Designing deviation settlement mechanisms for wind energy in India: balancing forecast accuracy, fairness and grid stability

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As renewable energy expands in India's electricity grid, the challenge of matching supply with demand is intensifying. This commentary highlights the evolving policy landscape for wind energy forecasting, with a particular focus on the design and implications of deviation settlement mechanisms.

India's electricity sector is undergoing a major transition as the country charts a path towards a low-carbon future. Weather-dependent renewable sources, including wind and solar, as well as hydropower, are central to this shift. Globally, renewable electricity has witnessed exponential growth in installed capacity in recent decades, accounting for 44% (solar) and 38% (wind) of total installed renewable capacity in 2024 (refs 1,2). Although renewable sources have lower capacity utilisation factors than fossil-fuelled sources, their contributions to the total electricity generation – 8.1% from wind and 6.9% from solar – are no longer negligible. In this context, India is emerging as a global leader in renewable electricity, ranking as the world's third-largest generator of electricity from wind and solar combined[3].

As wind generation exhibits significantly greater variability in India than other renewable resources such as solar[4], this commentary focuses on the evolving policy landscape in India surrounding wind energy forecasting, particularly the design of deviation settlement mechanisms (DSMs). These mechanisms are intended to incentivise forecast accuracy, reduce system balancing costs, and align incentives for renewable developers with the operational needs of grid operators. Striking the right balance in DSM design is crucial for supporting grid stability and promoting renewable energy growth.

The Central Electricity Authority projects that India's installed wind capacity will nearly double to 100 GW by 2030. This rapid expansion poses substantial operational challenges for grid managers, primarily owing to the variability and intermittency of wind power generation. Unlike thermal power, which can be dispatched on demand, wind power fluctuates across timescales – from minute-wise to inter-annual – creating hurdles for aligning power generation with real-time demand. Such alignment is necessary to avoid grid instability, frequency excursions and in extreme cases, blackouts.

Therefore, accurate wind generation forecasting is critical for grid management on operational and energy systems planning timescales. On operational timescales, forecasts enable scheduling and load balancing, whereas on longer timescales, they can reduce the cost of reserves and excess capacity and minimise reliance on fast-ramping backup generators and other ancillary services (e.g. energy storage). Short-term predictions, ranging from hours to days, are vital for routine grid operations and economic dispatch. However, extreme events such as wind droughts (extended periods of low wind impacting grid-scale power generation) pose additional risks. Therefore, forecasting day-to-day variations and low-probability, high-impact events, alongside uncertainty quantification, is crucial.

To manage renewable variability, India's regulatory framework includes a forecasting and scheduling code that mandates wind and solar generators – either directly or through Qualified Coordinating Agencies (QCAs) – to submit their generation schedules to the associated State Load Dispatch Centre (SLDC). These schedules are provided in 15-minute intervals and must cover all 96 time blocks of each day. Generally, the QCAs are expected to provide separate generation schedules to the SLDC for all wind and solar generators connected to the grid network. The day-ahead schedule comprises wind or solar energy generation scheduled for each 15-minute time block, starting from 00:00 hours of the following day, and the week-ahead schedule contains the same information for the next seven days.

Considering the practical difficulties of forecasting ahead, in the context of the chaotic dynamics of weather variations, the code allows for intra-day revisions through an advance notice to the SLDC. Revisions are effective from the sixth time block after submission, i.e. with a minimum notice of 90 min. Generators can revise schedules up to 16 times per day, allowing them to refine predictions based on updated weather data. There may be one revision for each time period of 90 min, starting from 00:00 hours of a particular day. As the prediction for every 90-minute block can be made with a lead time

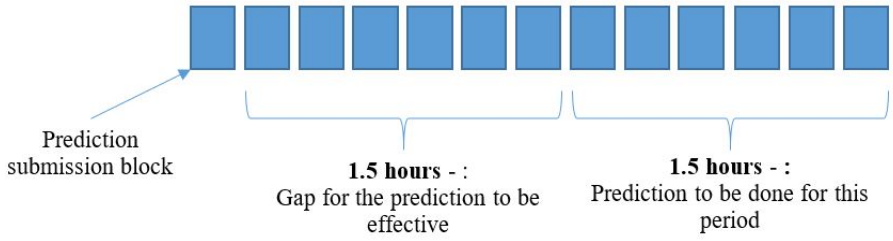


Figure 1. Schematic of the intra-day forecast revision schedule as per the existing deviation settlement mechanism.

of 90 min, the effective lead time for final forecasting is three hours (Figure 1).

DSMs play a pivotal role in this system by assigning financial consequences to deviations from the final forecast schedule. These charges are intended to reflect the costs incurred by grid operators in deploying ancillary services to maintain grid stability. DSM's deviation charges are designed to nudge participants towards greater forecast accuracy without unduly penalising them for the inherent variability of renewables.

The draft of the DSM regulations issued by the Central Electricity Regulatory Commission (CERC)[5], based on expert committee recommendations, proposed important refinements. Among these regulations, the introduction of a symmetric penalty structure for over- and under-injection is noteworthy. As per the expert committee formed by the CERC, the asymmetry in the existing DSM deviation charge structure for over- and under-injection for wind-solar (WS) sellers (as provided in the existing order dated 6 February 2023) led to a perverse tendency on the part of WS sellers to over-schedule and under-inject, especially for wind[6]. The revised draft DSM notification[5] aims to address this challenge. Similar to the earlier DSM notification, the charges are not linked to the grid frequency.

Under the new guidelines finalised, that is applicable till March 2026 (ref. 7), individual wind generators are permitted a ±15% deviation band around their scheduled generation without incurring additional penalties above the contract rate or the tariff for sale or purchase of power. However, starting from April 2026, the notification suggests a more optimistic band of ±10%. On average, this range aligns with the recent state-of-the-art wind power prediction methods applied to the Indian region using hybrid models[8,9]. However, Kumar *et al.*[10] highlighted the spatial variation in wind power predictability in India at various timescales. While the CERC DSM notification is based on a national level view, the impact of deviation is local, and a region-specific deviation band design may address the challenges related to the spatial variation in wind power predictability. Additionally, for forecasts submitted at the pooling station level, where the outputs of multiple wind farms are aggregated, the draft regulations proposed to set the acceptable deviation band without incurring penalties at ±5%. This tighter threshold is based on the reasonable hypothesis that aggregation reduces forecast error, with several independent forecast errors partially balancing each other out.

Such a provision rightly encourages cooperation among developers and creates incentives for forecasting at the pooling station level. However, the choice of the threshold at which penalties are levied requires empirical investigation of aggregation and its effects on the predictability of wind power and its forecasting errors. The degree of forecast improvement from aggregation remains an open question[11]. Figure 2 shows four sample case studies from different wind-rich districts of Madhya Pradesh. While aggregate prediction enhances forecast accuracy (shaded histogram), the improvements are modest. Factors such as geographic dispersion, correlation with the diurnal cycle, synoptic variability, and the type of background condition can each impact forecast accuracy at the pooling station level. Generally, multi-scale assessments of forecast error distributions are required prior to finalising tighter bands in binding regulations. In line with various stakeholder feedback, the final notification does not introduce such bands. However, critically designed bands for aggregate forecasting at the pooling station level may encourage improvements in forecast accuracy.

A critical component of DSM implementation is the quantification of forecasting errors, which determine the penalties. The most widely used formula calculates the absolute percentage error as follows[6]:

$$\text{Absolute error (\%)} = \frac{100 \times (\text{Generation}_{\text{actual}} - \text{Generation}_{\text{scheduled}})}{\text{Capacity}_{\text{available}}} \quad (1)$$

Owing to the available capacity in the denominator, this yields lower percentage errors (and thus lower penalties) when the capacity is high but the scheduled output is low. To address perceived inequities from this structure, alternative formulas have been proposed by state regulators. For example, Chhattisgarh's DSM draft guidelines[12] recommend a

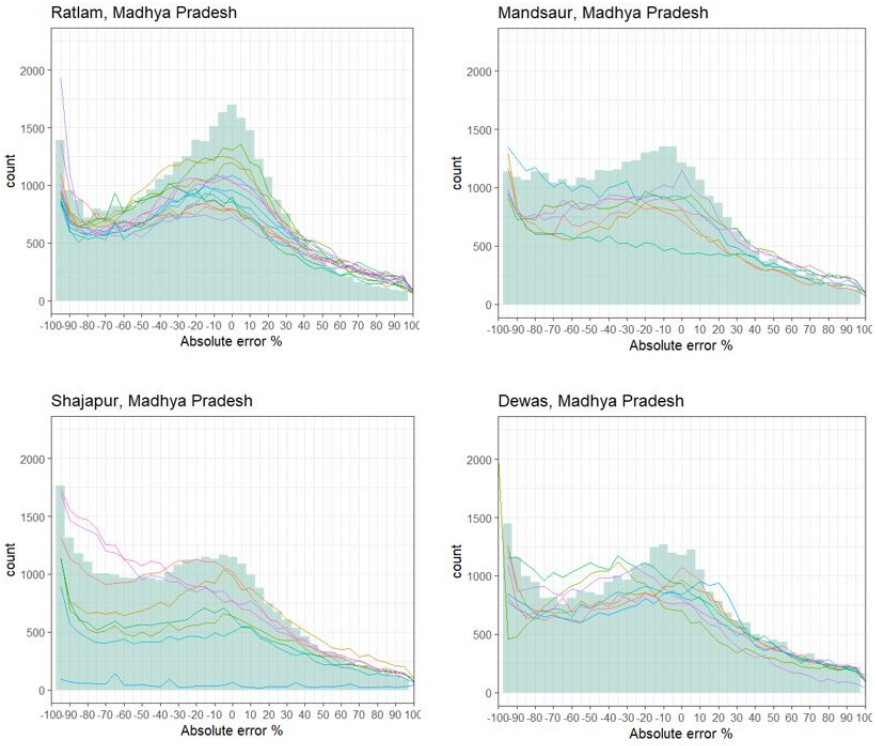


Figure 2. Impact of regional aggregation: case study of Madhya Pradesh for 2019. Curves depict forecast error (using eq. (3)) distribution for individual plants; the shaded histogram depicts the error distribution of the aggregate forecast for the district (data source: SCADA system, Madhya Pradesh). The pooling station is a much smaller area than the district.

weighted sum of the available capacity and scheduled generation as the denominator, as shown in eq. (2).

$$\text{Absolute error (\%)} = \frac{100 \times (\text{Generation}_{\text{actual}} - \text{Generation}_{\text{scheduled}})}{(X\% \times \text{Capacity}_{\text{available}}) + ((100 - X)\% \times \text{Generation}_{\text{scheduled}})} \quad (2)$$

This hybrid approach reflects the technical potential and the generator's scheduling intent and accuracy. Tamil Nadu[13] opted for this alternative formula:

$$\text{Absolute error (\%)} = \frac{100 \times (\text{Generation}_{\text{actual}} - \text{Generation}_{\text{scheduled}})}{\text{Generation}_{\text{scheduled}}} \quad \text{if } (\text{Generation}_{\text{schedule}} \neq 0) \quad (3)$$

This technique penalises deviations more harshly during periods of low scheduled output.

Furthermore, as India transitions away from predominantly baseload, coal-based generation – traditionally the main source of grid inertia – the absolute magnitude of deviations may become more critical than the relative errors of individual generators. Reduced inertia allows more rapid frequency changes, making large absolute deviations between scheduled and actual generation riskier. Therefore, future DSM frameworks might benefit from incorporating absolute deviation thresholds alongside or instead of percentage-based metrics.

Although the revised DSM regulations adopt a symmetric approach for over- and under-injection to ensure simplicity and clarity, challenges arise from the operational realities faced by grid operators. The impacts of generation imbalances vary asymmetrically depending on system load conditions.

For example, in low-demand periods, such as those during the Southwest monsoon, over-injection from must-run wind generators can overwhelm the grid, leading to curtailment or costly balancing actions. In contrast, during high-demand periods, especially peak summer months, over-generation can be beneficial, reducing the need for additional peaking capacity or imports. Moreover, forecast deviations during low-generation months might not impact the grid operators as much as deviations during high-wind months. The contribution of wind energy to the total generation is negligible during the low generation months.

These asymmetries suggest that a simple penalty structure is not necessarily optimal; instead, a more dynamic DSM design – potentially linked to real-time demand supply imbalances and reserve margins – could provide better incentives under evolving conditions. However, implementing such adaptive penalties would expand information and regulatory requirements and require coordinated supply and demand forecasting, greater engagement between system

operators and generators, and real-time monitoring and information sharing.

The development of effective DSM frameworks tailored to India's renewable growth and regional conditions involves addressing several open scientific and policy questions:

- Forecast aggregation: How much can pooling station aggregation lower forecast errors? Are there options for deviation tolerance that are consistent with evidence while accommodating variability and change? Similar questions have been raised in the literature[11].
- Metrics for deviation penalties: Is it useful to complement the current percentage-based metrics with absolute deviation thresholds, as expanding renewable energy contributions lower grid inertia?
- Forecast horizon: While DSM charges apply to intra-day forecasts, day-ahead and week-ahead forecasts are being collected but not penalised. Would introducing mild penalties for longer-range forecast inaccuracies improve accuracy and grid operations without discouraging participation?
- Context-aware penalties: Can DSM penalties be made responsive to time-of-day or seasonal grid conditions? Would a demand–supply-sensitive mechanism better reflect the operational costs and risks arising from deviations?
- DSM design for firm and dispatchable renewable energy (FDRE): How can a DSM mechanism be designed for FDRE systems, combining wind–solar–storage to achieve the committed demand fulfilment ratio, that optimises the penalty?

A multidisciplinary approach, bringing together expertise from power systems engineering, meteorology and climate science, economics, and regulatory governance, is required to address the above questions. Together, these teams can quantify forecast uncertainty, evaluate incentive compatibility of reporting, and calibrate penalties to actual operational costs of deviations.

The challenge of designing a DSM for wind energy integration reflects the wider complexity of transitioning to a renewable-powered grid. It requires aligning the interests of diverse stakeholders (generators, system operators and regulators) within a dynamic, uncertain environment. However, continuous advances in AI-based hybrid, short-term wind forecasting make the periodic reassessments of the 'no additional penalties' band in DSM policy essential[14].

India has made major strides in institutionalising forecast-based grid management through DSM regulations. However, as renewable generation rises and legacy features, including high inertia decline, these mechanisms must evolve. Evidence-based refinements – revised error metrics, adaptive penalty structures, and the explicit design of incentives for forecast accuracy – are key to balancing fairness, efficiency and reliability.

An evidence-based DSM framework can bridge India's energy transition goals, supporting developers in managing uncertainty while enabling grid stability. In doing so, DSM policy can become a critical enabler of India's broader energy transformation.

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