challenges of high-RE systems and support the evaluation of demand-side flexibility interventions presented in subsequent sections.

5.1. High-level results

Wind-dominant mixes minimize peak demand and costs, while solar-dominant mixes maximise them, with balanced mixes in between and requiring flexible resources like batteries.

The results in Table 5 highlight how different renewable energy scenarios impact selected key parameters of Puducherry's power system. The S_D scenario features the highest solar share (30%) and the lowest wind share (23%), while the W_D scenario is characterised by the highest wind share (54%) and the lowest solar share (11%); the Balanced scenario sits between these extremes. Notably, the S_D scenario records the highest net peak (556 MW) and system costs (₹5,780 Crore), reflecting the operational challenges and higher integration costs associated with solar-dominant mixes. Conversely, the W_D scenario achieves the lowest system costs (₹5,170Crore) and net peak (462 MW), underscoring the cost and operational benefits of higher wind penetration alongside reduced solar and BESS shares. The Balanced scenario demonstrates moderate values for almost all parameters. Across all cases, ramping requirements and battery needs vary with renewable shares, demonstrating the importance of flexible resources in managing net load volatility.

Table 5 : High-level results by scenario

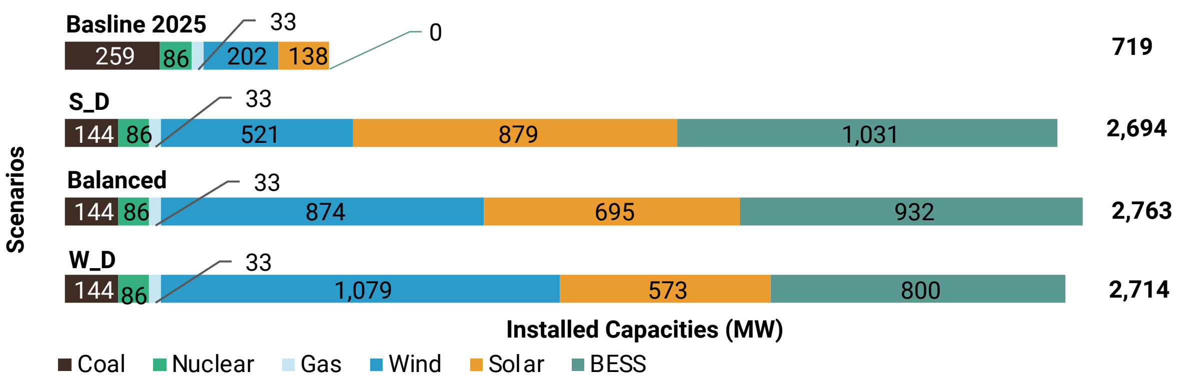
Parameters	S_D	Balanced	W_D
Wind share (%)	23%	39%	54%
Solar share (%)	30%	21%	11%
BESS share (%)	6%	4%	3%
Gross peak (MW)	631	631	631
Net peak (MW)	556	459	462
Max ramping event (MW)	344	402	346
Total system cost (₹ Crore)	5,780	5,578	5,170

5.2. Projected generation capacities

By FY 2029–30, solar and wind dominant scenarios markedly change the generation mix and drive higher, duration-specific BESS requirements, with the solar dominant case needing the largest storage power and energy to support growing system flexibility.

The capacity expansion modelling for FY 2029–30 shows a clear evolution in the installed generation mix across the three renewable energy scenarios as compared to the 2025 baseline scenario. As shown in Figure 15, the Solar Dominant (S_D) scenario results in the highest solar capacity, reaching 879 MW, while wind shows a 521 MW installed capacity. The balanced scenario (results in 874 MW of wind and 605 MW of solar. In scenario 3, the wind-dominated scenario (W_D), wind integration reaches its highest level at 1,079 MW, while solar capacity stands at 573 MW. Across all scenarios, gas and nuclear capacities remain constant, while coal capacity is reduced by 115 MW in all three cases. Battery energy storage (BESS) is the lowest under the W_D scenario (800 MW) and the highest under the S_D scenario (1031 MW). These outcomes reflect how the renewable technology mix and storage requirements shift under varying contributions from wind and solar.

Figure 15 Installed Capacities in Different Scenarios



Figures 16 and 17 present the optimised BESS capacities for both power and energy, categorised by storage duration across different scenarios. The S_D scenario drives the highest overall storage requirement, relying mainly on 2-hour and 4-hour systems to align with solar generation peaks during the day. Overall, installed BESS capacities range from 800 MW/2,442 MWh in the W_D scenario, 932 MW/2,902 MWh under the Balanced scenario, to 1,031 MW/3,215 MWh in the S_D scenario, reflecting the growing flexibility needs in Puducherry driven by greater solar energy integration.

Figure 16 BESS power capacity requirement by scenario (MW)

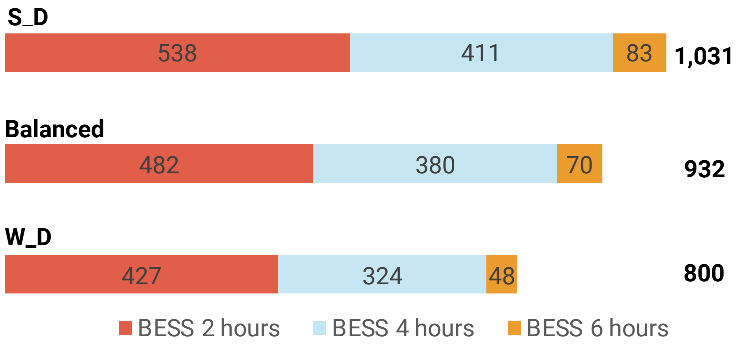
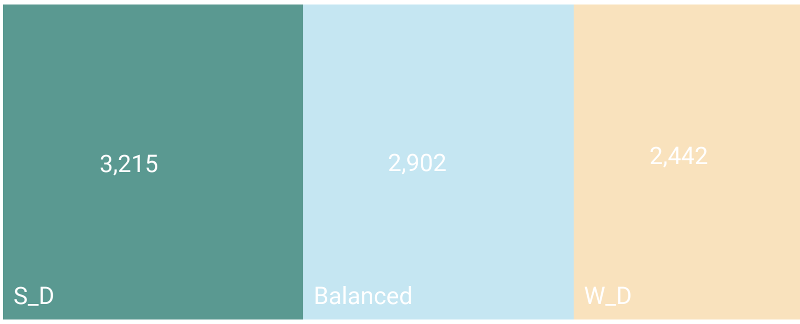


Figure 17 Battery energy capacity requirement by scenario (MWh)

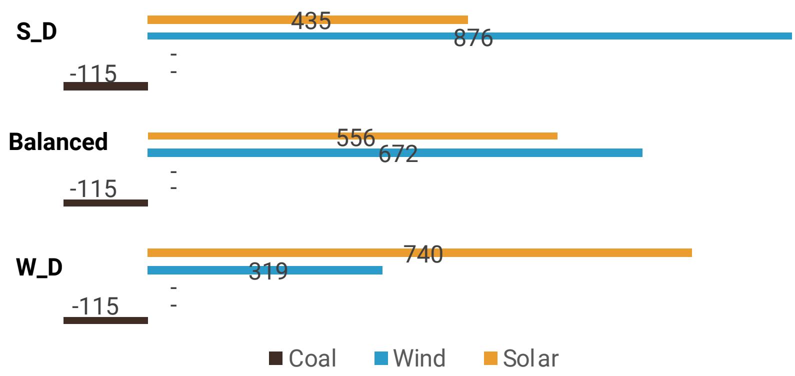


5.3 Change in generation capacity

The scenarios show large solar and wind additions alongside coal phase-down, while gas and nuclear remain unchanged as stable baseload capacity.

To better understand the structural evolution of the power generation, mix under each of the three scenarios, Figure 18 presents the relative change in installed capacities compared to the FY 2024-25 baseline. Solar capacity increases by a factor of six from 138 MW in 2025 to 879 MW in 2030 under the S_D. The W_D scenario, in contrast, shows a 5-fold increase in wind capacity, from 202 MW in 2025 to 1,079 MW in 2030. All three scenarios result in a reduction of coal power capacity on account of power plants reaching their end of life, along with partial coal retirement, emphasising its orientation toward a more diversified renewable mix. Across all scenarios, gas and nuclear remain unchanged, serving as stable, dispatchable baseload options within the system.

Figure 18 Relative Change in Capacity 2023 - 2030



5.4 System Cost Comparison

The wind-dominant scenario has the lowest cost, the balanced case is slightly higher, and the solar-dominant scenario is the most expensive due to greater storage, coal use, and market purchases.

Table 6 presents the total estimated system cost for the year FY 2029-30 under all three scenarios. The W_D case results in the lowest system cost with ₹ 5,170 Crore and the lowest cost of supply at ₹12.97/kWh, owing to both reduced variable costs and reduced fixed costs on account of lesser BESS capacity requirement, lower coal dispatch and better utilization of low-cost renewable sources. The Balanced case follows closely with ₹13.99/kWh. The S_D scenario has the highest cost of supply (₹14.49/kWh) due to higher battery storage requirements and increased coal usage, and power market purchases during solar unavailability periods. These results indicate that higher wind penetration not only reduces total system costs but also delivers co-benefits in terms of lower emissions and reduced flexibility requirements.

Table 6 System cost comparison by scenario

Cost parameter	S_D	Balanced	W_D
Fixed Cost (₹ Crore)	4,984	4,920	4,723
Variable Cost (₹ Crore)	796	658	447
Total System cost (₹ Crore)	5,780	5,578	5,170
Total Demand (GWh)	3,987	3,987	3,987
Cost of Supply (₹/kWh)	14.49	13.99	12.97

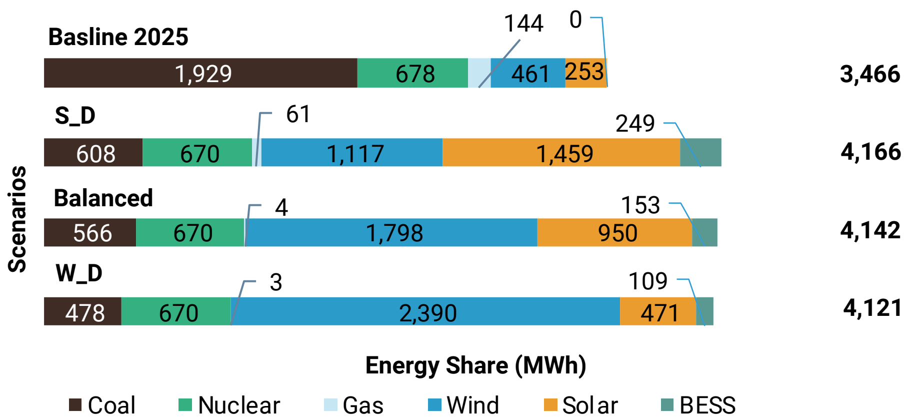
5.5 Energy share and Co_2 emissions by scenarios

Across all FY 2029–30 scenarios, wind and solar take a much larger share of generation while coal and gas decline, leading to lower emission intensities, with the wind-dominant case achieving the greatest CO_2 reduction.

Figure 19 illustrates the distribution of energy generation by source across various scenarios for the year FY 2029–30, highlighting both the total system output and each scenario's relative share of coal, gas, wind, solar, and battery storage (BESS). The baseline 2025 scenario is dominated by coal (56%), with renewables constituting a relatively small proportion (21%) of the mix. As the scenarios transition to the S_D to Balanced and W_D scenario for 2030, there is a marked increase in the share of wind and solar energy, accompanied by reductions in coal and gas contributions.

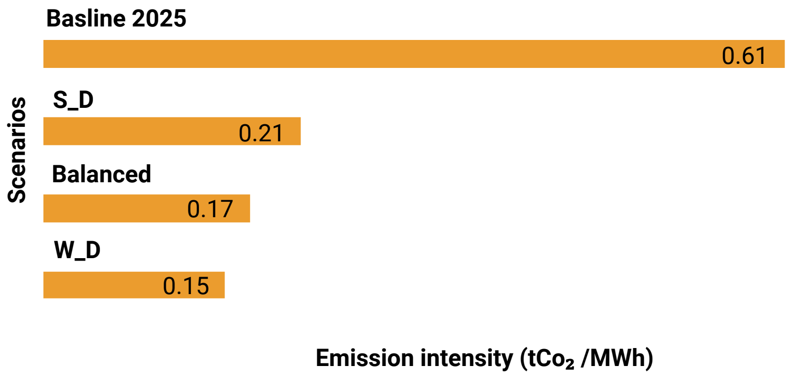
The S_D scenario shows a significant rise in solar output and a moderate increase in wind, resulting in a higher total generation and reduced reliance on fossil fuels. The Balanced scenario achieves a more even distribution between wind and solar while further curbing coal and gas generation. In the W_D scenario, wind energy forms the largest share of total output, further decreasing fossil fuel dependence and system emissions. Battery output increases modestly across the scenarios, supporting integration of higher renewable shares.

Figure 19 Energy share by source and scenario



Access to low-carbon electricity can be a significant advantage in attracting carbon-conscious industries and businesses. Compared with the baseline emission intensity for the year 2025, all three renewable energy (RE) scenarios for the year FY 2029-30 show substantial GHG emission reductions. Scenario W_D results in the lowest emission intensity of the power system, measured as tCO_2 per MWh.

Figure 20 Co_2 Emissions by scenario



5.6 Plant load factors

Key coal units such as Simhadri STPS 2, Vallur STPS, NLC TPS 2 STG 2, and NTPL run at high PLFs and provide vital baseload, while several Ramagundam and NLC units are at zero or very low PLF, and gas use in the solar-dominant case rises to support evening demand when wind is limited.

Table 7 highlights Plant Load Factors (PLFs) across all power plants. It is evident that Simhadri STPS Stage 2, Vallur STPS, Kudgi, NLC TPS expansions, NTPL, and Neyveli NTPS consistently operate at high PLFs (≥60%), showing their critical role in ensuring base load supply across all scenarios. In contrast, Ramagundam STPS (STG 1, 2, and 3) and NLC TPS 2 STG 1 report 0% PLF because end of lifetime. Talcher STPS 2 has very low PLF, reflecting limited economic utilisation and potential candidacy for retirement.

Gas in S_D is having a PLF 24% in comparison to suggesting during evening periods heavier reliance on gas due to a lack of wind. Nuclear units operate at 100% PLF across all scenarios, consistent with their baseload role and technical operating constraints. Overall, PLFs trend across scenarios reflect a gradual shift toward higher renewable integration, with dispatchable thermal and gas units increasingly providing flexibility and peak support rather than continuous baseload operation.

Table 7 PLF by power plant

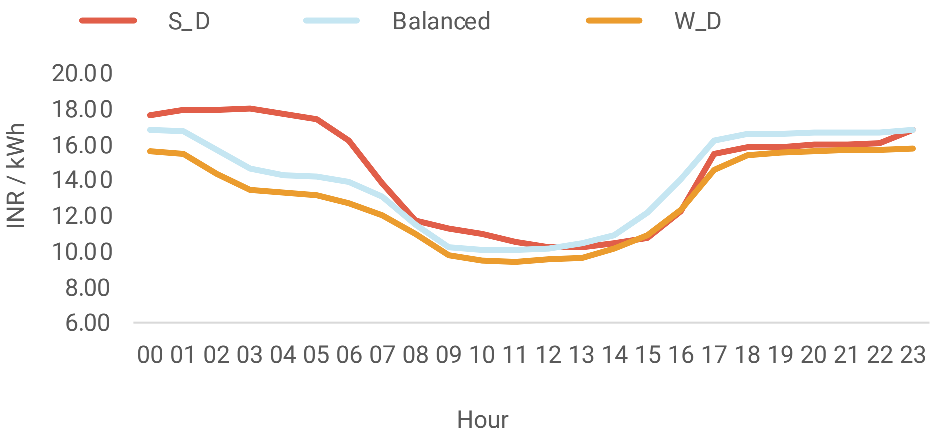
Power Plant	Category	S_D	Balanced	W_D
Solar utility scale	Solar	17%	17%	16%
Wind on-shore	Wind	24%	24%	24%
Ramagundam STPS STG 1 & 2	Coal	0%	0%	0%
Ramagundam STPS STG 3		0%	0%	0%
Talcher STPS 2		45%	39%	32%
Simhadri STPS 2		68%	61%	51%
Vallur STPS		69%	63%	53%
Kudgi		69%	64%	54%
NLC TPS 2 STG 1		0%	0%	0%
NLC TPS 2 STG 2		69%	66%	56%
NLC TPS 1 EXP		69%	67%	57%
NLC TPS 2 EXP		69%	68%	59%
NTPL(NLC)		69%	70%	60%
Neyveli NTPS		69%	70%	61%
MAPS	Nuclear	100%	100%	100%
Kaiga_1&2		100%	100%	100%
Kaiga_3&4		100%	100%	100%
KKNPP		100%	100%	100%
KKNPP_2		100%	100%	100%
Karikal GPP	Gas	24%	1%	1%

5.7 Cost of supply analysis

Puducherry's supply costs follow a U-shaped daily pattern—cheapest around midday when solar output is strong and highest in the early morning and evening—so shifting flexible demand to daytime hours can lower overall costs, with wind leaning or balanced mixes generally moderating costs better than solar dominant ones, especially in monsoon and winter.

The figure 21 indicates that Puducherry's annual average cost of electricity supply is highest in the early morning and evening, and lowest from late morning to early afternoon. The three curves follow the same U-shape, with the "S_D" case generally costing more than "Balanced" and "W_D". In practice, this means supply is cheapest around midday, when generation and network operation are more efficient, and most expensive during the evening peak, when higher demand forces the use of costlier power and raises losses. Consequently, shifting flexible consumption from evening and early-morning hours into the midday period would tend to lower overall supply costs and improve system efficiency.

Figure 21 : Annual average hourly cost of supply



Across all quarters, the three renewable scenarios (S_D, Balanced, W_D) show a similar “U-shaped” daily pattern, with the highest costs in the late evening/night and the lowest costs in mid-day when solar output is strongest (refer to Figure 22).

Q1: Apr–Jun: All scenarios see costs fall sharply from early morning peaks toward a broad minimum around hours 9–13, reflecting strong solar contribution in summer. The S_D (solar-dominated) case achieves the lowest mid-day costs but the highest cost during late night (hours 1 to 4). It further shows a steeper cost increase in late afternoon and evening, indicating higher evening balancing needs compared with the Balanced and W_D cases.

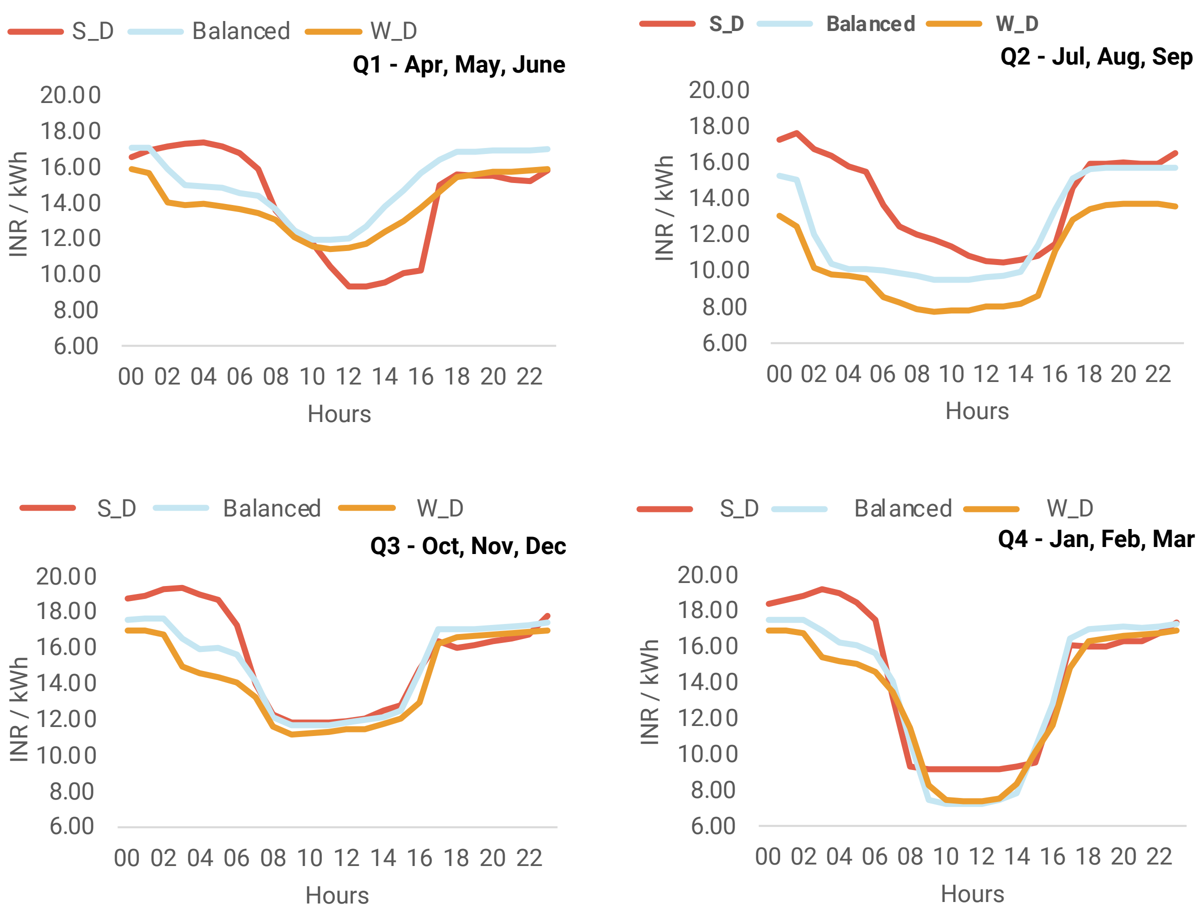
Q2: Jul–Sep: Costs start relatively high at night, then decline through the morning to a mid-day trough, but the S_D curve remains noticeably higher than in Q1, suggesting weaker or more variable solar resource during the monsoon period. The W_D (wind-dominated) and Balanced scenarios keep costs of supply lower and flatter for nearly all 24 hours of the day compared to S_D, implying that greater wind share helps moderate supply costs.

Q3: Oct–Dec: The three scenarios converge more closely, with similar low mid-day costs and a gradual rise toward evening, indicating that both solar and wind are contributing reasonably well and that system balancing needs are more uniform across scenarios. The S_D line is still higher around late night and early morning hours. (hours 1 to 4).

Q4: Jan–Mar; All scenarios exhibit the deepest mid-day cost valley of the year, but also the steepest rise from late afternoon into evening, pointing to pronounced evening ramp requirements in winter. The W_D scenario maintains the lowest costs from late afternoon through night.

Solar dominance delivers clear mid-day cost benefits in high-insolation months (Q1, Q4) but exposes the system to higher evening costs, especially in monsoon and winter. A wind-leaning or Balanced mix tends to smooth costs across the day and performs better in monsoon (Q2) and winter evenings (Q4), suggesting that planning for Puducherry should pair solar deployment with sufficient wind.

Figure 22 Average hourly cost of supply by quarter



5.8. Net load analysis

Net load patterns show that the solar dominant (S_D) scenario creates more extreme low and high net loads and steeper post solar ramps, increasing flexibility needs, while Wind Dominant (W_D) and balanced scenarios moderate evening peaks and reduce ramping requirements.

The net load distribution depicted in Figure 23 illustrates the frequency of net load occurrences across specific load range intervals for each of the three renewable energy scenarios. The S_D scenario exhibits higher counts at both extremes of the spectrum—the higher and lower load ranges—relative to the W_D and Balanced scenarios. This pattern suggests an increased requirement for grid flexibility measures, including energy storage solutions, demand response programs, and adaptable power generation resources.

Figure 23 Net Load Frequency Distribution by Scenario

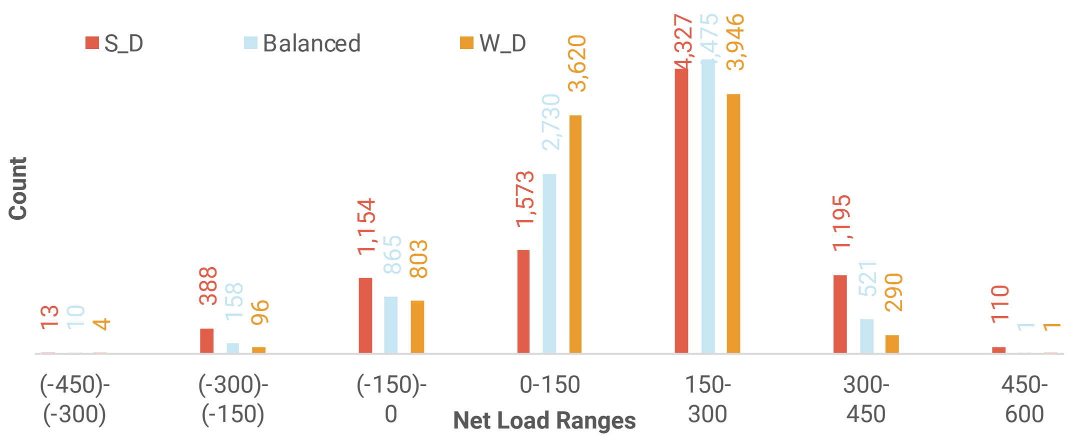


Figure 24 compares the average annual hourly net loads across the three scenarios. The net load here refers to the total load minus wind and solar generation. It serves as a good indicator of renewable energy contribution, as well as the grid integration challenges and flexibility requirements of the system. All three scenarios show negative or near-negative loads during peak solar generation hours, which is most pronounced in the S_D scenario. This indicates that the combined generation from wind and solar either matches or exceeds the demand. In such cases, grid operators must rely on energy storage systems, shiftable loads, marketplaces for selling excess generation, or curtailment of some solar and wind output. The S_D scenario exhibits a steep increase in net load during late afternoon and evening hours, implying higher ramping requirements from dispatchable resources. In comparison, the W_D and Balanced scenarios display smoother evening transitions, driven by higher wind availability during non-solar hours.

Figure 24 Average annual net load by scenario

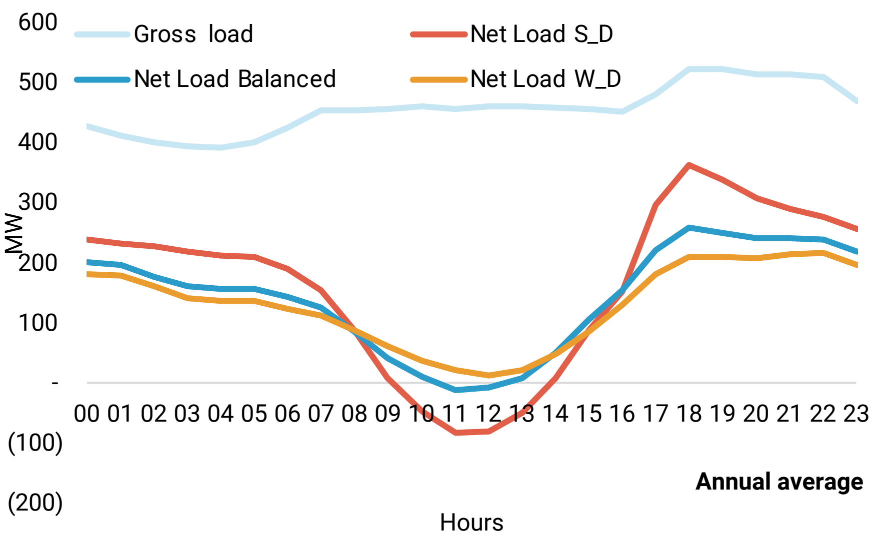
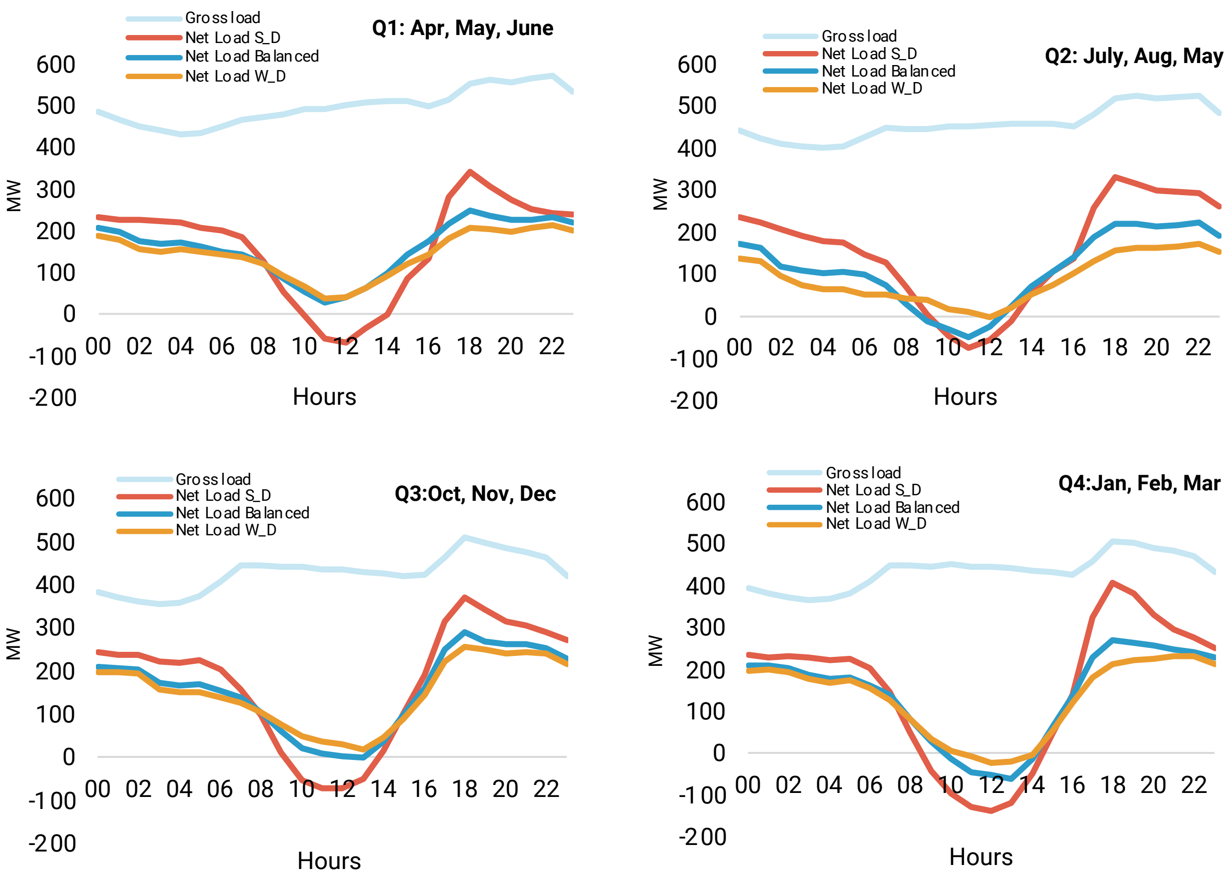


Figure 25 shows quarterly net load profiles for each scenario, highlighting seasonal differences in net load behaviour. The S_D scenario consistently exhibits deeper mid-day net load troughs and sharper evening ramps, particularly during high-solar quarters, while the W_D and Balanced scenarios demonstrate more stable net load profiles across seasons. These results underscore the role of wind generation in mitigating net load variability and reducing flexibility requirements over both daily and seasonal timescales.

Figure 25 Quarterly net loads by scenario



5.9 Deep dive – net load ramping

Net load ramping events mostly lie within ±100 MW, with the solar dominant case showing the highest counts of large ramps, wind dominant showing lower costs for moderate ramps, and the most extreme multi-hour ramps clustering in the afternoon and evening, especially in certain quarters.

Frequency Distribution of Ramping Instances: The first section visualises how often different ramping rates occur within three system conditions: S_D, Balanced, and W_D. In each scenario, the vast majority of ramping events are clustered between -100 and +100 MW per hour. S_D scenario accounts for the highest number of ramping events in the magnitude of 200 to 300 MW per hour (134 counts) and 300 to 400 MW per hour (5 counts), and the lowest in the Balanced scenario (with 2 counts for 200 to 300 MW per hour and 1 count for 300 to 400 MW per hour). Similarly, the high magnitude ramping down instance in the -400 to – 300 MW per hour range and the -300 to -200 MW per hour range have the highest count for the S_D scenario and the lowest count for the Balanced scenario.

The average cost of supply, shown alongside, is highest for the high ramping rates (200 to 400 MW per hour) under the S_D scenario. The chart also shows a clear difference in the average cost of supply for ramping events between -300 and -400 MW per hour, where the W_D scenario has a significantly lower average cost of supply compared to the S_D scenario.

Top 5% Ramping Up and Down Instances by Hour and Quarter: The top 5% of the most significant ramping events are mapped against hours of the day and grouped by quarter. This reveals a clear pattern, where the most extreme ramping typically occurs during the late afternoon and evening hours, especially between 17:00 and 20:00. However, this pattern is less pronounced for the W_D scenario in which the ramping up instances are equally distributed over the 24 hours of the day, particularly so in Q2, with the wind season ramping events are more distributed.

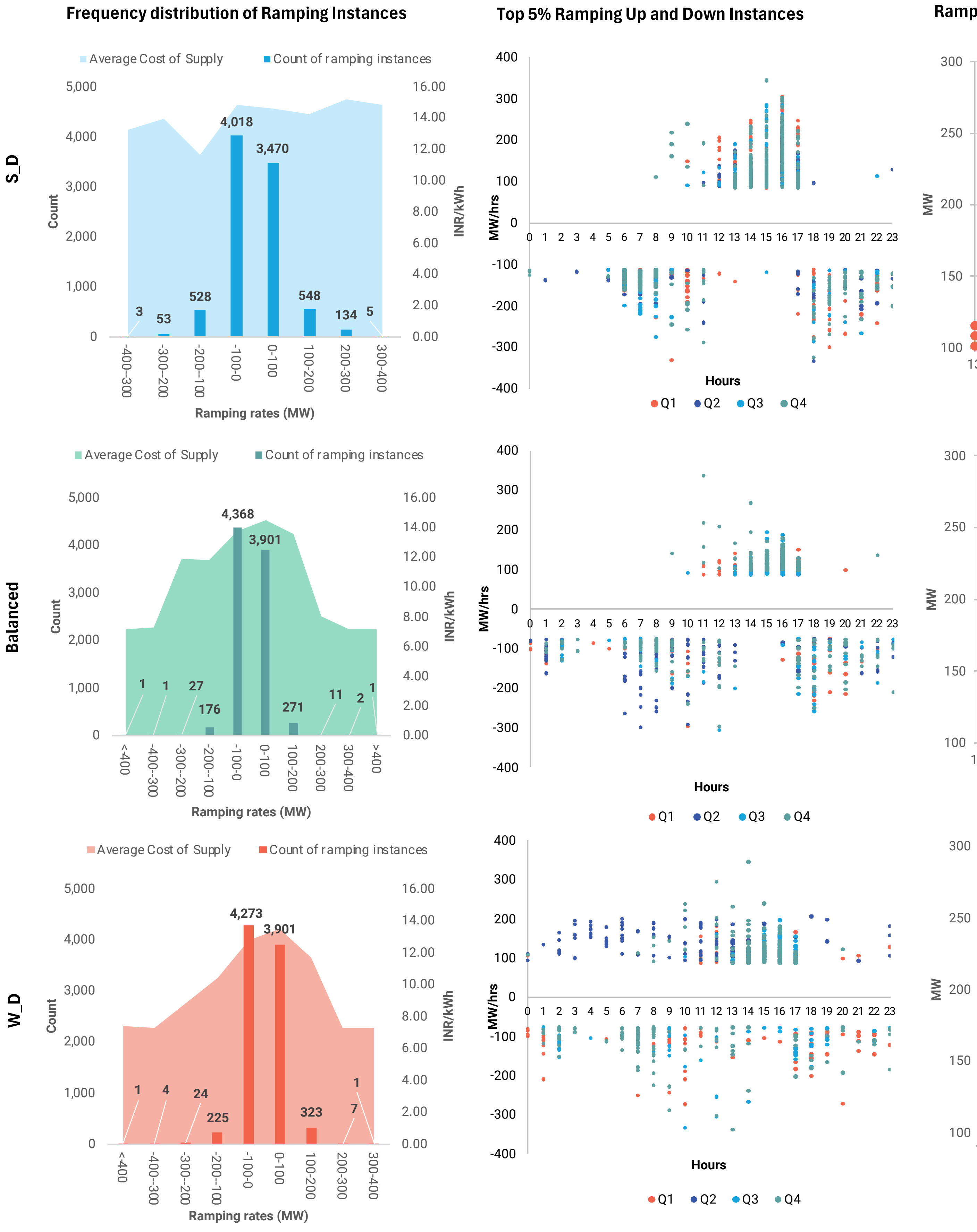
Ramping Instances > 100 MW by Duration: This portion examines only those ramping events that exceed 100 MW in magnitude and are of 3 to 4 hours duration over the course of the 24 hours of a day. These events require the highest degree of grid flexibility. All of these ramping instances, for all scenarios, occur between 13:00 hrs and 17:00 hrs. The S_D scenario has both the highest count of these ramping events and also shows the highest magnitude of these events

Ramping Instances > 100 MW/hr by Count and Duration: Here, high-magnitude ramping events are further categorised by how many hours they persist and which quarter they fall into. The majority of these ramping events greater than 100 MW per hour last for one hour only. Ramping events with 4-hour duration are found only in Q3 and Q4, and this is for all three scenarios, suggesting heightened volatility during parts of the year that may correspond to seasonal weather or load changes.

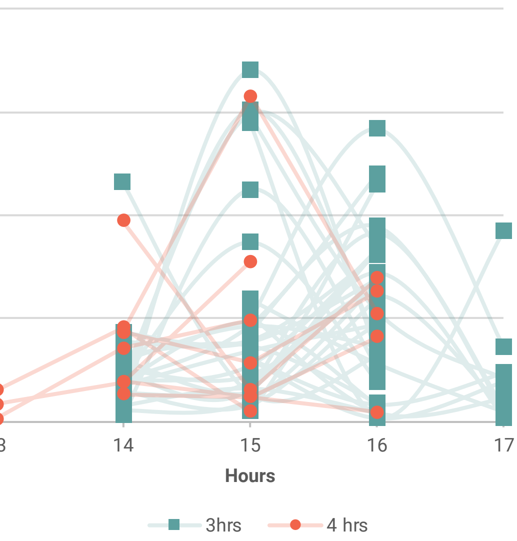
Top 15 Ramping Instances: The final section lists the most extreme single-hour ramping events for each scenario, noting the time of day and month they occur. It becomes evident that the largest swings in power output usually take place in the evening, again between 18:00 and 20:00 across all scenarios. However, there is a significant variant among the three scenarios in terms of the month and magnitude of the recorded ramping events.

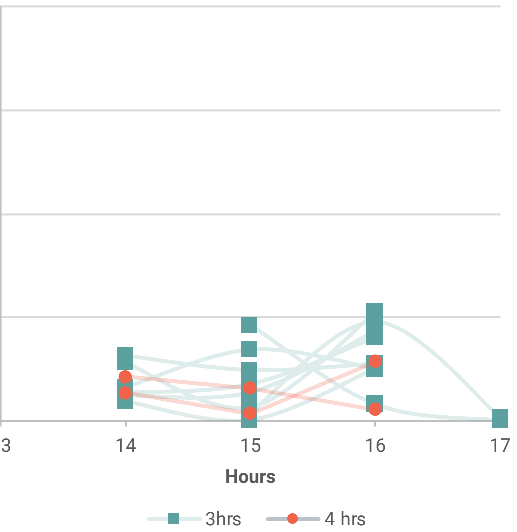
Overall, the ramping analysis demonstrates that solar-dominant system configurations significantly amplify both the frequency and severity of net load ramping events, particularly during the afternoon-to-evening transition. These effects translate into higher operational costs and greater reliance on flexible resources. In contrast, wind-leaning and balanced renewable mixes smooth ramping behaviour, disperse extreme events across a wider set of hours and seasons, and are associated with lower system costs during ramping conditions. These results highlight the critical role of resource diversity in managing ramping stress and underscore the need for flexibility measures—such as storage and demand-side interventions—to effectively manage high-solar systems.

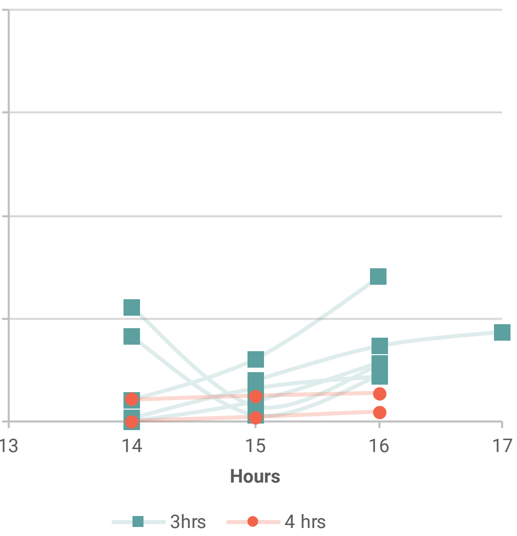
Figure 26 Ramping up instances by scenario



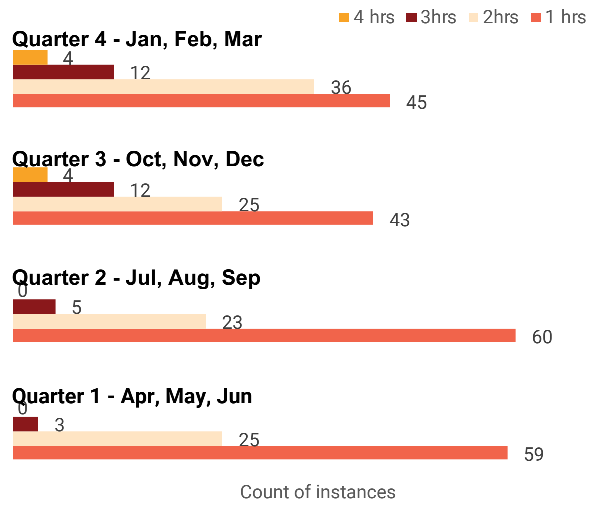
ing Instances > 100 MW by Duration

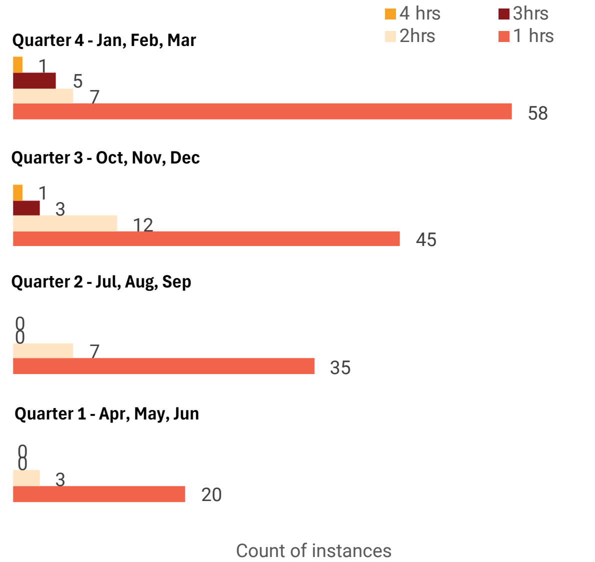


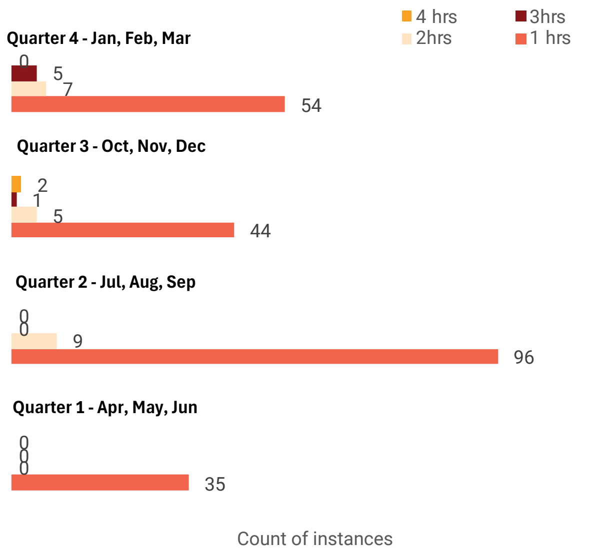




Ramping Instances by > 100 MW/hrs counts by Duration







Top 15 Ramping Instances

No	MW/hrs	Month	Time
1	344	February	15:00
2	305	April	16:00
3	304	April	16:00
4	303	March	16:00
5	301	February	16:00
6	299	April	16:00
7	298	April	16:00
8	297	March	16:00
9	295	December	16:00
10	294	March	16:00
11	294	April	16:00
12	293	February	16:00
13	288	April	16:00
14	285	November	15:00
15	284	December	16:00

No	MW/hrs	Month	Time
1	402	August	12:00
2	337	February	11:00
3	308	August	13:00
4	299	August	12:00
5	268	January	14:00
6	263	August	11:00
7	260	August	13:00
8	260	August	12:00
9	253	August	14:00
10	239	August	13:00
11	229	August	14:00
12	217	August	13:00
13	217	February	11:00
14	209	January	12:00
15	197	August	12:00

No	MW/hrs	Month	Time
1	346	February	14:00
2	294	February	12:00
3	239	January	15:00
4	238	February	10:00
5	230	February	13:00
6	222	February	10:00
7	206	July	18:00
8	203	February	12:00
9	200	August	06:00
10	199	August	10:00
11	198	July	19:00
12	198	August	12:00
13	197	November	16:00
14	196	January	14:00
15	196	August	03:00

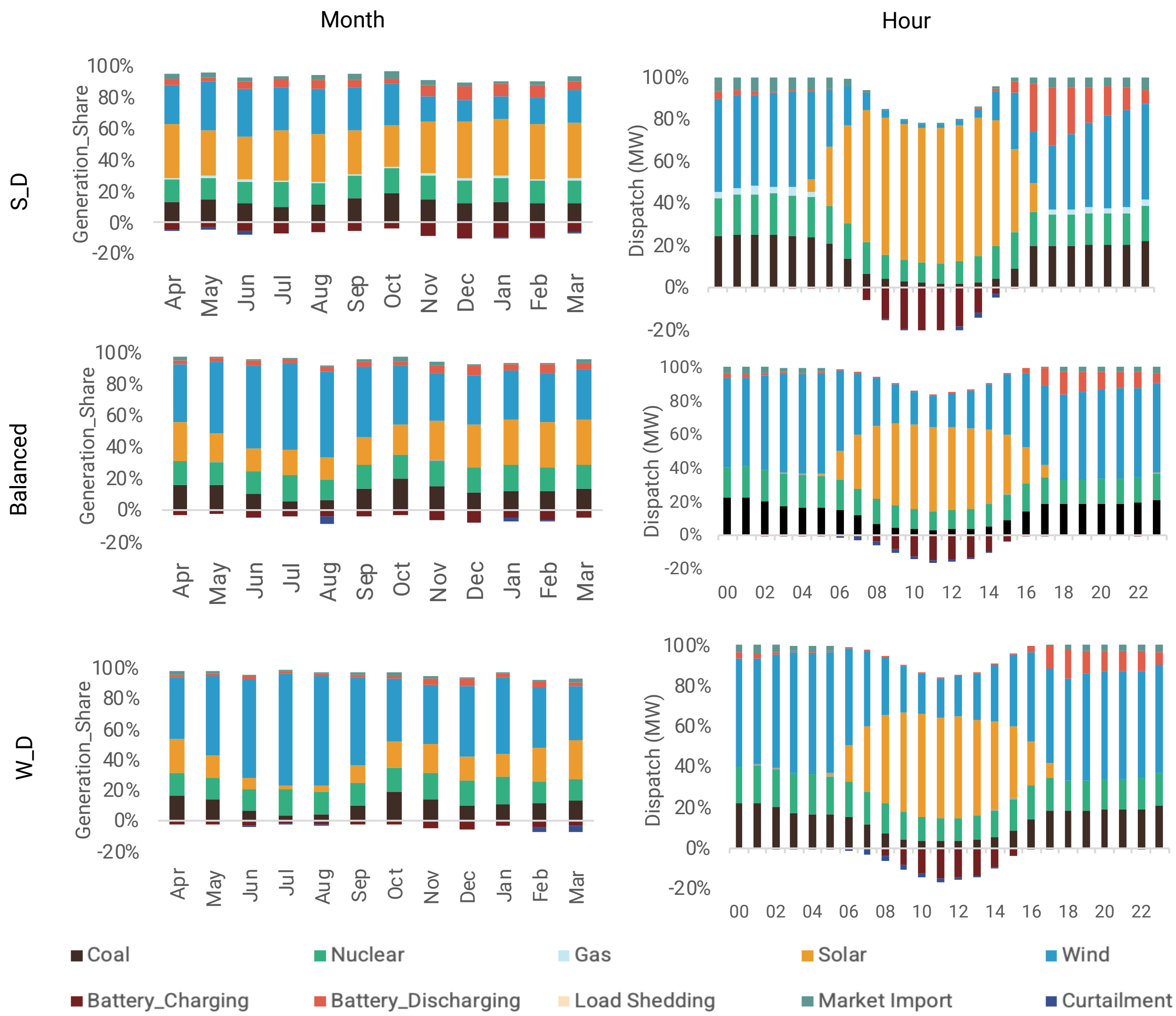
5.10 Energy Dispatch Analysis

Nuclear provides a steady year-round baseload share, while renewable contributions from solar and wind peak in the monsoon months and dip in October, with hourly dispatch showing daytime solar peaks and steadier wind output that supports supply during non-solar hours.

Across all three scenarios, monthly generation patterns depicted in Figure 27 show that nuclear energy maintains a consistent share throughout the year, contributing approximately 16% each month. This steady performance underscores the baseload nature of nuclear power, which operates continuously with minimal seasonal fluctuation. In contrast, the share of renewable energy—namely wind and solar—varies both across scenarios and throughout the year. In the Solar-Dominant (S_D) scenario, renewable energy achieves its highest contribution in June, reaching nearly 78% as a result of strong solar availability during that period. The Balanced scenario shows renewable energy peaking in July and August at about 83%, reflecting a synergistic effect between strong solar and wind profiles. The Wind-Dominant (W_D) scenario sees the highest renewable share in August, climbing to roughly 80%, a direct result of increased wind output. Each scenario's highest renewable shares align with the monsoon or periods of high wind, highlighting the system's reliance on seasonal patterns.

Conversely, the lowest renewable shares occur in October across all scenarios, with the S_D scenario dropping to about 56%, the Balanced scenario to 60%, and the W_D scenario maintaining a relatively higher share at 64%. This reduction corresponds to temporary lows in both wind and solar availability, demonstrating the impact of weather cycles on the generation mix. The role of gas generation changes considerably across scenarios—particularly in the S_D scenario, gas contributes around 1% from April to September and rises to 2% from October to March, stepping in when solar output wanes or extra ramping is required to meet demand.

Figure 27 : Monthly average and annual hourly average generation share by source across all scenarios.



The three charts on the right side in Figure 27 above display the hourly dispatch profiles for each scenario: Solar-Dominant (S_D), Balanced, and Wind-Dominant (W_D). Each chart reveals how the share of different sources changes throughout a typical day.
In the Solar-Dominant scenario, solar generation rises sharply in the morning, peaks between 10 AM and 2 PM, and then drops off rapidly by evening. During nighttime hours, dispatch relies heavily on non-solar sources such as wind, nuclear, and gas, which fill the gap left by the absence of solar energy.

The Balanced scenario demonstrates significant contributions from both solar and wind during daylight hours. Solar again rises sharply mid-morning and peaks midday, but wind also provides a stable share throughout the day and night. This results in a smoother dispatch profile, with less reliance on non-renewable sources during nighttime compared to the S_D scenario.

The Wind-Dominant scenario highlights strong wind generation throughout the day and night, particularly during non-solar hours. Solar contributes during midday but is less dominant than in the S_D scenario. Wind fills most of the supply outside the solar window, reducing the dependence on other sources after sunset and before sunrise.
Overall, these hourly charts illustrate the impact of renewable mix on grid flexibility, showing that solar peaks during the day and requires complementary sources at night, while wind provides steadier output that supports supply during times when solar is unavailable.

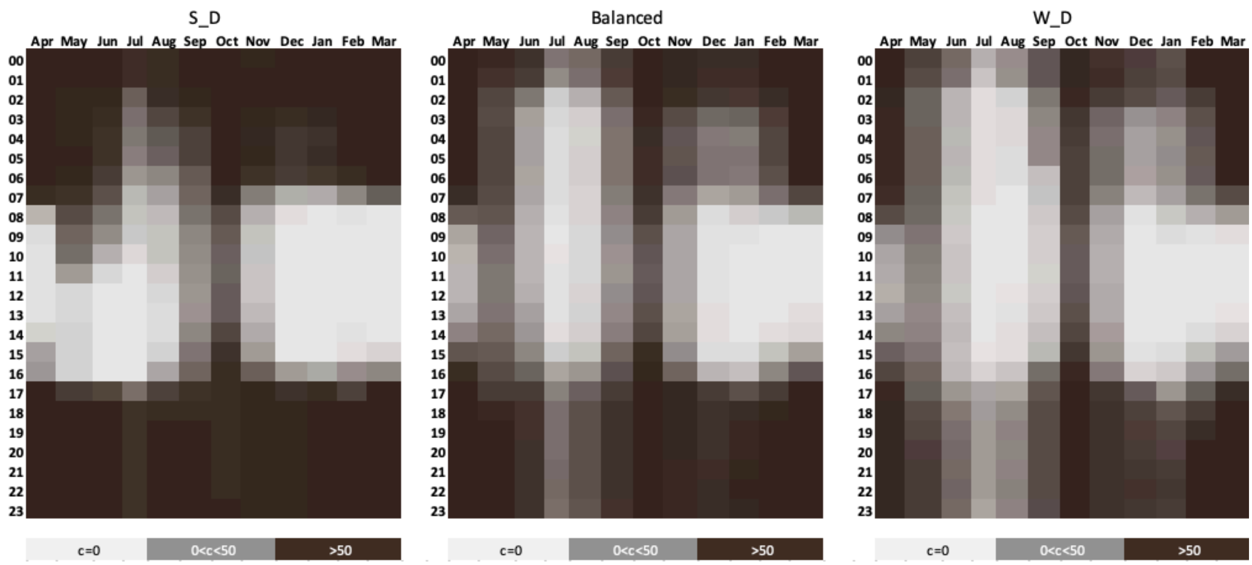
5.11 Coal Dispatch Patterns

Coal dispatch is highest in the solar-dominant case during the monsoon and remains elevated on some high-demand spring days, as limited wind, peak loads, and technical constraints prevent coal plants from ramping down even when solar output is strong.

Figure 28 highlights that coal dispatch during July and August is noticeably higher in the Solar-Dominant (S_D) scenario compared to the Balanced and Wind-Dominant (W_D) scenarios. This increase is mainly due to the lower penetration of wind in the S_D scenario, resulting in greater reliance on coal to meet demand. In contrast, both the Balanced and W_D scenarios maintain reduced coal use during these months, likely because sufficient wind generation is available to offset the seasonal decline in solar output. These scenarios also show a higher overall contribution from renewables, further reducing coal dependence compared to the S_D scenario.

During solar hours, approximately from 08:00 to 17:00 in April and May, both the Balanced and W_D scenarios exhibit elevated coal dispatch. This pattern is counterintuitive given the typically robust solar availability during these months. One explanation is that system demand is close to its annual peak, requiring additional thermal support despite high solar output. Additionally, technical constraints such as the minimum load requirements for coal plants limit their ability to ramp down during periods of strong solar generation, resulting in sustained coal operation even when renewables are

Figure 28 Average hourly coal dispatch for each month



5.12 Battery Storage Dispatch Patterns

Battery storage cycles most intensely in the solar-dominant case—charging during sunny hours and discharging to cover evening and winter deficits—while balanced and wind dominant systems lean more on wind to meet off-solar demand and therefore require less battery use.

Figure 29 presents the average hourly battery charging patterns across months for each scenario, while Figure 30 shows the corresponding discharging patterns. Storage utilization differs significantly among the scenarios. In the solar-dominant (S_D) scenario, battery storage exhibits the highest levels of activity—both charging and discharging—compared to the balanced and wind-dominant (W_D) cases. This demonstrates the strong dependence of battery charging on solar generation, with most charging taking place during hours of high solar output and discharging occurring to satisfy evening or non-solar demand.

The most pronounced battery discharging activity is observed during the months of November through February, when reduced solar availability coincides with increased evening demand. By contrast, the balanced and wind-dominant scenarios display lower reliance on battery storage. Greater wind penetration in these scenarios helps meet demand during non-solar hours, thus reducing the need for batteries to balance supply. These observed heatmap patterns highlight the complementarity between solar resources and battery storage and show that wind-dominant systems are able to minimize battery cycling requirements. This relationship is apparent in both the charging and discharging heatmaps, which visually capture the dynamic storage operations across scenarios and seasons

Figure 29 Average hourly BESS charging pattern across months for each scenario

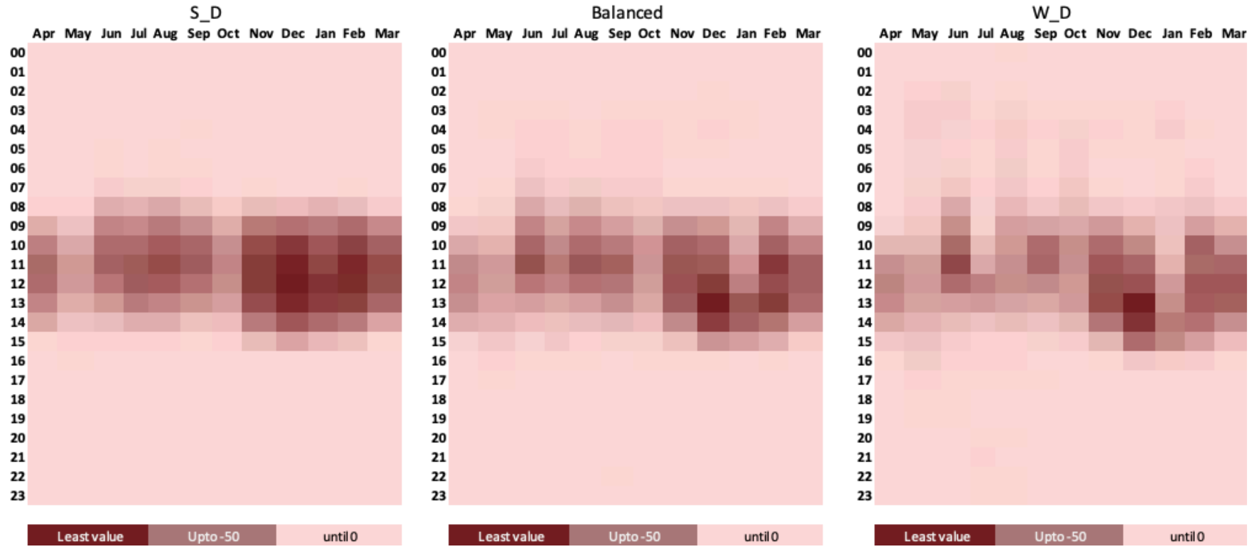
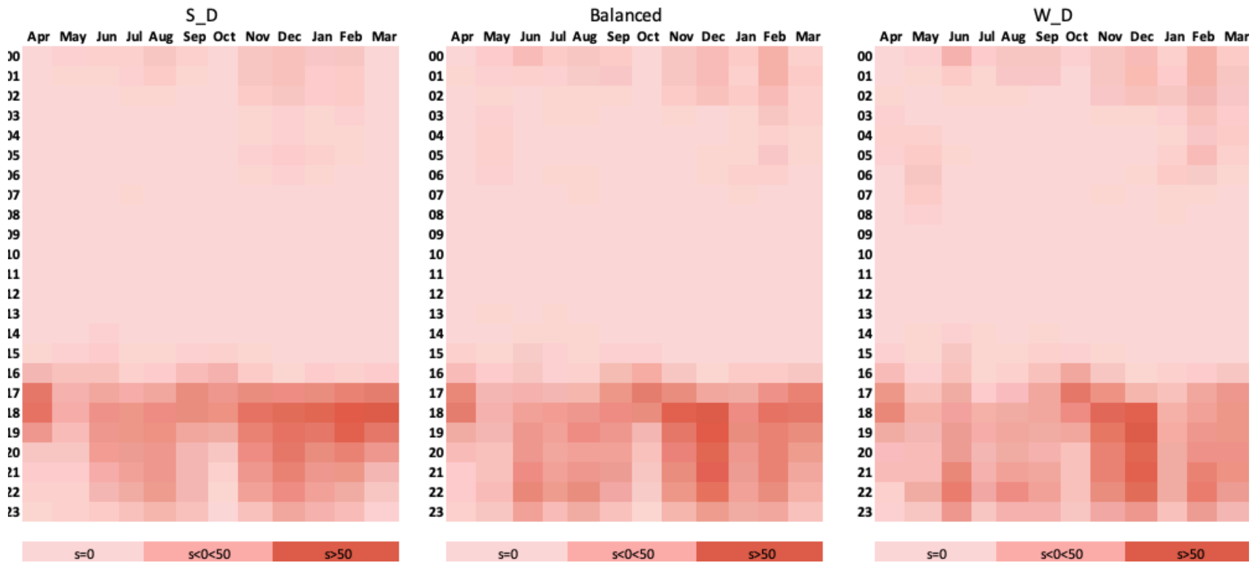


Figure 30 Average hourly BESS discharging pattern across months for each scenario



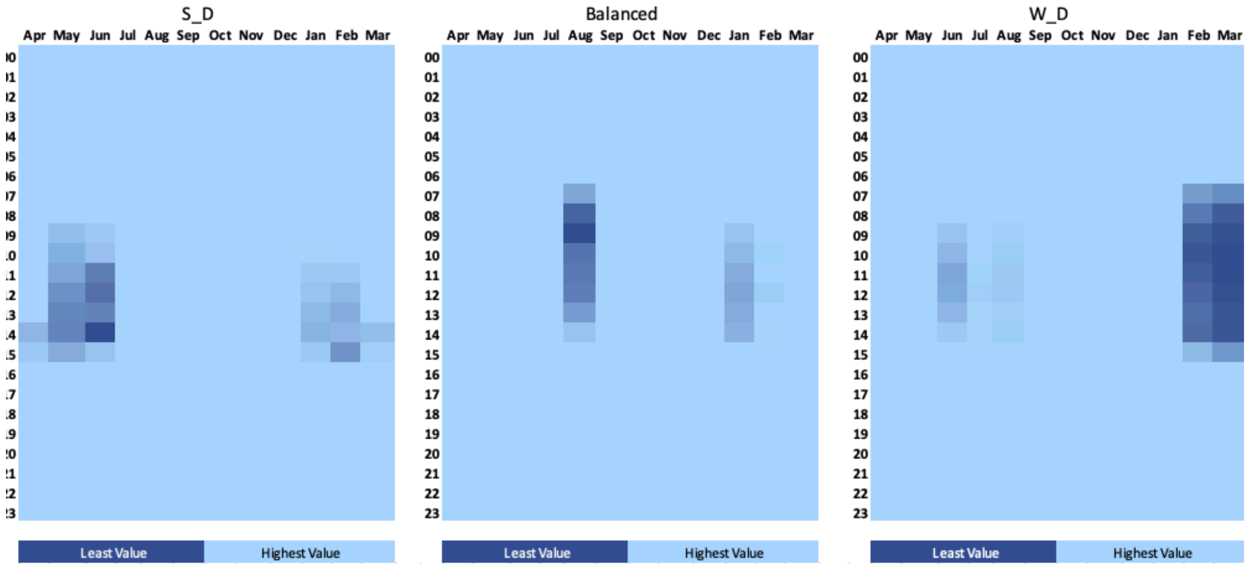
5.13 Curtailment trends

Curtailment is highest in the wind-dominant scenario—especially during daytime hours when both wind and solar are strong—while storage use peaks in the solar-dominant case, and all scenarios see seasonal curtailment spikes driven by periods of overgeneration from wind and solar.

Figure 31 displays the average curtailment patterns observed across the different scenarios. A clear contrast emerges between storage operation and renewable energy (RE) curtailment across the three scenarios. Storage utilisation is highest in the Solar-Dominant (S_D) scenario, while curtailment is most pronounced in the Wind-Dominant (W_D) scenario. This indicates that, although W_D benefits from greater renewable output, particularly from wind, the system struggles to fully integrate this energy, resulting in significant curtailment. In the W_D scenario, curtailment is especially concentrated during solar hours, from 08:00 to 16:00, when both wind and solar generation reach high levels, but the system lacks sufficient flexibility to absorb the surplus.

In both the S_D and Balanced scenarios, curtailment spikes notably during June and July, even though solar availability is not at its annual maximum. This suggests wind generation is the primary driver for curtailment during these months. The W_D scenario, on the other hand, shows a marked increase in curtailment during March and April, particularly in daytime hours. The dense orange bands in the heatmap suggest that overgeneration from both solar and persistent wind is contributing to these higher curtailment levels.

Figure 31 Average curtailment patterns observed across different scenarios



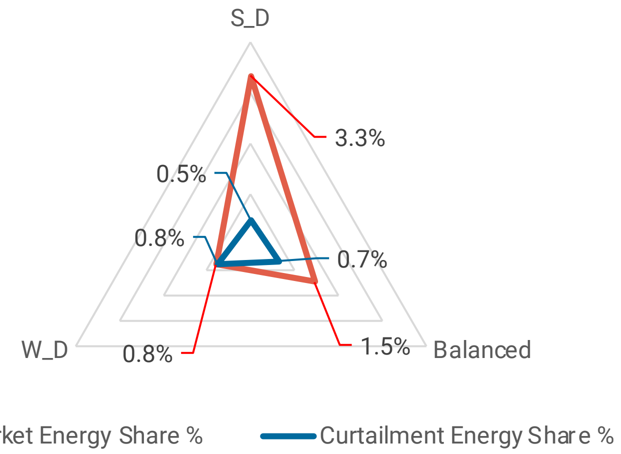
5.14 RE curtailment and market purchase

The solar-dominant case buys the most from external markets but curtails the least RE, while the wind-dominant case minimises market purchases at the cost of higher curtailment, underscoring the value of stronger demand side flexibility to absorb surplus generation.

The comparative analysis of market energy share and curtailment of wind or solar energy across the three scenarios highlights distinct operational challenges and benefits. The S_D scenario records the highest market energy share (3.35%), reflecting a greater reliance on external market purchases to meet demand, likely due to limited system flexibility and a lower renewable surplus. RE curtailment is lowest in this scenario (0.50%). In the Balanced scenario, market purchases decrease to 1.46% compared to S_D, while RE curtailment rises slightly to 0.65%. The W_D scenario demonstrates the lowest market dependency (1.25%) but the highest RE curtailment (1.22%). This increase in curtailment is driven by oversupply during peak wind generation hours, surpassing available storage and system absorption capacity.

Overall, the trade-off between market dependence and renewable energy curtailment across scenarios highlights a key system optimisation challenge. While higher wind penetration reduces reliance on external markets, it also increases periods of surplus generation that the system is unable to absorb. Addressing this imbalance through improved demand-side flexibility and load alignment can help simultaneously reduce curtailment and market exposure, enabling more efficient utilisation of renewable resources and lowering overall system costs.

Figure 32 Curtailment and market purchases by scenario



	S_D	Balanced	W_D
Market Energy Share (MWh)	1,44,316	61,367	32,852
Curtailment Energy Share (MWh)	21,363	27,389	30,840

06

12.26 ₹/kWh
Time of use tariffs for the lower the cost of supply

Up to 72%
Time-of-use tariffs allow higher integration of renewables

0.09 t/CO_2/MWh
Carbon emission intensity is further lowered

TIME VARYING TARIFFS AS A FLEXIBILITY STRATEGY

In this chapter, four different Time-of-Use (ToU) tariff scenarios are presented. These ToU tariffs are simulated only for the Wind-Dominated Renewable Energy (RE) scenario, as this scenario demonstrates the lowest system cost, the lowest carbon emission intensity, and fewer instances of high ramping.

The Time-of-Use (ToU) scenarios differ across five key parameters:

- Variation in the magnitude of the peak-hour tariff increase.
- Variation in the off-peak-hour tariff rebate.
- Variation in the time slots designated for peak hours.
- Variation in the time slots designated for off-peak hours.
- Inclusion of a “solar sponge” period — a tariff rebate applied during hours of high solar generation.

Table 8 ToU Scenario Design Parameters

Scenario	Peak tariff increase	Off- peak tariff rebate	Peak hours	Off-peak hours	Solar Sponge	Applicable to
W_D BAU	20%	10%	18:00 to 22:00	22:00 to 06:00	No	HT/EHT industrial consumers
W_D NoToU	0%	0%	N/A	N/A	No	All consumers
W_D ToU_1	25%	15%	6:00 to 7:00 and 17:00 to 23:00	0:00 to 5:00	No	All consumers
W_D ToU_2	25%	15%	6:00 to 7:00 and 17:00 to 23:00	0:00 to 5:00	10:00 to 16:00 (15% reduction)	All consumers

The W_D Bau case is the same as the W_D scenario of the earlier chapter; the BAU in this context reflects the current ToU tariff design applicable in Puducherry. As of 2025, Time-of-Use tariffs are available only for large industrial (HT/EHT) consumers in Puducherry, and are not yet applicable to all categories, particularly domestic users.

The peak tariff rate determines electricity costs during peak hours, while the rebate provides a discount for electricity consumed during designated off-peak hours. These defined time periods dictate when the higher tariff or rebate applies. The “solar sponge” is a specific tariff rebate that encourages solar energy consumption, prevents curtailment of solar power, and reduces the need for energy storage.

6.1 High Level Results

Targeted ToU tariff designs, especially W_D ToU_2, enable Puducherry’s wind dominated system to integrate the highest shares of wind and solar while delivering the lowest peaks, reduced ramping, and the lowest overall system costs.

The results in Table 9 illustrate how varying renewable energy scenarios and tariff structures shape key performance parameters of Puducherry’s power system. Across all four cases, wind consistently contributes a high share to the mix—ranging from 54% in W_D BAU to 59% in both W_D NoToU and W_D ToU_2 - while the solar share remains lower, from 11% up to 13% in W_D ToU_2. Battery Energy Storage System (BESS) shares are modest in all scenarios, holding between 2% and 3%. The W_D ToU_2 scenario that introduces a solar sponge, a tariff rebate during solar hours, enables higher utilisation of both wind and solar generation compared to other tariff cases.

Gross and net peak and system cost outcomes differ notably across the scenarios, with the WD_ToU_2 outperforming the other scenarios on all three parameters. It achieves the lowest gross peak with 613 MW, the lowest net peak of 398 MW and the lowest system cost at ₹4,869 crore. Maximum ramping events, which quantify short-term fluctuations in net demand, are similarly impacted. WD_BAU and WD_NoToU record the highest values at 346 MW, while time-of-use scenarios (W_D ToU_1 and W_D ToU_2) reduce these ramping events to 303 MW and 307 MW, respectively, demonstrating the ability of tariff restructuring to smooth load profiles and facilitate renewable integration.

Overall, the table underscores that targeted ToU tariff interventions (particularly WD_ToU_2) deliver both lower system costs and reduced peak/ramping challenges, highlighting the value of flexible demand management for Puducherry’s future power planning.

Table 9 High-level results by scenario

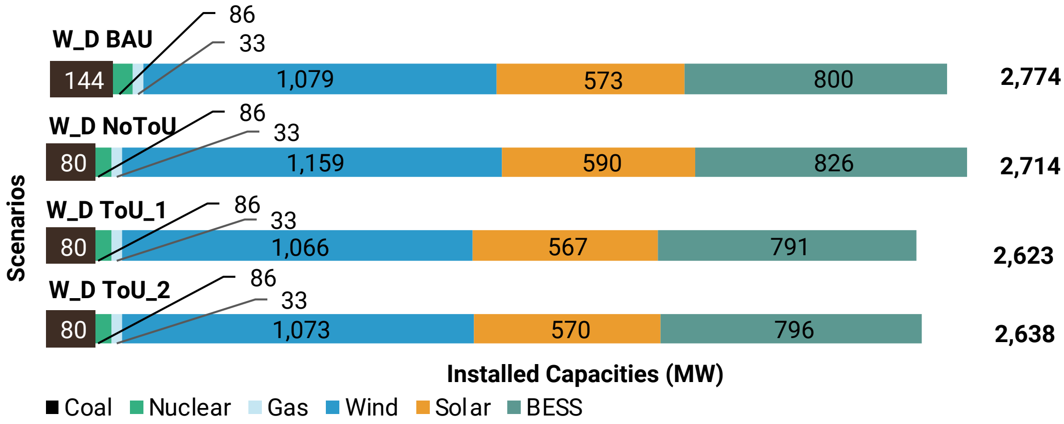
Parameters	W_D BAU	W_D NoToU	W_D ToU_1	W_D ToU_2
Wind share (%)	54%	59%	58%	59%
Solar share (%)	11%	11%	11%	13%
BESS share (%)	3%	2%	2%	2%
Gross peak (MW)	631	660	613	613
Net peak (MW)	462	430	459	398
Max ramping event (MW)	346	346	303	307
Total system cost (₹ Crore)	5,179	5,513	5,065	4,869

6.2 Projected generation capacities

A modified ToU tariff in the wind-dominated scenario cuts total power generation capacity from 2,714 MW to 2,638 MW (2.84%).

Introducing a modified ToU tariff design in the wind-dominated scenario slightly lowers the total generation capacity required while keeping the technology mix broadly similar. Moving from the W_D BAU to W_D ToU_2 scenario, the total installed capacity reduces from 2,714 MW to 2,638 MW, a reduction of 76 MW or 2.84% mainly through modest reductions in wind, solar and BESS, a clear reduction in coal while maintaining the same nuclear and gas capacities. Under W_D NoToU, W_D ToU_1, and W_D ToU_2, coal plants with a plant load factor below 40% are phased out, reinforcing the shift away from inefficient coal as demand becomes better aligned with wind generation.

Figure 33 Installed Capacities in Different Scenarios



6.3 System Cost Comparison

Time-of-use tariffs substantially lower total system costs and average supply prices, with the most advanced design (W_D ToU_2) delivering the cheapest power by shifting demand to lower-cost hours and reducing both fixed and variable cost requirements.

The system cost comparison presented in Table 10 demonstrates that adopting ToU tariff designs can significantly impact both total system costs and the cost of electricity supply. The scenario with the most advanced ToU design (W_D ToU_2) achieves the lowest total system cost (₹4,868 crore) and the lowest cost of supply (₹12.26/kWh), compared to the business-as-usual (W_D BAU) and W_D NoToU cases. This reduction in system cost is driven by lower fixed and variable costs, highlighting the operational and economic efficiency gained through ToU tariffs. By incentivising demand shifts to lower-cost periods, ToU designs optimise resource utilisation and minimise the need for expensive peak-time supply, delivering tangible cost benefits to the power system.

Table 10 System cost comparison by scenario

Cost parameter	W_D BAU	W_D NoToU	W_D ToU_1	W_D ToU_2
Fixed Cost (₹ Crore)	4,723	4,998	4,655	4,488
Variable Cost (₹ Crore)	447	515	409	380
Total System cost (₹ Crore)	5,170	5,513	5,064	4,868
Total Demand (GWh)	3,987	4,094	3,949	3,972
Cost of Supply (₹/kWh)	12.97	13.47	12.82	12.26

6.4 Energy share and CO_2 emissions by scenarios

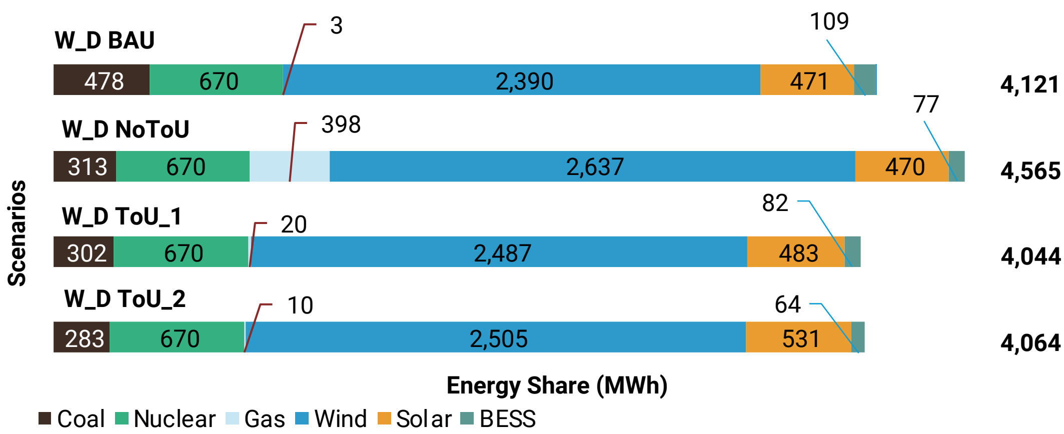
Retiring low PLF coal units and introducing ToU tariffs shifts generation toward wind and solar, cuts reliance on coal, lowers gas and storage needs, and reduces CO_2 intensity from 0.15 to 0.09 tCO_2/MWh in the most advanced ToU case.

Figure 34 below illustrates the shift in energy generation across different scenarios. For the newly added scenarios - W_D NoToU, W_D ToU_1, and W_D ToU_2 - the closure of coal power plants operating with an annual Plant Load Factor (PLF) below 40% has been incorporated. In the business-as-usual scenario (W_D BAU), coal plants with less than 40% annual PLF remained in operation, resulting in a noticeably higher coal contribution. This share drops sharply in the subsequent scenarios, as inefficient coal units are retired. Coal's share thus declines from 478 MWh in W_D BAU to 313 MWh in W_D NoToU, and further down to 283 MWh in W_D ToU_2, clearly demonstrating the impact of this revised methodology.

Nuclear supply remains steady across all scenarios, emphasising its stable role in the generation mix. Gas generation increases significantly in the W_D NoToU scenario, reaching 398 MWh, and plays a crucial role in system balancing, especially following coal plant closures and without the influence of ToU tariffs to shift demand. Despite this initial rise, gas's share drops considerably in the ToU scenarios as demand flexibility improves.

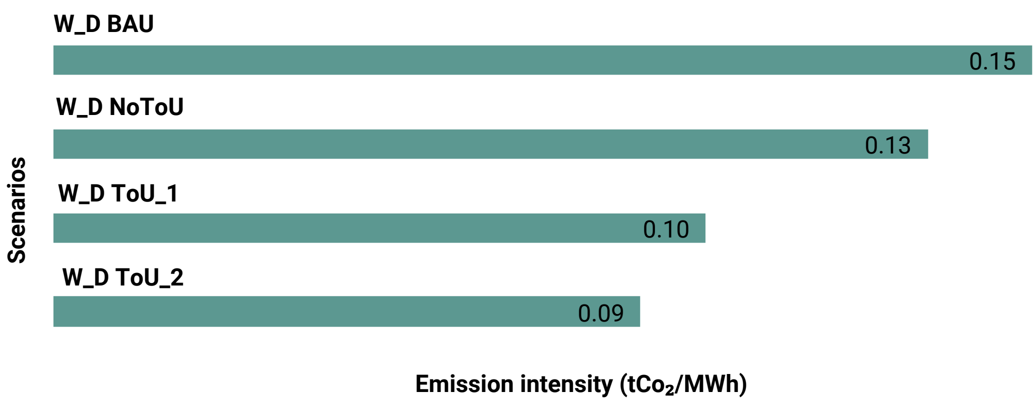
Overall, the chart demonstrates that flexibility provided by ToU tariffs not only facilitates the retirement of underperforming coal units, but also helps in reducing the demand for other flexible resources such as gas and battery energy storage systems (BESS).

Figure 34 Energy share by source and scenario



The CO_2 emissions intensity declines noticeably across scenarios, with the lowest emissions achieved under the most advanced ToU tariff case (W_D ToU_2) at 0.09 tCO_2/MWh. This trend highlights how introducing ToU tariffs and increasing renewable energy shares substantially reduce the carbon footprint of the power system compared to the business-as-usual scenario, which has the highest intensity of 0.15 tCO_2/MWh.

Figure 35 Co₂ Emissions by scenario



6.5 Plant load factors

Coal units with PLF below 40% are phased out and remaining coal plants see lower PLFs while gas units, especially in the W_D NoToU case, run harder to provide balancing, with nuclear and renewables unchanged.

In this section, the analysis is refined by explicitly phasing out coal power plants operating at annual PLFs below 40%, to better reflect realistic operational conditions. Consequently, the Talcher STPS 2 unit, which was identified by its low utilization rate, was shut down according to the new criteria. The closure of Talcher STPS 2 under the W_D NoToU, W_D ToU_1, and W_D ToU_2 scenarios is highlighted in Table 11 below.

The table further illustrates a reduction in PLF for all coal power plants under W_D NoToU, W_D ToU_1, and W_D ToU_2, as well as an increase in PLF for gas power plants—particularly under the W_D NoToU scenario—signifying a growing role for gas-fired units in providing system balancing services. Overall, the PLF trends indicate a structural shift in which coal increasingly moves away from baseload operation, while demand flexibility under ToU pricing reduces the need for gas-fired balancing.

Table 11 PLF by the power plant

Power Plant	Category	W_D BAU	W_D NoToU	W_D ToU_1	W_D ToU_2
Solar utility scale	Solar	16%	17%	17%	17%
Wind on-shore	Wind	24%	24%	24%	24%
Ramagundam STPS STG 1 & 2	Coal	0%	0%	0%	0%
Ramagundam STPS STG 3		0%	0%	0%	0%
Talcher STPS 2		32%	0%	0%	0%
Simhadri STPS 2		51%	45%	43%	40%
Vallur STPS		53%	47%	44%	42%
Kudgi		54%	48%	46%	42%
NLC TPS 2 STG 1		0%	0%	0%	0%
NLC TPS 2 STG 2		56%	49%	48%	45%
NLC TPS 1 EXP		57%	51%	49%	46%
NLC TPS 2 EXP		59%	52%	51%	48%
NTPL(NLC)		60%	54%	53%	49%
Neyveli NTPS		61%	55%	54%	51%
MAPS	Nuclear	100%	100%	100%	51%
Kaiga_1&2		100%	100%	100%	100%
Kaiga_3&4		100%	100%	100%	100%
KKNPP		100%	100%	100%	100%
KKNPP_2		100%	100%	100%	100%
Karikal GPP	Gas	1%	16%	8%	4%

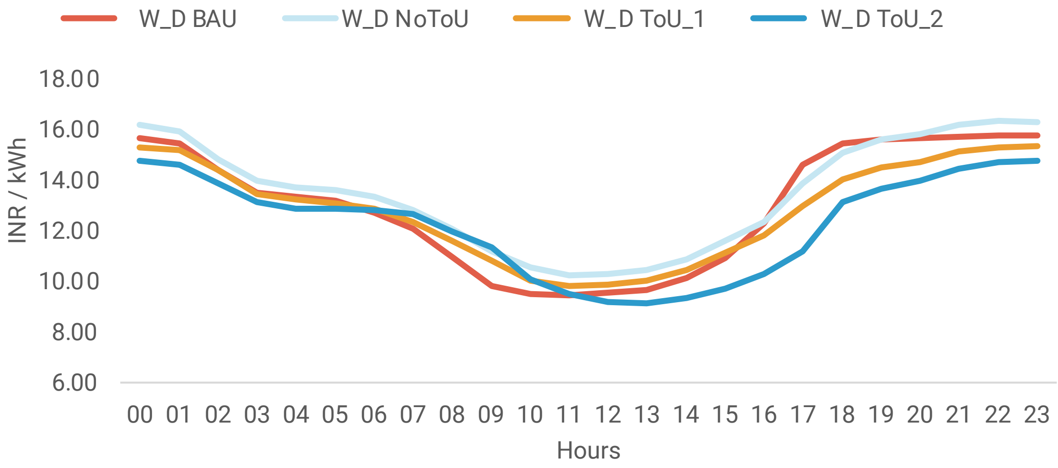
6.6 Cost of supply analysis

The cost of electricity supply in all scenarios is lowest from late morning to early afternoon and highest in the early morning and evening, so shifting flexible demand toward midday hours can reduce overall system costs and improve efficiency.

Puducherry's annual average cost of supply, of all 4 simulated ToU scenarios, follows a clear U-shape across the day, with the lowest costs from roughly 9:00–14:00 and the highest costs in the early morning and especially during the evening peak (around 17:00–21:00). All four tariff designs (W_D BAU, W_D NoToU, W_D ToU_1, and W_D ToU_2) share this pattern, but W_D ToU_2 slightly deepens the mid-day valley and keeps evening costs somewhat lower than the business-as-usual curve by rewarding consumption during sunshine hours.

In practical terms, supply is cheapest around midday, when solar output is high and system operation is more efficient, and most expensive in the evening, when higher demand requires costlier power and increases network losses. Shifting flexible consumption—such as cooling, water pumping, or EV charging—from early-morning and evening hours into the late-morning and early-afternoon window would therefore reduce overall supply costs and enhance system efficiency, with ToU-style tariffs helping to signal and enable this shift.

Figure 36 : Annual average hourly cost of supply



Q1: Apr–Jun: In all four scenarios, the costs of energy supply drop quickly from the early-morning peak to a broad mid-day minimum around hours 9–13, driven by strong solar output on top of wind. Under W_D ToU_2, the sunshine-hour rebate accentuates this valley relative to the other designs while late-night and evening costs remain higher, indicating that evening balancing needs are still significant even in this high-solar quarter.

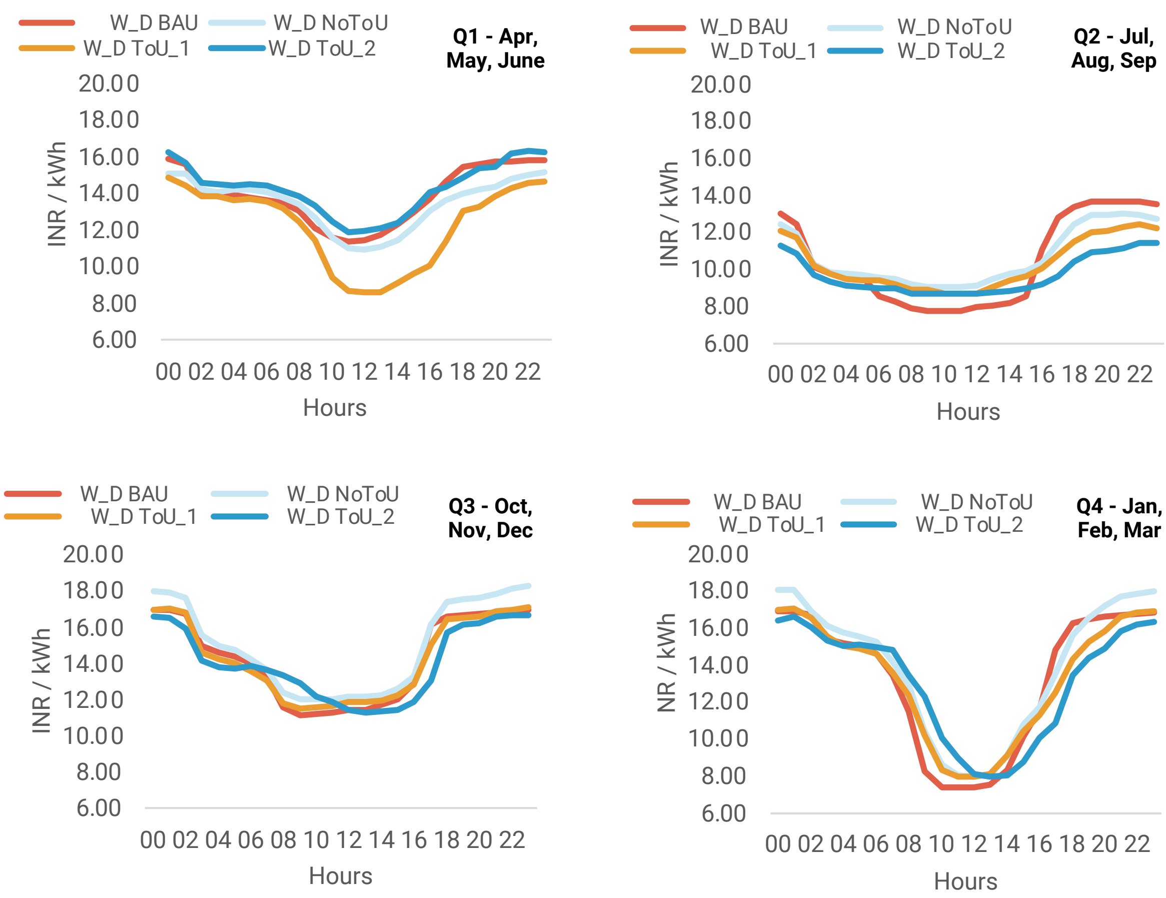
Q2: Jul–Sep: Night-time costs start higher and stay elevated longer than in Q1, then decline toward a mid-day trough that is shallower because solar is weaker or more variable in the monsoon season. The wind-dominant designs, especially with W_D ToU_2, keep the curve lower and flatter across most hours, showing that strong wind plus a mid-day rebate helps contain costs despite reduced solar support.

Q3: Oct–Dec: All four scenarios lie closer together, with similar low mid-day costs and a smoother rise into the evening, consistent with both resources contributing steadily and relatively even balancing needs across the day. The designs without a strong sunshine rebate show slightly higher late-night and early-morning costs, whereas W_D ToU_2 flattens mid-day more clearly but with only modest differences at night.

Q4: Jan–Mar: This quarter shows the deepest mid-day cost valley but also the sharpest climb from mid-afternoon into the evening peak, indicating strong winter ramping requirements. The wind-dominant W_D variants with W_D ToU_2 maintain the lowest costs from late afternoon through night, highlighting wind's role in limiting evening and night-time costs when solar availability is lowest.

The four panels show that adding a sunshine-hour rebate (W_D ToU_2) lowers and flattens the midday cost of supply in every quarter while slightly increasing or leaving unchanged the evening and early-morning cost, thus shifting economic incentives toward daytime use and away from wind-driven low-cost night hours.

Figure 37 Average hourly cost of supply by quarter

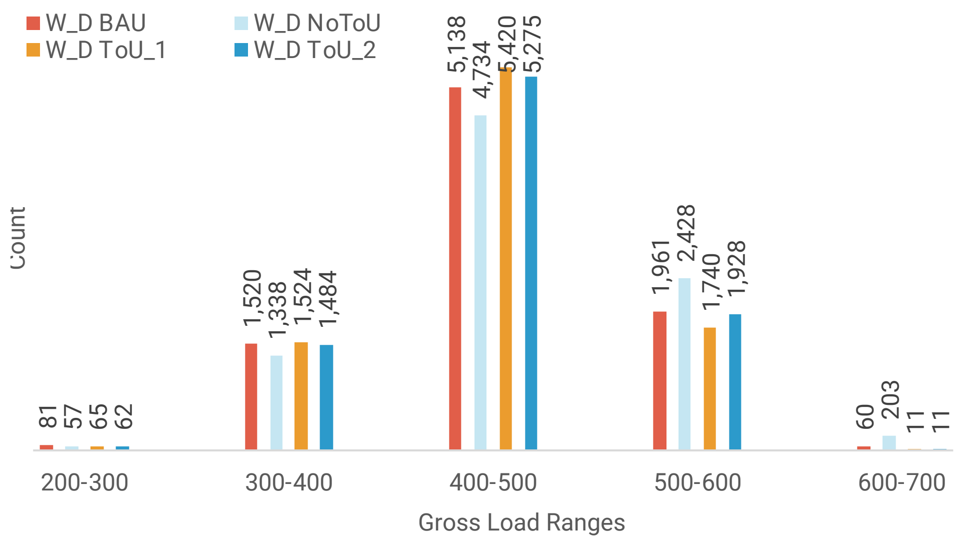


6.7 Impact on Peak Load

Time-of-use tariffs in the wind-dominant cases smooth the load profile by cutting evening peaks, avoiding extreme low and high demand periods, and shifting more consumption into solar hours, with the W_D ToU_2 design producing the flattest, most grid-friendly curve.

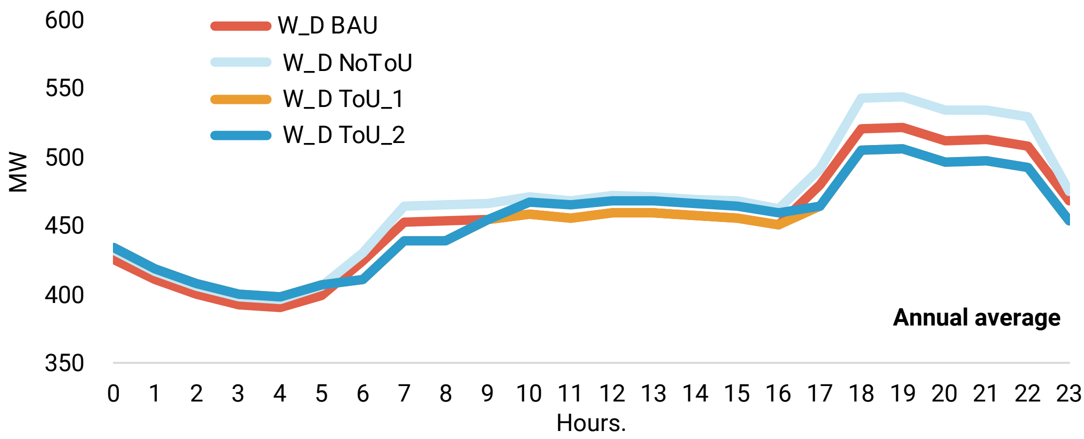
The distribution of hourly gross load across scenarios shows that the adoption of time-of-use tariffs for the W_D ToU_1 and W_D ToU_2 scenarios effectively reduces the frequency of high peak loads and minimises periods of both very low and very high demand. This leads to a more balanced, efficient, and manageable system operation, helping to avoid stress on grid infrastructure and lowering the risk of costly supply fluctuations.

Figure 38 Gross load frequency distribution by scenario



The average hourly gross load profiles in Figure 39 show that higher evening peak tariffs in the W_D BAU, W_D ToU_1, and W_D ToU_2 scenarios lead to a pronounced reduction in evening peak demand compared to the W_D NoToU scenario. Notably, the W_D ToU_2 scenario achieves the flattest load curve, reducing both morning and evening peaks while shifting demand towards solar hours.

Figure 39 Average hourly annual gross load by scenario



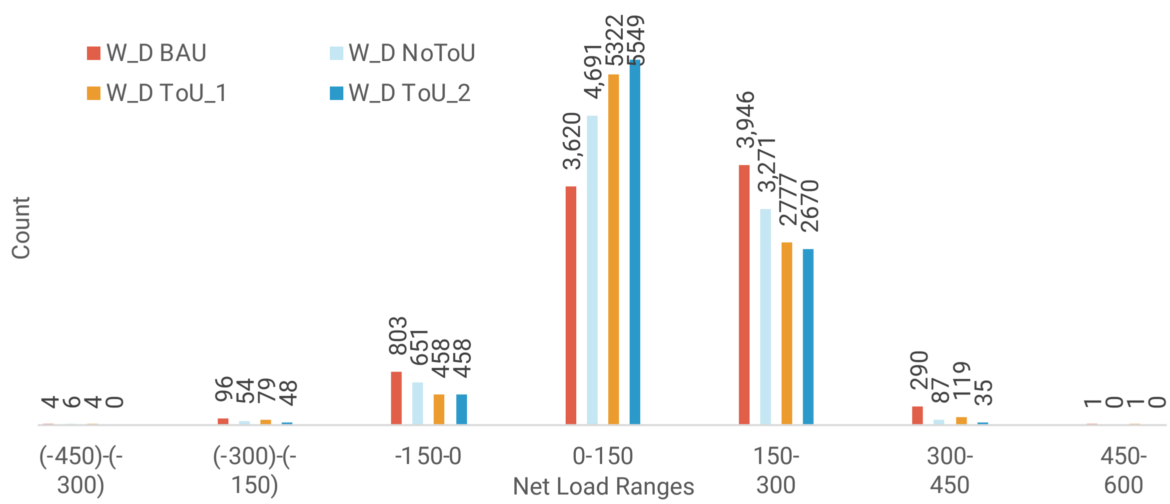
6.8 Net load analysis

Advanced wind-dominant ToU designs, especially W_D ToU_2 , sharply cut extreme high and negative net load events and act as a "solar sponge" in late afternoons, flattening the load curve and delivering smoother, more predictable grid operations than business as usual or NoToU cases.

Most net load events occur within moderate ranges, primarily between 0 and 300, as shown in the figure 40. The chart shows that both extreme negative net loads (below -300) and extreme positive net loads (above 300) occur rarely across all scenarios. For extreme negative loads, W_D ToU_2 records the lowest number of events (e.g. zero events) in the range -450 to -300, and 48 counts in the range -300 to -150, and for peak positive loads, W_D ToU_2 also posts fewer occurrences (35 in the 300–450 range, 0 in 450–600), compared to other scenarios. Business-as-usual (W_D BAU) and W_D NoToU have higher counts in these extreme ranges.

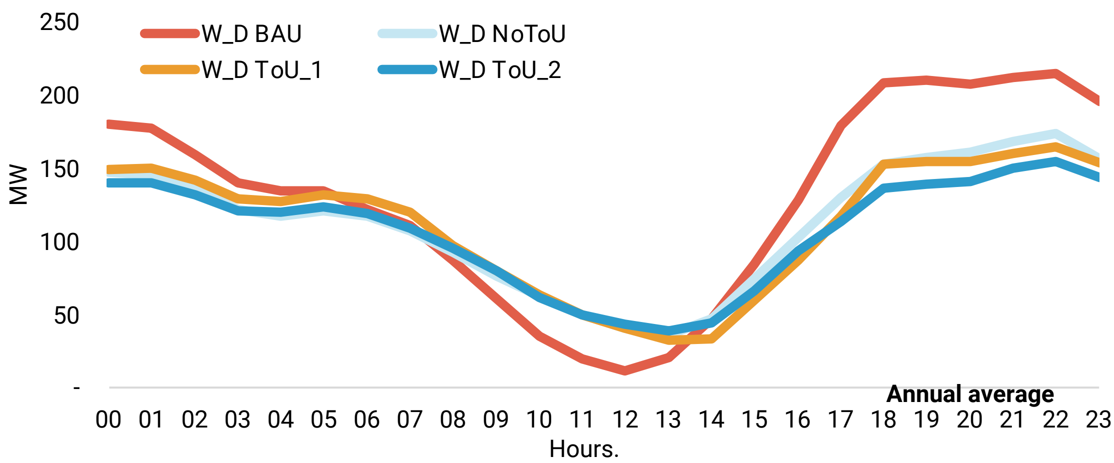
This demonstrates that the W_D ToU_2 scenario—representing an advanced Time of Use policy—is most effective at reducing both peak loads and negative loads on the grid. The intervention smooths the load profile, lowering the frequency of both abnormally high and low events, suggesting more stable and predictable grid operations. By comparison, scenarios without such policies (W_D BAU, W_D NoToU) show more frequent extremes, indicating less effective mitigation of outlier events.

Figure 40 Net load frequency distribution by scenario



The 'solar sponge' effect in the W_D ToU_2 scenario is evident in Figure 41, with increased net load during late afternoon hours. Both W_D ToU_1 and W_D ToU_2 scenarios help to flatten the load curve by reducing peak and valley events, resulting in smoother and more efficient system operations. Together, these results show that advanced ToU designs not only reduce peaks but also compress the full range of net-load variability, creating a more predictable operating envelope for the grid.

Figure 41 Average annual hourly net load by scenario



6.9 Deep dive – net load ramping

Net load ramping is dominated by small to moderate events across all four scenarios, with extreme multi-hour or very high magnitude ramps relatively rare.

Frequency distribution

The first section shows the frequency of ramping rates for four system conditions: W_D BAU, W_D NoToU, W_D ToU_1, and W_D ToU_2. In every case, most events fall between -100 and +100 MW per hour, with W_D BAU and W_D NoToU having the largest numbers of events in the ±100–200 MW ranges, and W_D ToU_1 and W_D ToU_2 showing fewer very large ramps beyond ±300 MW per hour.

The average energy cost plotted with each histogram varies only modestly across bins but tends to be highest for ramp-down events (around -200 to -100 MW per hour) for W_D ToU_1 and W_D ToU_2 and in the -100 and +100 MW per hour range for W_D BAU and W_D NoToU.

Top 5% ramps by hour

The top 5% up and down ramps, shown by hour and quarter, are concentrated mainly between 8:00 and 22:00, with notable clusters in the afternoon and early evening. There is hardly any noticeable difference between the 4 scenarios.

Ramps >100 MW by duration

For ramps exceeding 100 MW with durations of 3–4 hours, events occur between about 12:00 and 17:00 across all scenarios, rather than extending into late evening. W_D BAU has the highest number and magnitude of these multi-hour events, while W_D ToU_2 shows fewer and somewhat smaller multi-hour ramps, indicating reduced flexibility requirements.

>100 MW/hr by count and duration

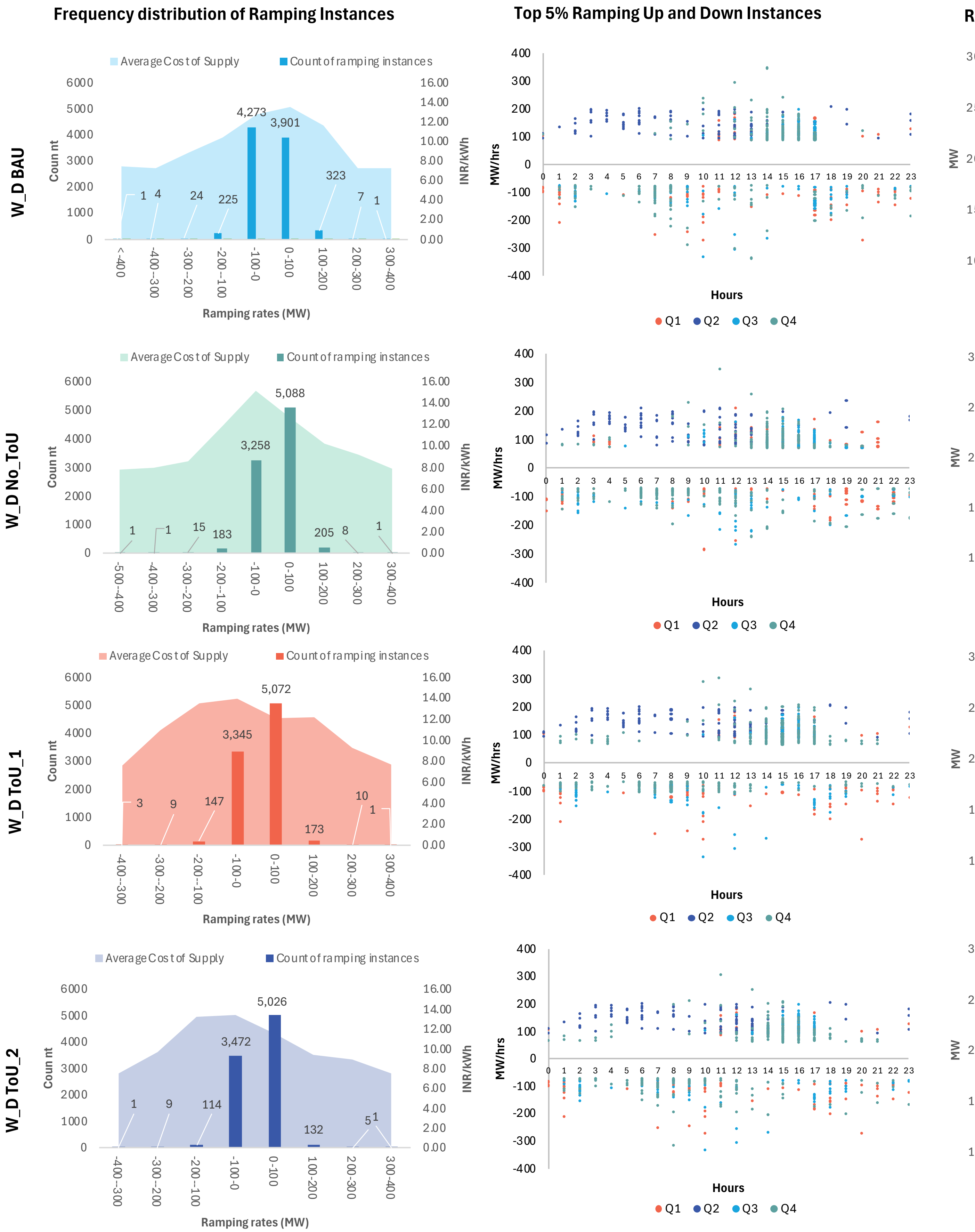
High-magnitude ramps above 100 MW per hour are mostly of 1-hour duration in all scenarios, with decreasing counts as duration increases to 2, 3, and 4 hours. W_D ToU_2 has no ramping event of 4 hours duration, only one 3-hour duration ramping event in Q1 and the least number of 2-hour ramping events. Most of its ramping events are concentrated in Q4, whereas the highest number of ramping events from W_D BAU and W_D NoToU occur in Q2.

Top 15 single-hour ramps

The tables of the top 15 single-hour ramping events for each scenario show the largest ramps ranging roughly from 162 to 346 MW per hour. These extreme events occur over a wide range of hours from late morning to evening and across many months, with W_D BAU and W_D NoToU showing the single highest magnitude ramping event.

The ramping analysis confirms that while extreme net load ramps are infrequent in all scenarios, the introduction of ToU tariffs particularly in the W_D ToU_2 reduces the frequency and duration of the most operationally challenging ramping events. By limiting prolonged multi-hour ramps and lowering peak ramp magnitudes, advanced ToU designs shrink the system's flexibility envelope and improve operational predictability without materially altering the timing of ramping occurrences.

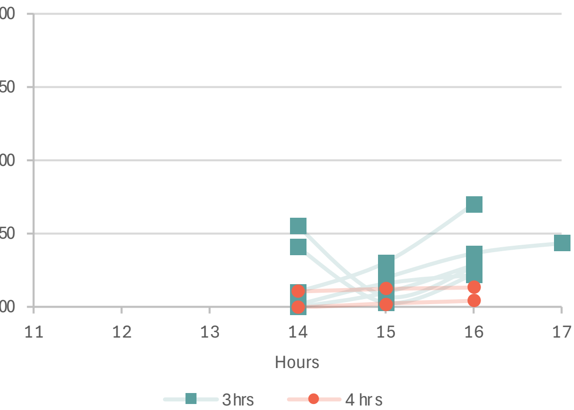
Figure 42 Ramping up instances by scenario

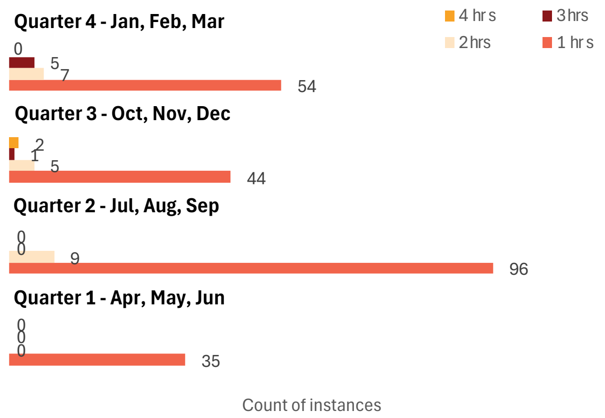


amping Instances > 100 MW by Duration

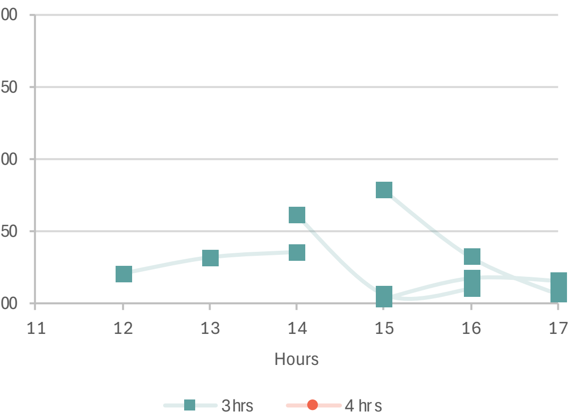
Ramping Instances by > 100 MW/hrs counts by Duration

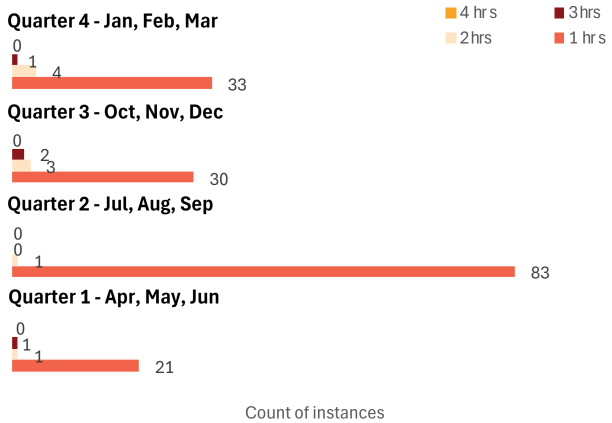
Top 15 Ramping Instances



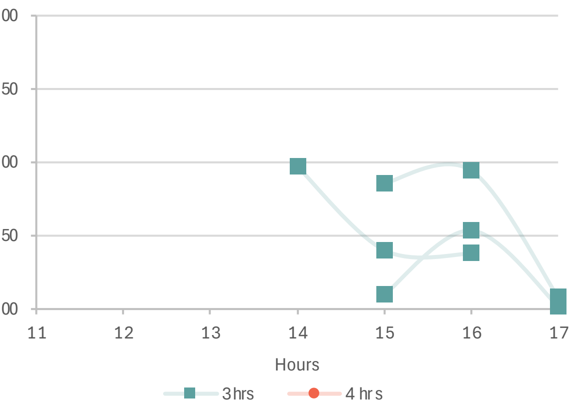


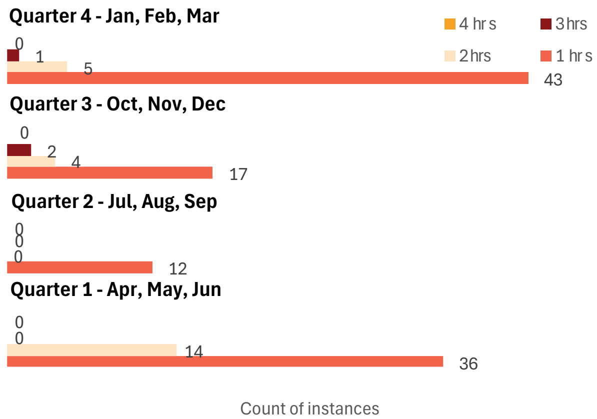
No	MW/hrs	Month	Time
1	346	February	14:00
2	294	February	12:00
3	239	January	15:00
4	238	February	10:00
5	230	February	13:00
6	222	February	10:00
7	206	July	18:00
8	203	February	12:00
9	200	August	06:00
10	199	August	10:00
11	198	July	19:00
12	198	August	12:00
13	197	November	16:00
14	196	January	14:00
15	196	August	03:00



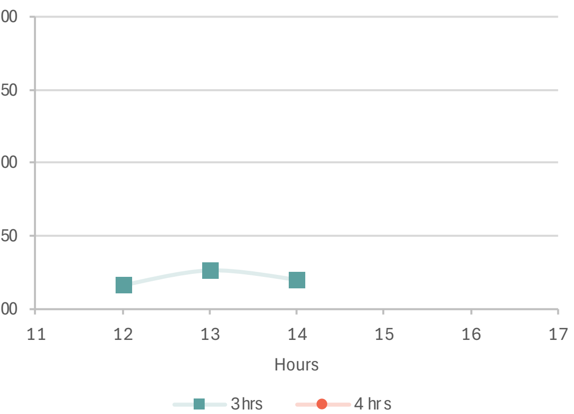


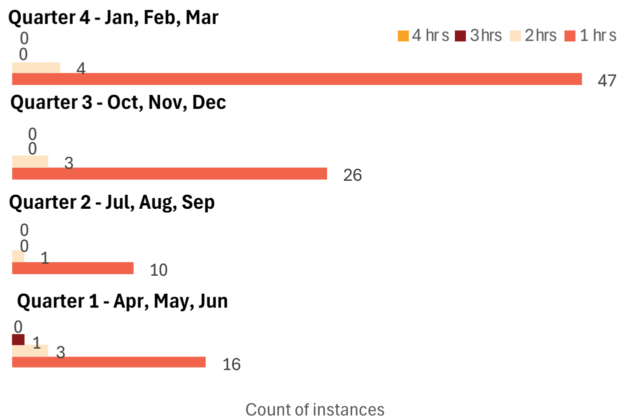
No	MW/hr	Month	Time
1	346	February	11:00
2	259	January	13:00
3	236	July	19:00
4	229	February	09:00
5	210	June	12:00
6	210	August	06:00
7	209	September	11:00
8	206	January	15:00
9	206	September	11:00
10	199	August	10:00
11	198	July	15:00
12	198	September	08:00
13	196	January	14:00
14	196	August	03:00
15	195	July	18:00





No	MW/hrs	Month	Time
1	303	March	11:00
2	290	February	10:00
3	263	January	13:00
4	226	June	12:00
5	223	June	13:00
6	221	March	12:00
7	209	January	16:00
8	207	February	11:00
9	205	June	12:00
10	201	March	16:00
11	200	March	15:00
12	199	March	17:00
13	197	March	14:00
14	195	March	14:00
15	195	February	14:00





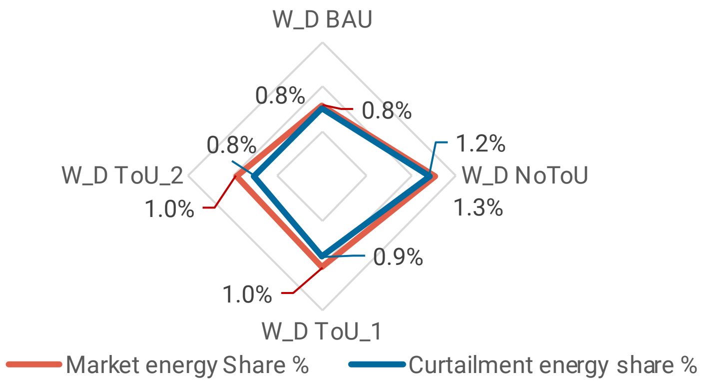
No	MW/hr	Month	Time
1	307	February	11:00
2	250	January	13:00
3	212	February	09:00
4	209	March	15:00
5	204	January	15:00
6	202	March	14:00
7	198	February	08:00
8	196	January	11:00
9	195	June	12:00
10	191	March	15:00
11	177	December	15:00
12	175	September	13:00
13	171	February	14:00
14	169	December	17:00
15	162	April	16:00

6.10 Curtailment and market purchase

W_D ToU_2 delivers the best alignment of renewables and demand, combining the lowest curtailment with the smallest market purchases and thus limiting both wastage and external energy procurement.

In the W_D BAU scenario, RE curtailment stands at approximately 0.73%, accompanied by market energy purchases close to 0.79%. This represents a baseline scenario without specific time-of-use interventions. The W_D NoToU scenario shows the highest curtailment with 1.20% and the highest market share with 1.27% of total energy generation. More desired differences arise in the ToU scenarios. W_D ToU_2 achieves a lowest curtailment rate of 0.74% and a market share of 0.48% while W_D ToU_1 results in 0.76% curtailment and 1.25% of market share. The low market share of W_D ToU_2 is a clear indicator of better synchronisation between renewable energy availability and demand, reducing wastage and external energy procurement

Figure 43 RE curtailment and market purchases by scenario



	W_D BAU	W_D NoToU	W_D ToU_1	W_D ToU_2
Market Energy Share (MWh)	32,852	54,128	41,659	38,982
Curtailment Energy Share (MWh)	30,840	51,010	37,163	31,078

07

12.11 ₹/kWh
Active demand response further lowers the cost of supply

Up to 73%
Renewable energy can be integrated

0.09 t/CO_2/MWh
Carbon emission intensity is further lowered

Demand Response As A Flexibility Strategy

Active demand response (ADR) offers a cost-effective pathway for enhancing grid reliability and reducing overall system costs. By strategically managing electricity demand during peak hours, ADR enables grid operators to balance supply and demand more efficiently, defer costly infrastructure upgrades, and facilitate higher integration of renewable energy sources.

This study focuses on a targeted ADR program for industrial consumers in Puducherry, under which participating industries agree to reduce their electricity load up to 20 times per year for a one-hour duration in exchange for financial incentives. These interventions will be activated during the top 20 net load peak hours identified under the W_D ToU2 scenarios.

Three different ADR scenarios with varying magnitudes of shiftable industry loads (e.g. a percentage of industry load in the respective peak hour), as shown in Table 12 below, are modelled. The analysis aims to explore the potential of this "low-hanging fruit" measure in mitigating extreme peak load events, minimising peak ramping requirements, and advancing system-wide cost optimisation. Ultimately, the objective is to assess how industrial ADR participation can contribute to a more flexible, resilient, and renewable-friendly power system.

Table 12 Active Demand Response Scenarios

Scenario	Shiftable load as (%)
ADR 1	4%
ADR 2	6%
ADR 3	8%

7.1 High-level results

Progressively stronger ADR deliver modest peak and ramping reductions and lowers total system costs, while moderately increasing wind, solar, and BESS shares.

Across all four scenarios, the generation mix remains almost identical, with wind holding a dominant 59–60% share, solar at 13%, and BESS at 2%, indicating that changes in outcomes are driven mainly by demand-side flexibility rather than large shifts in capacity composition. Gross and net peaks fall slightly but steadily from W_D ToU_2 through ADR 1–ADR 3 (gross peak from 613 MW to 607 MW and net peak from 398 MW to 401 MW), while maximum ramping events decline from 307 MW to 300 MW, showing that progressively stronger ADR smooths the load profile and reduces short term variability. Total system costs also drop monotonically from 4,869 (₹ Crore) in W_D ToU_2 to 4,809 (₹ Crore) in ADR3, highlighting that advanced ADR delivers incremental cost savings and operational benefits without requiring major changes to the renewable and storage shares in the system.

Table 13 High-level results by scenario

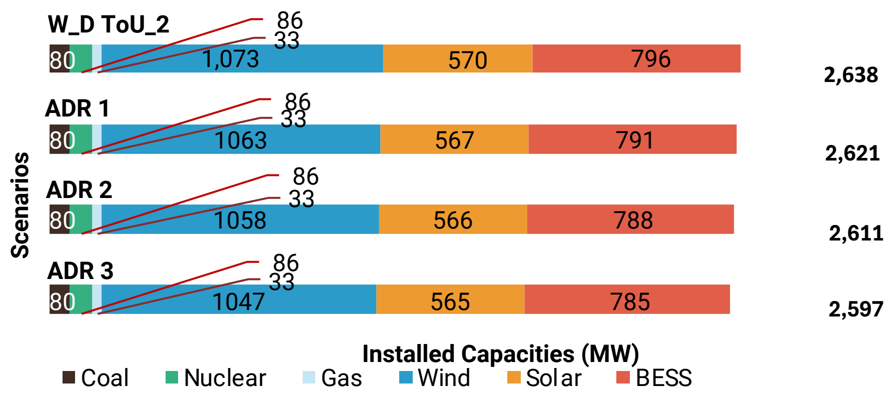
Parameters	W_D ToU_2	ADR 1	ADR 2	ADR 3
Wind share (%)	59%	59%	60%	60%
Solar share (%)	13%	13%	13%	13%
BESS share (%)	2%	2%	2%	2%
Gross peak (MW)	613	610	608	607
Net peak (MW)	398	397	396	394
Max ramping event (MW)	307	304	303	300
Total system cost (₹ Crore)	**4,869**	**4,838**	**4,828**	**4,809**

7.2 Projected generation capacities

ADR cuts the need for new assets, reducing total capacity (including BESS, wind, and solar) and lowering installed generation.

In the more advanced ADR scenario (ADR 3), the total installed capacity required to meet demand falls because active demand response substitutes for some generation and storage needs. This is most visible in the marked reduction in battery energy storage system (BESS) capacity, along with lower wind and solar capacities, indicating that flexible demand reduces the amount of variable renewable and storage capacity the system must build to maintain reliability. For example, the total installed generation capacity comparing W_D ToU_2 and ADR 3 reduce from 2,638 MW to 2,597, a reduction of 41 MW or 1.55%. BESS reduces from 796 MW to 785 MW, indicating the efficiency of ADR.

Figure 44 Installed Capacities in Different Scenarios



7.3 System Cost Comparison

Stronger ADR measures layered onto W_D ToU_2 cut total system costs and reduce the cost of supply from ₹12.26/kWh to ₹12.11/kWh, showing that enhanced demand response improves cost efficiency

Introducing increasingly ambitious ADR measures on top of the W_D ToU_2 scenario steadily reduces both fixed and variable system costs, bringing total system cost down from ₹4,868 crore without ADR to ₹4,809 crore under ADR 3. Because total demand is held constant across scenarios, these savings directly translate into a lower cost of supply, which falls from ₹12.26/kWh to ₹12.11/kWh, indicating that stronger demand response improves overall cost efficiency.

Table 14 System cost comparison by scenario

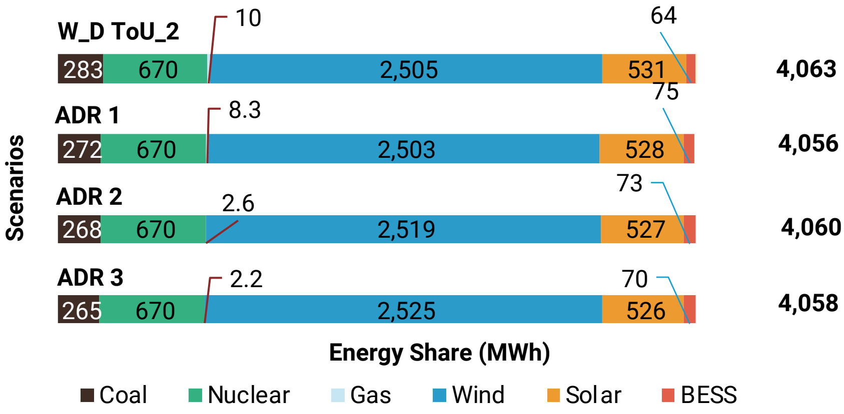
Cost parameter	W_D ToU_2	ADR 1	ADR 2	ADR 3
Fixed Cost (₹ Crore)	4,488	4,469	4,460	4,444
Variable Cost (₹ Crore)	380	369	368	365
Total System cost (₹ Crore)	4,868	4,838	4,828	4,809
Total Demand (GWh)	3,972	3,972	3,972	3,972
Cost of Supply (₹/kWh)	12.26	12.18	12.16	12.11

7.4 Energy share and CO_2 emissions by scenarios

ADR measures displace coal and gas with slightly more wind and storage, which in turn lowers emission intensity.

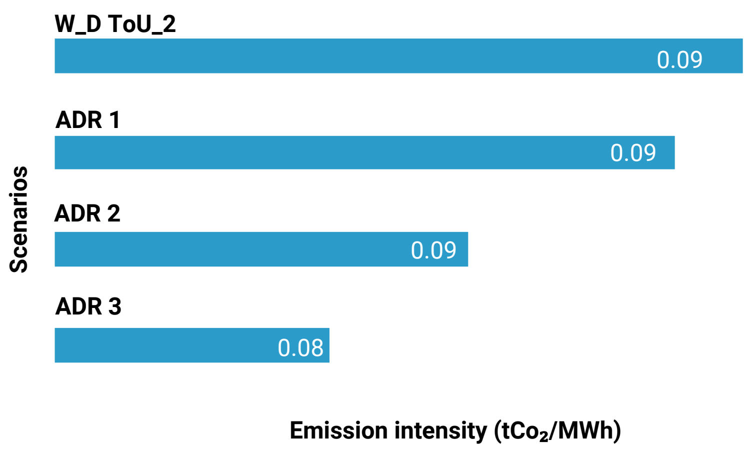
The chart shows that total energy generation remains almost constant across all scenarios, varying only slightly around 4,060 MWh. Coal and gas generation decrease across all three ADR scenarios, while both wind generation and BESS exhibit a moderate increasing trend. Overall, ADR results in a small reduction in coal use and a slightly greater reliance on storage, while keeping total generation and the shares of nuclear, wind, and solar nearly unchanged.

Figure 45 Energy share by source and scenario



Emission intensity decreases progressively from the W_D ToU_2 to ADR 3. W_D ToU_2 has the highest emission intensity at 0.090 tCO2/MWh, followed by ADR 1 at 0.089 tCO2/MWh, ADR 2 at 0.086 tCO2/MWh, and ADR 3 with the lowest value of 0.084 tCO2/MWh. This pattern indicates that the introduction and strengthening of ADR measures steadily improve the carbon performance of the system.

Figure 46 Co_2 Emissions by scenario



7.5 Plant load factors

Time-of-use tariffs and ADR together push the system toward lower utilisation of coal plants— while also slightly reducing the already low PLF of gas units, signalling less need for peaking and fast response generation as demand becomes more flexible.

The simulation of ToU tariffs in the previous chapter resulted in a reduced PLF for coal-fired power plants and a higher PLF for gas-fired plants. This was primarily due to the retirement of coal plants with a PLF below 40%. The introduction of ADR further reinforces the trend of lowering coal PLF. However, it also leads to a reduction in the PLF for gas compared with the W_D ToU2 scenario, indicating reduced demand for fast-response generators as a result of ADR.

Table 15 PLF by the power plant

Power Plant	Category	W_D ToU_2	ADR 1	ADR 2	ADR 3
Solar utility scale	Solar	17%	17%	17%	17%
Wind on-shore	Wind	24%	24%	24%	24%
Ramagundam STPS STG 1 & 2	Coal	0%	0%	0%	0%
Ramagundam STPS STG 3		0%	0%	0%	0%
Talcher STPS 2		0%	0%	0%	0%
Simhadri STPS 2		40%	40%	40%	40%
Vallur STPS		42%	40%	40%	40%
Kudgi		42%	40%	40%	40%
NLC TPS 2 STG 1		0%	0%	0%	0%
NLC TPS 2 STG 2		45%	43%	43%	42%
NLC TPS 1 EXP		46%	44%	43%	43%
NLC TPS 2 EXP		48%	42%	41%	40%
NTPL(NLC)		49%	44%	44%	43%
Neyveli NTPS		51%	46%	45%	45%
MAPS	Nuclear	100%	100%	100%	100%
Kaiga_1&2		100%	100%	100%	100%
Kaiga_3&4		100%	100%	100%	100%
KKNPP		100%	100%	100%	100%
KKNPP_2		100%	100%	100%	100%
Karikal GPP	Gas	4%	3%	1%	1%

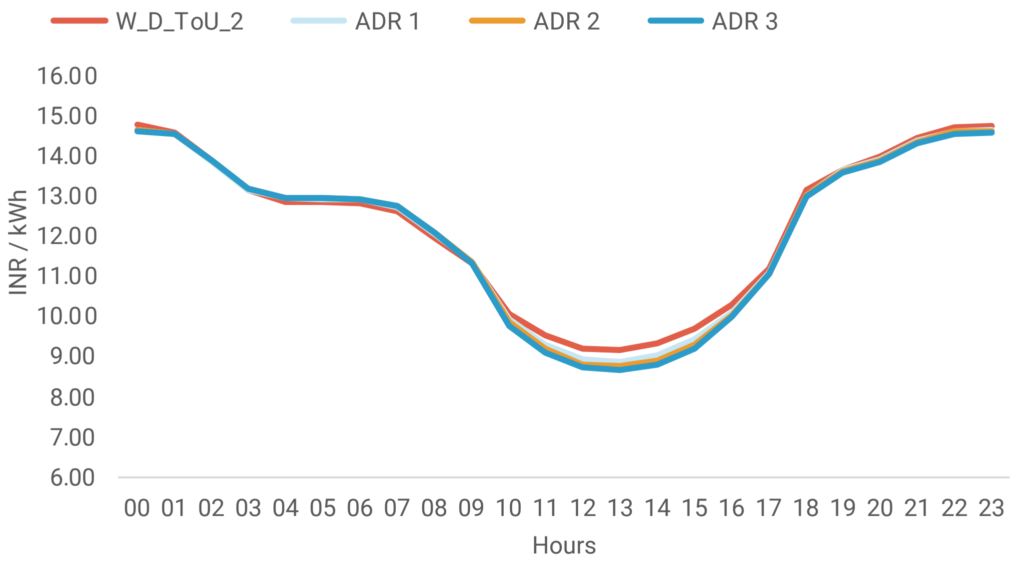
7.6 Cost of supply analysis

The cost of electricity supply in all four scenarios is lowest from late morning to early afternoon and highest in the early morning and evening, indicating that shifting flexible demand toward midday hours can lower total system costs and improve efficiency.

Across the day, the average cost of supply follows a clear U-shape, with the lowest values between 10:00 and 16:00 and the highest values in the early morning and during the evening peak from about 17:00 to 21:00. All four cost curves shown in the figure 47 share this same basic pattern.

While all scenarios follow a similar profile, the ADR-type designs slightly deepen the mid-day cost minimum and keep evening costs somewhat lower than the reference curve. This reflects the impact of stronger incentives for customers to consume more power during low-cost daylight hours. In practical terms, electricity is cheapest around midday, when solar output is higher and system operation is more efficient, and most expensive in the evening, when rising demand requires costlier generation and increases network losses.

Figure 47 Annual average hourly cost of supply



Across all four seasons, the hourly cost of electricity supply broadly retains a U-shaped profile, with lower costs from late morning into the afternoon and higher costs in the early morning and evening. Seasonal differences, however, change how deep the mid-day valley is and how pronounced the evening peak becomes.

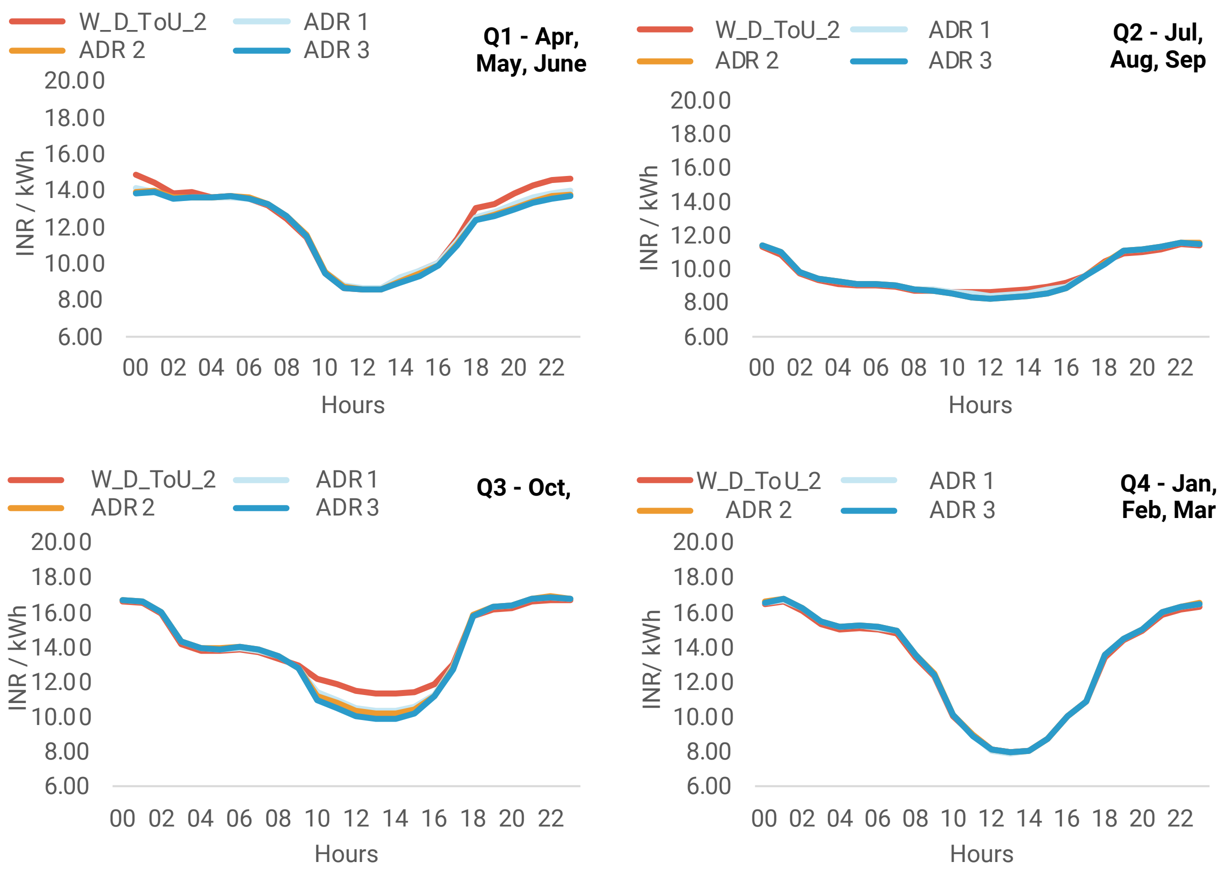
Q1: Apr–Jun: In Q1, supply costs dip steadily from the early morning to reach a pronounced minimum around the late-morning to early-afternoon hours, before rising sharply into the evening peak. The ADR-type designs slightly accentuate this mid-day low and keep evening costs below the reference curve of W_D ToU_2.

Q2: Jul–Sep: During Q2, the cost curve flattens somewhat, with a broad, shallow low extending through much of the daytime and a more modest evening increase. Differences between the four tariff designs are relatively small in this season.

Q3: Oct–Dec: Q3 shows a steep cost decline after the early morning and a deep, narrow trough around mid-day, followed by a sharp evening rise. Here, the ADR designs most clearly undercut the reference curve of W_D ToU_2 at mid-day and slightly soften the evening peak.

Q4: Jan–Mar: In Q4, supply costs remain relatively high through the morning, bottom out around mid-day, and then climb gradually into the evening. This suggests fewer high-stress hours requiring ADR activation during this period.

Figure 48 Average hourly cost of supply by quarter



7.7 Net load analysis

ADR scenarios flatten the net-load profile by reducing both very high and very low net-load hours, resulting in smoother and more stable grid operations compared with the WD_ToU2 case.

Under the WD_ToU2 reference, the grid still sees many hours with very high net loads in the 200–300 MW and 300–400 MW ranges, which are the most stressful to serve.
With ADR in place, these extreme peaks become noticeably less frequent, especially under ADR 3, meaning more of those hours move into moderate net-load ranges. At the same time, the number of hours in the 0–200 MW band increases, so system operation is concentrated in easier-to-manage conditions rather than at the extremes. On the low-net-load side, ADR also slightly reduces the incidence of very low or negative net loads, helping avoid over-generation and curtailment. Overall, ADR progressively flattens the net-load profile, trimming both peaks and valleys and leading to smoother, more stable grid operations compared with the WD_ToU2 case.

Figure 49 Net load frequency distribution by scenario

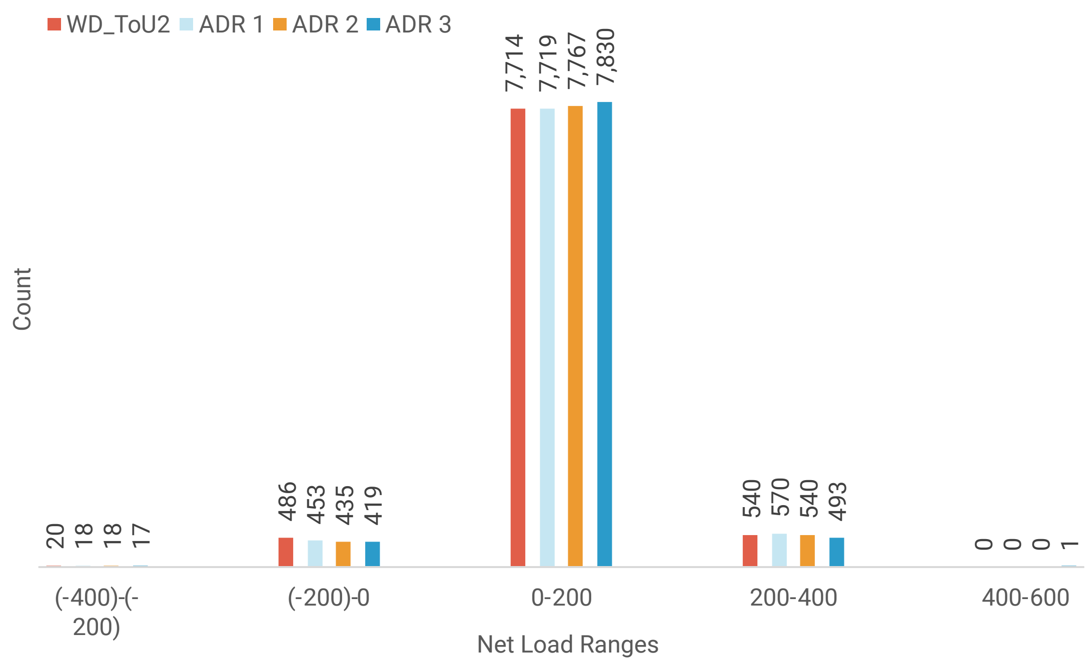
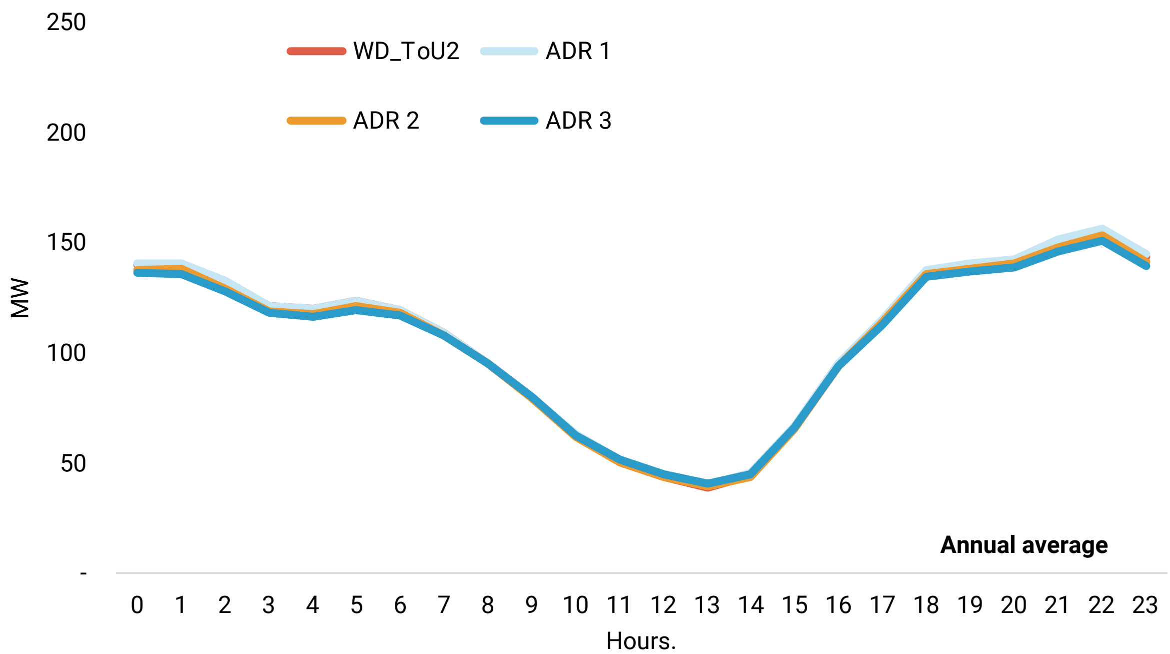


Figure 50 Average annual hourly net load by scenario



7.8 Deep dive – net load ramping

Ramping behaviour across W_D ToU_2, ADR 1, ADR 2 and ADR 3 is dominated by small to moderate events, with very high single-hour or multi-hour ramps comparatively rare across all four cases.

Frequency distribution: The frequency distribution shows that, for each of W_D ToU_2, ADR 1, ADR 2 and ADR 3, most ramping instances fall in the central bands, with only a small share of events in the extreme negative or positive ranges. Average cost of supply varies only gradually across the scenarios but tends to be higher for ramp-down events in the -100 to -200 MW per hour range and slightly lower for strong ramp-up events across the four scenarios.

Top 5% ramps by hour: The scatter plots of the top 5% ramp-up and ramp-down events by hour and quarter indicate that these largest ramps cluster mainly between late morning and late evening, with relatively few extreme events overnight.

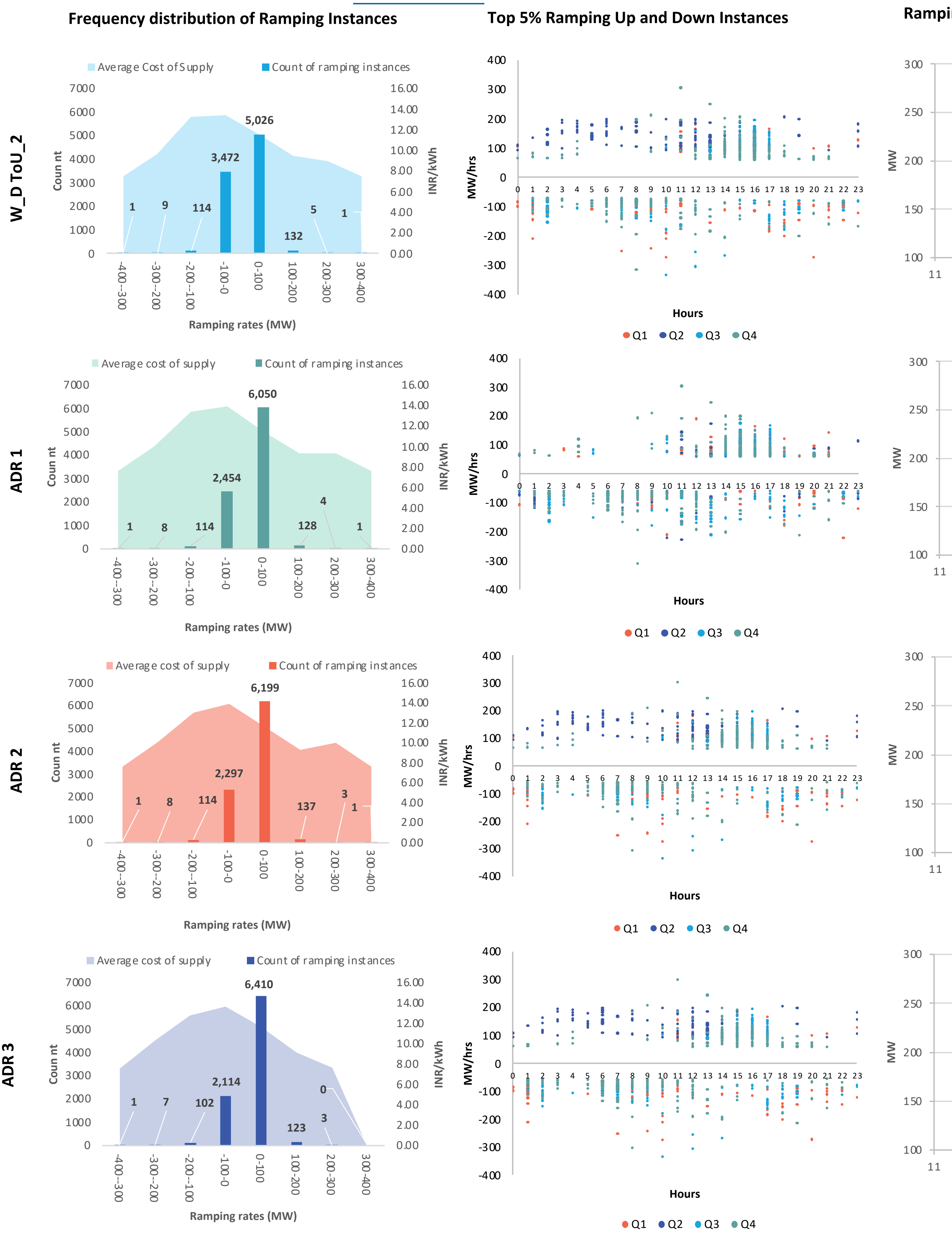
Ramps >100 MW by duration: For events exceeding 100 MW, the duration plots show that multi-hour ramping (3–4 hours) across all scenarios has been reduced to a single instance. This represents a significant improvement compared with the W_D Base scenario, which had multiple 3-hour and 4-hour ramping instances exceeding 100 MW each.

>100 MW/hr counts by duration: The bar charts of counts by duration confirm that ramps above 100 MW per hour are predominantly single-hour events in all four cases, with sharply declining counts for 2-, 3- and not a single count of a 4-hour duration ramping event in the greater than 100 MW /hr magnitudes.

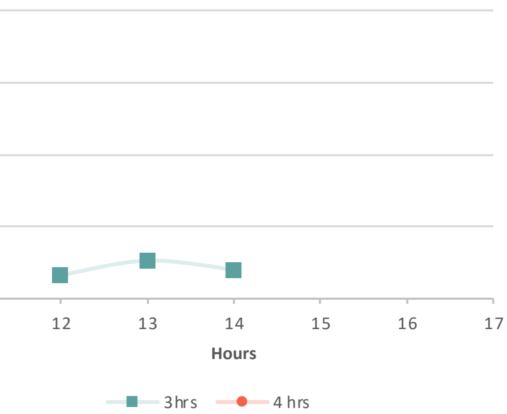
Top 15 single-hour ramps
The top 15 single-hour ramping events across W_D ToU_2, ADR 1, ADR 2 and ADR 3 span a broad range of hours from late morning through evening, confirming that extreme ramping is not confined to a narrow part of the day. These events occur in many different months, indicating that high single-hour ramps are a year-round feature rather than being concentrated in a single season. The table clearly shows the reduced peak event magnitude with the increasing intensity of active demand response from ADR 1 to ADR 3, where the ADR3 case has the lowest net peak load events.

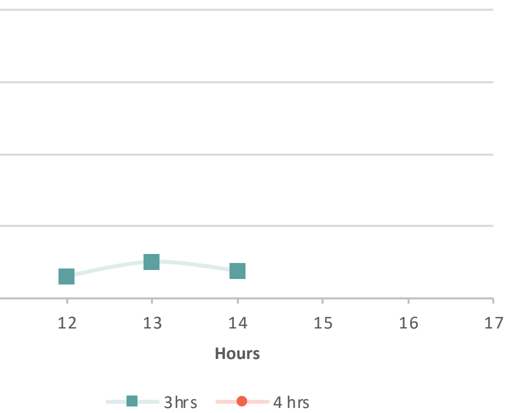
The ramping analysis confirms that layering active demand response on top of time-of-use tariffs meaningfully improves system flexibility. While short-duration ramps remain an inherent feature of a high-renewable system, ADR substantially limits the magnitude and persistence of extreme events. In particular, the near elimination of multi-hour high-magnitude ramps under ADR highlights its effectiveness in reducing operational stress, lowering balancing costs, and improving system predictability without requiring additional generation or storage capacity.

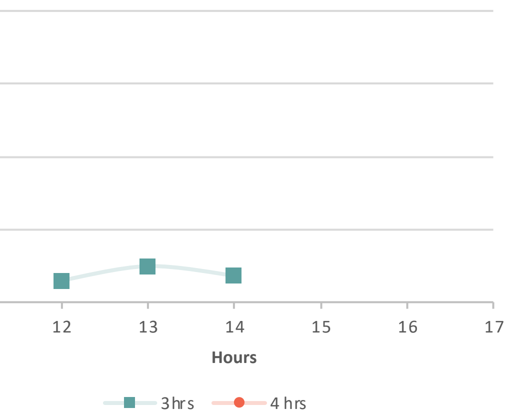
Figure 51 Ramping up instances by scenario

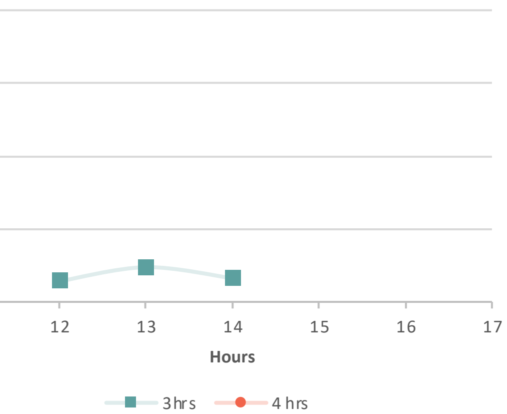


ng Instances > 100 MW by Duration

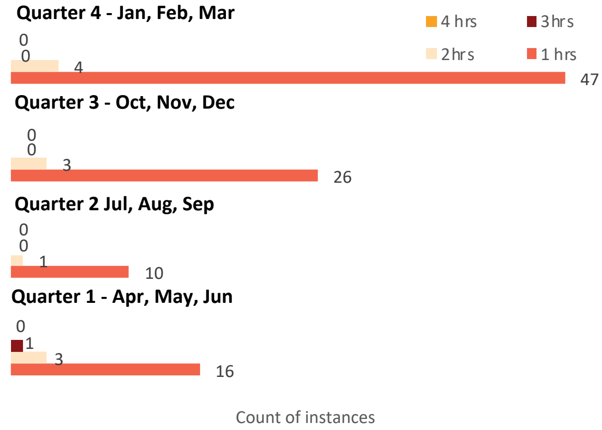


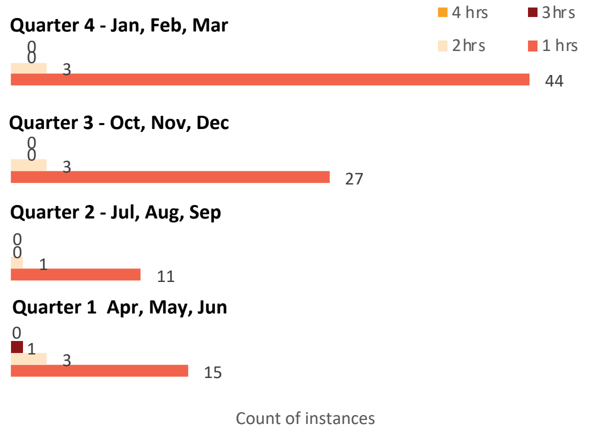


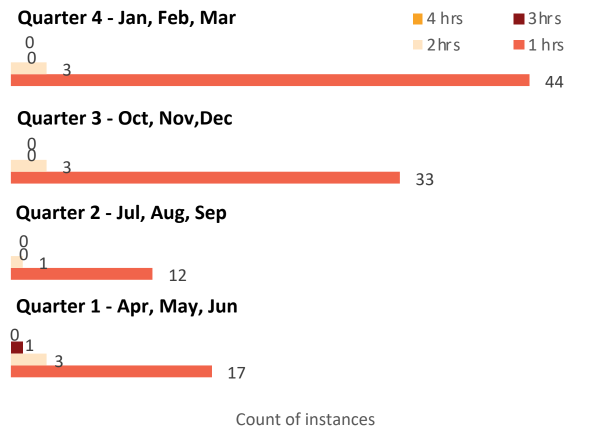


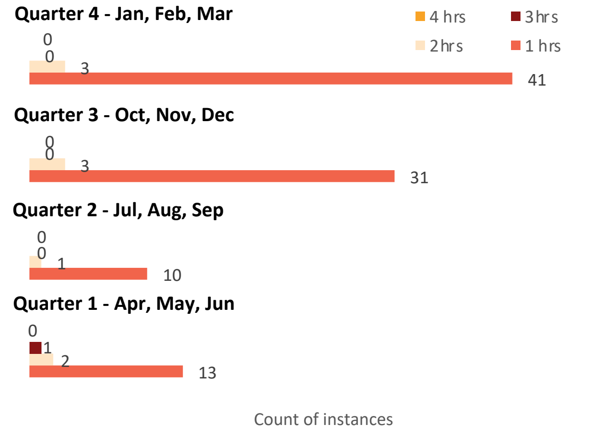


Ramping Instances by > 100 MW/hrs counts by Duration









Top 15 Ramping Instances

No	MW/hr	Month	Time
1	307	February	11:00
2	250	January	13:00
3	212	February	09:00
4	209	March	15:00
5	204	January	15:00
6	202	March	14:00
7	198	February	08:00
8	196	January	11:00
9	195	June	12:00
10	191	March	15:00
11	177	December	15:00
12	175	September	13:00
13	171	February	14:00
14	169	December	17:00
15	162	April	16:00

No	MW/hrs	Month	Time
1	304	February	11:00
2	248	January	13:00
3	210	February	09:00
4	207	March	15:00
5	200	March	14:00
6	200	January	15:00
7	193	February	08:00
8	191	January	11:00
9	191	June	12:00
10	189	March	15:00
11	175	December	15:00
12	174	September	13:00
13	170	February	14:00
14	168	December	17:00
15	164	April	16:00

No	MW/hrs	Month	Time
1	303	February	11:00
2	247	January	13:00
3	209	February	09:00
4	206	March	15:00
5	199	March	14:00
6	197	January	15:00
7	191	February	08:00
8	189	January	11:00
9	188	June	12:00
10	185	March	15:00
11	175	December	15:00
12	173	September	13:00
13	170	October	15:00
14	169	February	14:00
15	168	December	17:00

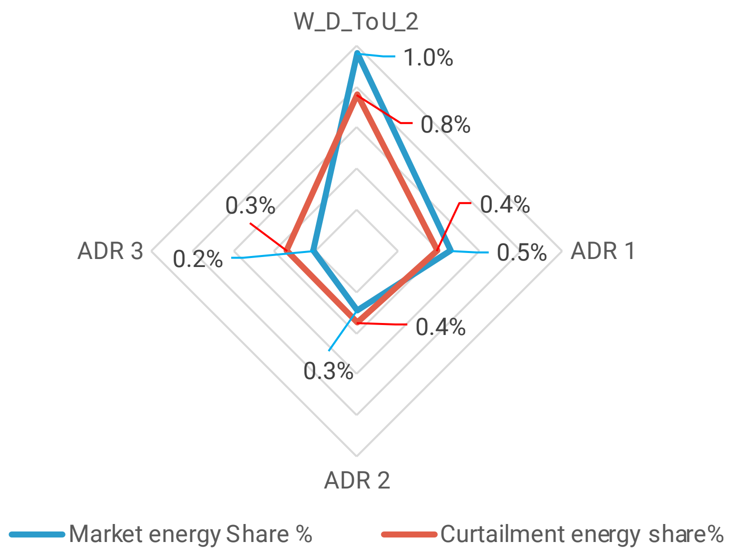
No	MW/hrs	Month	Time
1	300	February	11:00
2	245	January	13:00
3	207	February	09:00
4	198	March	14:00
5	193	January	15:00
6	192	March	15:00
7	187	February	08:00
8	185	January	11:00
9	184	June	12:00
10	179	March	15:00
11	173	December	15:00
12	171	September	13:00
13	169	February	14:00
14	158	October	15:00
15	155	February	14:00

7.9 Curtailment and market purchase

ADR reduces renewable curtailment and market purchases by better aligning renewables with demand, thereby lowering system costs and emissions.

In the W_D ToU_2 scenario, RE curtailment stands at approximately 1.0%, accompanied by market energy purchases close to 0.8%. ADR 1 and ADR 2 exhibit intermediate performance, with curtailment shares of about 0.4% each, while their market energy shares are around 0.5% and 0.3% respectively. ADR 3 achieves the lowest curtailment rate of about 0.2% and the lowest market energy share of roughly 0.3%, indicating better alignment between renewable energy availability and demand, with reduced wastage and lower dependence on external market energy. In terms of absolute numbers, comparing W_D ToU_2 to ADR, the market energy share reduced from 38,982 MWh to 8,704 MWh, a 78% reduction, while the curtailment reduced from 31,079 MWh to 13,653 MWh, which is a 56% reduction. This is a significant improvement that is also reflected in the lower system cost and the lower emission intensity of the ADR scenarios.

Figure 52 RE curtailment and market purchases by scenario



	W_D ToU_2	ADR 1	ADR 2	ADR 3
Market Energy Share (MWh)	38,982	18,794	11,992	8,704
Curtailment Energy Share (MWh)	31,078	15,850	14,395	13,653

08

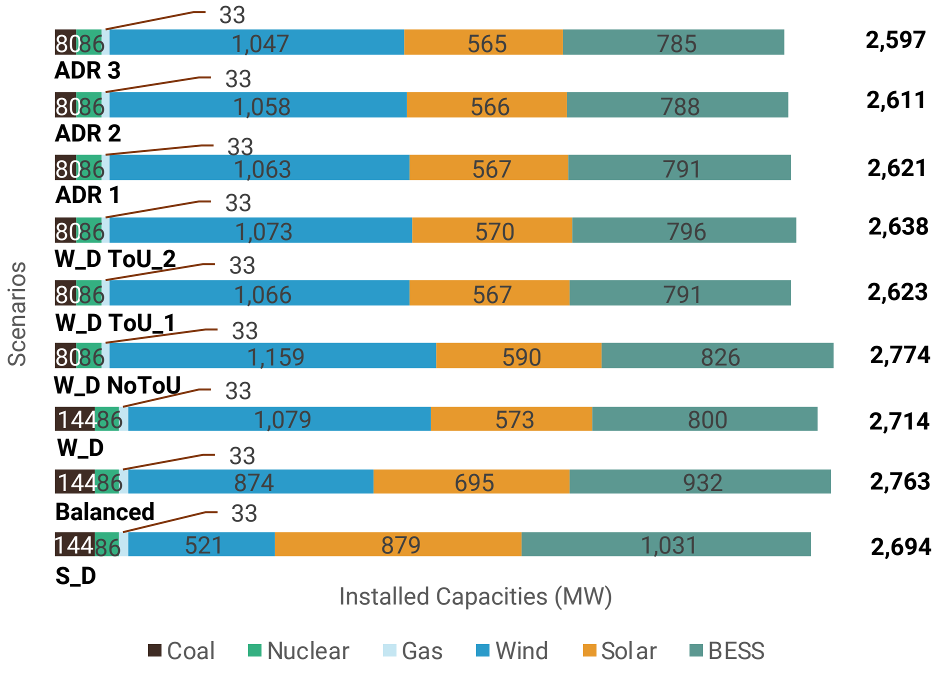
Summary & Recommendations

8.1 Projected generation capacities

As the ToU tariffs and industrial demand response are added to the Wind Dominant (W_D) base case, total installed capacity falls because flexible, price-responsive loads reduce peak demand and the need for new supply.

Across the base renewable energy (RE) scenarios, Solar Dominant (S_D), Balanced and Wind Dominant (W_D), the S_D scenario results in the lowest power generation capacity; however, it needs the highest total installed BESS capacity. W_D already lowers this requirement as wind generation supports meeting evening loads. When scenarios are built on W_D and then add time-of-use tariffs (W_D ToU_1 and W_D ToU_2), the total installed capacity needed falls further. The introduction of time-varying prices encourages consumers to shift consumption away from peak periods, which reduces the size of the supply portfolio required to reliably meet demand. The scenarios with active demand response for industrial consumers (ADR 1–3) continue this trend, achieving the lowest total capacities among the W_D-based flexibility cases.

Figure 53 : Generation capacity requirements by scenario

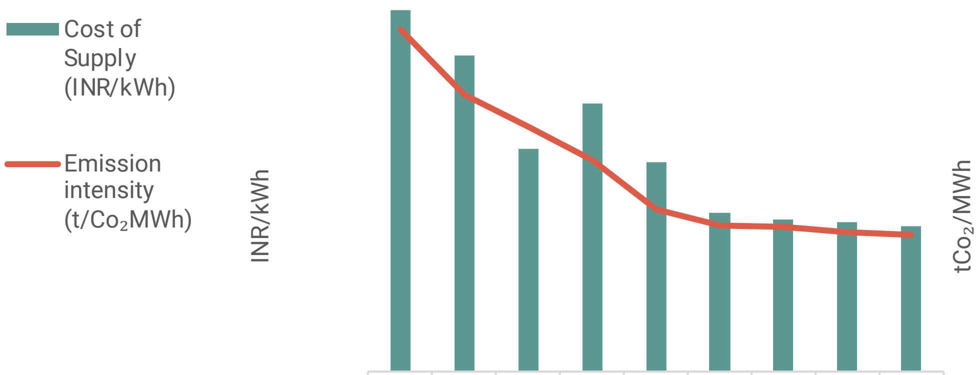


8.2 Cost of supply & emissions

Moving from the base RE cases to scenarios with ToU tariffs and active demand response steadily cuts both unit supply costs and emissions, making a high renewables system cheaper and cleaner.

Across the progression from base renewable energy scenarios to demand-flexibility cases, both cost of supply per unit and the emission intensity steadily decline. Introducing modified ToU tariffs lowers costs and emissions compared with W_D BAU and W_D NoToU, as shifting demand away from peak hours enables more efficient use of renewables and lowers reliance on fossil generation. Adding active demand response in the ADR scenarios deepens these gains: ADR 1–3 deliver the lowest cost of supply and the lowest emission intensities, showing that combining high renewables with flexible, responsive demand is more economical and cleaner than relying on supply-side measures alone.

Figure 54 : Cost of supply and emission intensity by scenario



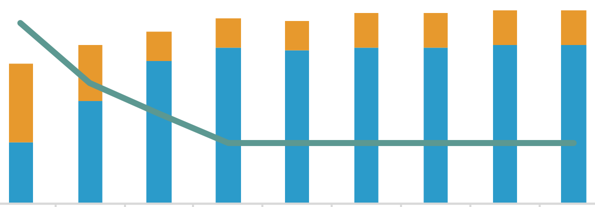
	S_D	Balanced	W_D	W_D No ToU	W_D ToU_1	W_D ToU_2	ADR 1	ADR 2	ADR 3
Cost of Supply (INR/kWh)	14.5	14.0	13.0	13.5	12.8	12.3	12.2	12.2	12.1
Emission intensity (t/Co_2MWh)	0.21	0.17	0.15	0.13	0.10	0.09	0.09	0.09	0.08

8.3 RE share & BESS

As demand flexibility is added, a high wind output and reduced need for storage are expected.

Wind's share of annual generation increases markedly as the system moves from the base RE scenarios to the W_D-based ToU and ADR cases, eventually stabilising at about 60% of generation. Overall, the RE share increases from 65% under the W_D scenario to 73% under the ADR 3 scenario. This indicates that the benefit of demand flexibility in reducing curtailment and integrating a higher RE share while limiting BESS utilisation.

Figure 55 Wind & Solar share and BESS contribution by scenario



	SD	Balanced	WD	WD_ NoToU	W_D ToU_1	W_D ToU_2	ADR 1	ADR 2	ADR 3
Solar share (%)	30%	21%	11%	11%	11%	13%	13%	13%	13%
Wind share (%)	23%	39%	54%	59%	58%	59%	59%	60%	60%
BESS share (%)	6%	4%	3%	2%	2%	2%	2%	2%	2%

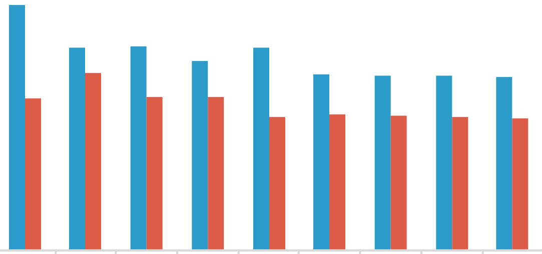
Wind share (%) Solar share (%) BESS share (%)

8.4 Net peak load and ramping

Demand flexibility in the W_D-based scenarios significantly lowers both net peak demand and ramping needs compared with S_D.

Net peak demand and maximum ramping requirements are highest in the S_D scenario and fall as the system moves toward W_D and then introduces demand flexibility options. The W_D and W_D NoToU cases already reduce the net peak relative to S_D, but ToU tariffs (W_D ToU_1 and W_D ToU_2) and especially ADR scenarios (ADR 1–3) bring both net peak and ramping needs down further. This demonstrates that combining high wind penetration with flexible demand not only lowers system peak requirements but also smooths short-term fluctuations, easing operational stress on the grid.

Figure 56 : Highest net peak load instance and ramping event by scenario



	SD	Balanced	WD	WD_NoToU	W_D ToU_1	W_D ToU_2	ADR 1	ADR 2	ADR 3
Net peak (MW)	556	459	462	430	459	398	397	396	394
Max ramping event (MW)	344	402	346	346	303	307	304	303	300

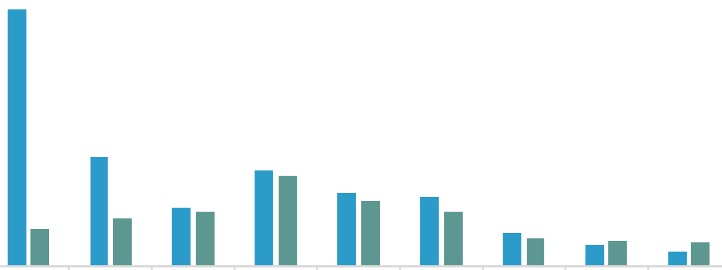
■ Net peak (MW) ■ Max ramping event (MW)

8.5 Market imports & curtailment

Market imports and renewable curtailment are highest in S_D and fall steadily through W_D, ToU, and ADR scenarios, showing that demand flexibility improves self-sufficiency and reduces wasted renewable energy.

The chart shows that both market imports and renewable curtailment are highest in the S_D scenario and decline steadily as the system moves toward W_D and then adds demand flexibility. Balanced and W_D already cut imports substantially relative to S_D, although curtailment remains material due to surplus renewable generation during certain hours. In W_D NoToU and the ToU cases, imports and curtailment both drop further, indicating that time-varying prices help align demand with renewable output and reduce surplus energy. The ADR scenarios achieve the lowest levels of both imports and curtailment, suggesting that active demand response not only improves self-sufficiency but also enables more complete utilisation of available renewable generation.

Figure 57 Market imports and curtailment by scenario



	SD	Balanced	WD	W_D NoToU	W_D ToU_1	W_D ToU_2	ADR 1	ADR 2	ADR 3
Market import (MWh)	1,44,31	61,367	32,852	54,128	41,659	38,982	18,794	11,992	8,704
Curtailment (MWh)	21,363	27,389	30,840	51,010	37,163	31,078	15,850	14,395	13,653

■ Market import (MWh) ■ Curtailment (MWh)

8.6 Recommendations

- Recognise the value of wind and diversify procurement. Develop a structured wind procurement strategy that complements local solar by sourcing wind from multiple resource regions. A geographically diversified wind portfolio will smooth net load profiles, reduce reliance on coal, lower curtailment and decrease costs of supply across the year.

- Deepen solar integration with flexibility measures. Prioritise rooftop and distributed solar in urban and industrial areas, so that local generation reduces feeder-level peaks and losses while maximising self-consumption.

- Deploy grid-scale storage and optimise siting. Prioritise battery energy storage systems at substations and renewable pooling points where they can relieve evening ramps, absorb mid-day solar surplus, and defer network upgrades. Conduct detailed siting studies that consider land availability, grid congestion, and co-location with solar and wind plants to minimise losses and integration costs. Further incentivise behind-the-meter energy storage systems.

- Redesign time-of-use (ToU) tariffs around solar hours. Introduce sharper price differentials or explicit tariff rebates during high-solar, low-cost midday hours to shift some loads away from evening peaks. Aligning prices with system costs will reduce reliance on storage and market purchases, lower overall supply costs, and smooth both gross and net load profiles.

- Scale up active demand response for large consumers. Establish contracted demand response programs with industries, commercial complexes, and large public consumers that can curtail or shift load during a limited number of critical peak hours each year.

- Position Puducherry as a low-emission power hub. Leverage the high renewable share, declining emission intensity, and competitive ToU tariff structures to market Puducherry as a clean-power destination for data centres, green manufacturing, and services. Publishing clear 2030 emission benchmarks for supplied electricity and offering green supply contracts can help attract new investment and jobs while reinforcing decarbonisation goals.

09

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10

Appendix : RTS Installed Capacities

Table 16 RTS Projections

Year	2018-19	2019–20	2020–21	2021–22	2022-23	2023-24
Installed Capacity (MW)	3.11	5.48	9.30	12.71	34.55	48.85

Adopted from ICED

The above installed capacities have been multiplied by hourly CF values taken from (Ninja Renewables) corresponding to each specific year and added to the demand to represent the gross demand.

Appendix 2 Constraints for the Capacity Expansion Model
The following are the mathematical equations and constraints that have been followed for the integrated capacity expansion and economic dispatch model.

Table 17: Mathematical equations and constraints

No.	Constraint/Equation Name	Formula	Notes
1	Installed Capacity Constraint	$\sum$ Installed Capacity $\geq$ (1 + Operating Margin) × Peak Demand	Operating Margin (α) typically assumed as 10%
2	Demand Balance Constraint	$\sum P_{g,t} + \sum P_{st,dis} - \sum P_{st,ch} = D_t, \forall t$	Generation and storage discharge meet the demand
3	Generator Capacity Constraint	$0 \leq P_{g,t} \leq P_{g,max}, \forall g, t$	Generator output limits
4	SOC Update Equation	$SOC_{s,t} = SOC_{s,t-1} + \eta_{s,ch} \cdot P_{st,ch} \cdot \Delta t - (P_{st,dis} \cdot \Delta t / \eta_{s,dis}), \forall s, t$	Storage state of charge (SOC) update
5	SOC Limits	$SOC_{s,min} \leq SOC_{s,t} \leq SOC_{s,max}, \forall s, t$	SOC must be within min and max limits
6	Storage Charging Limit	$0 \leq P_{st,ch} \leq P_{st,ch,max}, \forall s, t$	Charging power limit for storage
7	Storage Discharging Limit	$0 \leq P_{st,dis} \leq P_{st,dis,max}, \forall s, t$	Discharging power limit for storage
8	Objective Function – Cost Minimization	$\sum Cg \cdot P_{g,t} \cdot T + \sum C_{s,storage} \cdot (P_{st,ch} + P_{st,dis})$	Minimize generation and storage cost
9	Operating Margin / Reserve Margin Constraint	$\sum P_{g,nom} \geq (1 + \alpha) \cdot$ Peak Demand	α is assumed to be 10%
10	Plant Load Factor (PLF) Calculation	$PLF_g = (\sum_t P_{g,t}) / (P_{g,nom} \cdot T) \cdot 100$	Measures the utilization of generator capacity
11	Power Output of Generator	$P_{g,t}$ = power output of generator g at time t	Description of variable
12	Rated Capacity of Generator	$P_{g,nom}$ = rated capacity of generator g	Description of variable
13	Total Hours	T = total number of hours in the period	Period length for PLF calculation

Assumptions:

- Economic dispatch includes generation ramping limits, minimum up/down times, and efficiency losses.
- Fixed Cost assumptions for coal and gas have been taken from JERC tariff orders and assumed to be escalating by 2% every year.
- Variable cost prices for coal-based generators have been assumed from JERC tariff orders.
- Plant retirements have been considered based on lifetime and based on overall system cost. Technical lifetime for plants has been taken from the ICED portal.
- RE fleet and nuclear are assumed to be a must-run generators, which implies there is no marginal cost of generation.
- Storage systems are charged at 50% of the average generational cost and 15% of the average generational cost.
- Load shedding costs have been assumed to be the top 1% of day day-ahead market.
- Curtailment cost has been assumed to be Rs 15,000/MWh.

Table 18 Technical Assumptions for Conventional Generators

Technology	Ramping (%/ min)	Minimum Operational condition (%)	Maximum Operational Condition (%)	Hot Start up Time (hrs)	Warm Start up time(hrs)	Cold Start up Time (hrs)
Coal	1	40%	90%	2	5	10
Nuclear	Const. Load	50%	100%	-	-	-
Gas	5	40%	95%	1.5	2	3

Data Adopted from: CEA Technology Catalogue [2020]

Table 19 Historical Capping Rates

Year	Capping Rates (₹ per kWh)
2014	8
2015	8
2016	8
2017	8
2018	9
2019	9
2020	10
2021	10
2022	12
2023	12
2024	10

Table 20 Fixed and Variable Cost for conventional base generators 2029-30

Power Plants	Fixed Cost (Rs Cr / MW)	Variable Cost (Rs/MWh)
RSTPS Stage I & II	92.90	4,180
RSTPS Stage III	104.55	4,250
Talcher Stage II	79.93	1,940
Simhadri Stage II	175.40	4,090
(NTECL)	424.00	3,410
NLC TPS II Stage I	53.11	3,420
NLC TPS II Stage II	72.57	3,560
NLC TPS I (Expn)	123.20	3,190
NLC TPS II (Expn)	203.15	3,620
NTPL (Tuticorin)	254.52	4,740
NNTPS(OTHERS)	2605.27	2,900
PPCL	149.61	7,360
NTPC Kudgi	1023.86	5,230
MAPS	0.00	-
KAIGA 1&2	0.00	-
KAIGA 3 &4	0.00	-
KUNDANKULAM U1 &U2	0.00	-

Data Adopted from: JERC Tariff orders (2018-19 to 2023-24)

Table 21 Cost assumptions for RE fleet

Technology	Lifetime	Fixed Cost
Solar	25	53.56
Wind	25	99.68

Data Adopted from: TERI (2024)

Table 22 Technical Assumptions for BESS

Storage	Charging & Discharging Efficiency	Standing Loss	DoD	Deployment Year	Fixed Costs (Rs Lakhs/ MW)
2 hours	85%	0.01%	20%	2026-27	35.95
4 hours	85%	0.01%	20%	2027-28	55.74
6 hours	85%	0.01%	20%	2028-29	90.49

Data Adopted from: CEA Technology Catalogue [2020], latest Gujrat orders for BESS

Table 23 Represents values from Day Ahead Market in Rs/ Kwh

Case Scenario	Price
Top 10%	12.37
Top 5%	12.84
Top 1%	14.00

Data Adopted from: IEX Market data sheet (2023-24)

Table 24 Reliability Matrix

Reliability Matrix	Condition
LOLP	0.2%
NENS	0.05%

Data Adopted from: National electricity Plan (2023)