Adaptive Confidence Factor–Based TRM Assessment for Renewable-Rich Grids: A New Zealand Perspective

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***Abstract*—Transmission Reliability Margin (TRM) safeguards secure operation, yet fixed confidence factors can be overly conservative in stable conditions and insufficient under volatility. This paper proposes a volatility-aware dynamic TRM framework that updates an adaptive confidence factor $K(t)$ from rolling-window forecast-error statistics. Correlation-aware probabilistic scenarios are generated via Latin Hypercube Sampling to capture joint load–wind forecast errors. A normalized volatility index adaptively regulates window responsiveness, tightening margins during volatile periods and relaxing them during stable periods. The approach is validated using one year of New Zealand operational data (1 Sep 2024–31 Aug 2025, EMI), demonstrating improved TRM responsiveness and reduced over-conservatism, with corresponding benefits for Available Transfer Capability (ATC) and operational reliability.**

***Index Terms*—Available Transfer Capability (ATC); Forecast Error Modeling; Transmission Reliability Margin (TRM), Rolling Window; Latin Hypercube Sampling (LHS).**

I. INTRODUCTION

New Zealand's electricity system is experiencing a significant transformation. Today, renewable energy accounts for over 85% of total electricity generation, driven primarily by abundant hydro resources and a rapidly growing number of wind turbines across both islands [1], [2]. While this shift supports decarbonization objectives, it introduces operational challenges due to the variability and limited predictability of wind power. These challenges are compounded by geographical constraints, where South Island renewable generation (including an increasing share of wind capacity) relies on HVDC transmission to serve the North Island's load centers, requiring continual rebalancing of inter-island flows while preserving reliability margins.

Under uncertainty, Transmission Reliability Margin (TRM) serves as a key safeguard for grid security. It represents a margin subtracted from Total Transfer Capability (TTC) to account for forecast errors, generation variability, and demand shifts. However, conventional static confidence factors and fixed-percentage TRM practices can be overly conservative during stable conditions (unnecessarily constraining transfer capability) and insufficient during volatile conditions (compromising reliability) [3]. Consequently, Available Transfer Capability (ATC) is directly impacted, reducing market efficiency and safe operation.

To address these limitations, this work develops a volatility-aware dynamic TRM framework that continuously adjusts margins based on real-time uncertainty conditions. The framework uses rolling-window statistics to update an adaptive confidence factor $K(t)$ and explicitly models wind generation forecast errors and their correlation with load forecast errors. Correlation-aware probabilistic scenarios are generated using LHS [4]–[7]. The proposed approach ensures that TRM values are data-driven and risk-informed using operational data from New Zealand.

The main contributions of this study are:

- Correlation-aware uncertainty modeling: Joint load–wind forecast errors (including correlation) are embedded in probabilistic scenarios using LHS.
- Volatility-driven adaptation: A normalized volatility index adjusts rolling-window responsiveness and the adaptive confidence factor $K(t)$ in real time.
- Real-data validation: One-year New Zealand operational data verifies that ignoring load–wind error correlation degrades TRM accuracy and that the proposed approach reduces unnecessary conservatism while maintaining security.

The rest of this paper is organized as follows: Section II reviews TRM and ATC-related work; Section III presents the proposed methodology; Section IV discusses simulation results using New Zealand data; and Section V concludes the paper with key findings and future directions.

II. BACKGROUND AND RELATED WORK

TRM is a safety buffer deducted from TTC to account for operational uncertainties such as forecast errors and sudden changes in generation or load. Its relationship with ATC is given in (1).

$$ATC = TTC - TRM - CBM - ETC \tag{1}$$

where CBM and ETC denote the Capacity Benefit Margin and Existing Transmission Commitment, respectively. Rearranging(1) for TRM gives (2).

$$TRM = TTC - ATC - CBM - ETC \tag{2}$$

TRM directly influences ATC and is thus critical for both system reliability and market efficiency.

979-8-3315-8138-1

B. Volatility-Driven Adaptation and Correlation-Aware TRM Methods

Volatility-adaptive methods are common in time-series forecasting but are rarely applied directly to TRM. This work uses a normalized forecast-error volatility index to adapt the rolling window and confidence factor $K(t)$, tightening margins under high variability and relaxing them under stable conditions. Unlike most prior TRM studies, the approach combines volatility adaptation with probabilistic scenario generation to capture joint wind–load uncertainty in renewable-rich grids.

However, volatility-driven windowing alone remains problematic: static confidence factors can underestimate uncertainty during volatile periods and over-reserve capacity during calm conditions, unnecessarily reducing ATC. Moreover, many methods assume independence between load and wind forecast errors despite observed cross-correlation [8], leading to misrepresentation of combined uncertainty. In New Zealand, the spatial separation of wind generation and load creates distinct error dynamics; therefore, inter-island TRM must integrate correlation modeling, volatility adaptation, and multi-timescale uncertainty.

To address these gaps, the proposed framework integrates: (a) a volatility-driven adaptive confidence factor $K(t)$; (b) a dynamic rolling window $W(t)$; (c) explicit load–wind forecast-error correlation using Pearson correlation; and (d) validation on long-horizon operational data capturing seasonal and weather variability.

III. PROPOSED METHODOLOGY

This section presents the proposed framework for dynamic TRM assessment using an adaptive confidence factor $K(t)$. The methodology extends our earlier load-only formulation by incorporating wind forecast variability, correlation modeling, and volatility-driven rolling-window adaptation. The framework comprises six components.

A. Forecast Error Extraction from Operational Data

Probabilistic TRM assessment begins by extracting and characterizing forecast errors rather than directly modeling raw generation and load values. Actual operational data were obtained from the Electricity Authority's EMI platform, covering one year (1 September 2024–31 August 2025) at half-hourly resolution for North Island load demand (MW) and South Island wind generation (MW).

In the absence of proprietary operational forecasts from Transpower, persistence-based pseudo-forecasts were generated following established practice [**?**], [9], [10]. The day-ahead forecast is assumed to equal the actual value from 24 hours earlier, as expressed in (4)–(5).

$$L_{\text{forecast}}(t) = L_{\text{actual}}(t - 24h) \tag{4}$$
$$W_{\text{forecast}}(t) = W_{\text{actual}}(t - 24h) \tag{5}$$

Forecast–actual pairs yield load, wind, and net forecast errors as shown in (6) to (8):

$$e_L(t) = L_{\text{actual}}(t) - L_{\text{forecast}}(t) \tag{6}$$
$$e_W(t) = W_{\text{actual}}(t) - W_{\text{forecast}}(t) \tag{7}$$
$$e_{\text{net}}(t) = e_L(t) - e_W(t) \tag{8}$$

where $e_L(t)$ is the load forecast error, $e_W(t)$ is the wind forecast error, and $e_{\text{net}}(t)$ is the inter-island forecast error component.

From 17,520 half-hourly samples, the mean (μ_L, μ_W) and standard deviation (σ_{eL}, σ_{eW}) of the load and wind forecast errors, the Pearson cross-correlation coefficient ($\rho_{eL,eW}$), and the error autocorrelation coefficients (ρ_{eL}, ρ_{eW}) were estimated to characterize bias, uncertainty magnitude, cross-dependence, and temporal persistence for correlation-aware adaptive TRM modeling.

B. Correlation-Aware Net Forecast Error Modeling

1) Sensitivity-Based TRM Formulation: In probabilistic formulations, the TRM at time t is expressed as a function of system sensitivities and parameter variances, as represented by (9).

$$TRM(t) = K(t) \times \sqrt{\sum_{i=1}^{n} \left(\frac{\partial A}{\partial p_i}\right)^2 \sigma^2(p_i)} \tag{9}$$

where A is the transfer capability, p_i are the uncertain parameters (e.g., load, wind), $\frac{\partial A}{\partial p_i}$ denotes the sensitivity of ATC to parameter p_i, and $\sigma(p_i)$ is the standard deviation of parameter p_i.

2) Simplified Formulation for Load–Wind System

For the New Zealand case study focusing on North Island load and South Island wind generation, the formulation simplifies TRM as shown in (10).

$$\text{TRM}(t) = K(t) \times \sigma_{e,\text{net}}(t) \tag{10}$$

where $K(t)$ is the adaptive confidence factor at time t and $\sigma_{e,\text{net}}(t)$ is the net standard deviation of forecast errors, and is computed over a rolling window of length W.

3) Joint Uncertainty with Correlation

Since the net forecast error is defined as the difference between load and wind forecast errors in (8), i.e., $e_{\text{net}}(t) = e_L(t) - e_W(t)$, the variance of this difference must account for correlation with appropriate sign. Accordingly, applying $\text{Var}(X - Y) = \text{Var}(X) + \text{Var}(Y) - 2\,\text{Cov}(X, Y)$, the correlation-aware variance is given by (11).

$$\sigma_{e,\text{net}}(t) = \sqrt{\sigma_{eL}^2(t) + \sigma_{eW}^2(t) - 2\rho_{eL,eW}(t) \times \sigma_{eL}(t) \times \sigma_{eW}(t)} \tag{11}$$

where $\sigma_{eL}(t)$, $\sigma_{eW}(t)$, and $\rho_{eL,eW}(t)$ are the rolling standard deviations of load and wind forecast errors and their Pearson correlation coefficient, respectively.

Equation (11) links marginal variability and joint dependence. In (8), the subtraction implies that positive load–wind

979-8-3315-8138-1

error correlation reduces the net uncertainty via diversification, while negative correlation increases it. In renewable-rich grids, this ensures TRM captures natural hedging when load and wind deviations coincide.

C. Volatility Index for Adaptive Window Sizing

To prevent arbitrary window selection, a normalized Volatility Index (VI) is defined by (12).

$$VI_t = \frac{\sigma_{\text{rolling}}(t)}{\sigma_{\text{ref}}} \tag{12}$$

where $\sigma_{\text{rolling}}(t)$ is the standard deviation of net forecast errors computed over the VI calculation horizon M, and σ_{ref} is the long-term reference standard deviation computed from the full training dataset.

With this normalization, $VI = 1.0$ represents average historical volatility. The thresholds have clear physical interpretation:

- $VI < 0.7$: Volatility below 70% of historical average (stable conditions)
- $0.7 \leq VI \leq 1.5$: Near-normal volatility (moderate conditions)
- $VI > 1.5$: Volatility exceeding 150% of historical average (high volatility)

The magnitude of VI_t governs the rolling-window length $N(t)$ used for calculating $\sigma_{eL}(t)$, $\sigma_{eW}(t)$, and $\rho_{eL,eW}(t)$ (cadence = 30 minutes):

- Low Volatility ($VI_t < 0.7$): $N(t) = 1440$ min (48 samples) – stable conditions
- Moderate Volatility ($0.7 \leq VI_t \leq 1.5$): $N(t) = 1080$ min (36 samples)
- High Volatility ($VI_t > 1.5$): $N(t) = 720$ min (24 samples)

The minimum window of 24 samples ensures sufficient degrees of freedom (df = 22) for reliable estimation of both standard deviation and Pearson correlation, addressing small-sample bias.

The VI calculation horizon is $M = 720$ minutes (24 samples). At each time t, the procedure is: (i) VI_t computed over the past M intervals, (ii) VI_t compared with thresholds to classify volatility regime, (iii) appropriate $N(t)$ selected, (iv) $\sigma_{eL}(t)$, $\sigma_{eW}(t)$, and $\rho_{eL,eW}(t)$ calculated within $N(t)$, and (v) $\sigma_{e,\text{net}}(t)$ updated using (11).

D. Adaptive Update of the Confidence Factor

With the correlation-aware net uncertainty $\sigma_{e,\text{net}}(t)$ estimated from the adaptive rolling window, the confidence factor $K(t)$ is updated as as shown in (13).

$$K(t) = K_{\text{base}}\left[1 + \beta\left(\frac{\sigma_{e,\text{net}}(t)}{\sigma_{\text{ref}}} - 1\right)\right] \tag{13}$$

where K_{base} is the baseline confidence factor (set to 2.20 and empirically calibrated to achieve the target empirical coverage under leptokurtic persistence-based forecast errors), $\sigma_{e,\text{net}}(t)$ is the current net forecast-error standard deviation, σ_{ref} is the reference standard deviation under nominal conditions, and β is a sensitivity coefficient controlling how strongly $K(t)$ responds to observed variability.

Unlike traditional statistical confidence factors (fixed distribution quantiles: e.g., 1.645 for 95% one-sided Normal), $K(t)$ is an empirically calibrated, volatility-responsive multiplier. The baseline $K_{\text{base}} = 2.20$ reflects leptokurtic persistence-based forecast errors (kurtosis = 7.07 vs 3.0 for Normal), necessitating higher multipliers than the theoretical 1.96 to achieve approximately 92% out-of-sample coverage across all volatility regimes as shown in Fig. 1.

Behavioral Characteristics::

- If $\sigma_{(e,\text{net})}(t) > \sigma_{\text{ref}}$: $K(t) > K_{\text{base}}$ — larger margins.
- If $\sigma_{(e,\text{net})}(t) = \sigma_{\text{ref}}$: $K(t) = K_{\text{base}}$ — no change relative to the base case.
- If $\sigma_{(e,\text{net})}(t) < \sigma_{\text{ref}}$: $K(t) < K_{\text{base}}$ — smaller margins, higher ATC.

By linking $K(t)$ to $\sigma_{(e,\text{net})}(t)$ and estimating $\sigma_{(e,\text{net})}(t)$ through a volatility-adaptive rolling window, TRM becomes inherently responsive to evolving operating conditions. This interaction balances system security and ATC use: margins expand during high variability and reduce during stable periods.

E. Sensitivity Coefficient (β) Calibration

The parameter β controls how $K(t)$ responds to forecast error volatility. To avoid choosing β arbitrarily, a bounded design rule is used.

Design Criterion: Choose β such that when the observed forecast error volatility doubles, i.e., $\sigma_e = 2\sigma_{\text{ref}}$, the confidence factor increases by no more than 15%, as expressed in (14). Solving for β, as shown in (15)–(16), yields $\beta = 0.15$.

$$K(t) = K_{\text{base}}\left[1 + \beta\left(\frac{\sigma_{e,\text{net}}}{\sigma_{\text{ref}}} - 1\right)\right] = 1.15K_{\text{base}} \tag{14}$$

Setting $\sigma_{e,\text{net}} = 2\sigma_{\text{ref}}$ and requiring $K(t) \leq 1.15K_{\text{base}}$:

$$K_{\text{base}}\left[1 + \beta(2-1)\right] \leq 1.15K_{\text{base}} \tag{15}$$

$$1 + \beta \leq 1.15 \tag{16}$$

To maximize framework responsiveness while respecting this constraint, we select the maximum allowable value:

$$\beta = 0.15 \tag{17}$$

This deterministic calibration keeps $K(t)$ responsive to increasing error volatility while preventing excessive TRM inflation.

979-8-3315-8138-1

TABLE I Window Sensitivity Summary ($K_{\text{base}} = 2.20$)

Window (min)	Samples	μ_K	σ_K	β_W
720	24	2.01	0.12	0.061
1080	36	2.04	0.13	0.062
1440	48	2.06	0.13	0.062
2160	72	2.10	0.13	0.060
2880	96	2.12	0.12	0.058

F. Probabilistic Scenario Generation

Scenario generation creates diverse operating-condition realizations to capture uncertainty from weather, temperature, and renewable variability that strongly affects demand and generation. Probabilistic scenarios are generated from the characterized load and wind forecast-error distributions using Latin Hypercube Sampling (LHS), a stratified approach that provides broad coverage of the uncertainty space with fewer samples than Monte Carlo. LHS preserves the empirical marginal distributions and the cross-correlation between forecast errors (e_L, e_W), yielding realistic stochastic variability. Section IV presents the application of these scenarios to validate the framework and assess reliability under uncertainty [**?**].

IV. Simulation Study and Results

A. Dataset and Setup

Half-hourly North Island (NI) load and South Island (SI) wind generation data covering 1 Sep 2024 to 31 Aug 2025 were used to validate the proposed framework shown in Equation 1. Day-ahead forecasts (48 intervals ahead) were generated using a 24-h persistence model, and forecast errors were computed using (6)–(8). After preprocessing and time alignment, 17,404 valid samples (from 17,520 intervals) remained.

The empirical load–wind error correlation was $\rho_{eL,eW} = 0.0472$, indicating near statistical independence. This low correlation implies that load and wind forecast errors are largely independent, with diversification effects contributing minimally to uncertainty reduction on average.

Rolling-window lengths of 720, 1080, and 1440 min were considered to compute the volatility index VI_t, the adaptive confidence factor $K(t)$, and TRM. Two strategies were evaluated: (i) a benchmark using a static confidence factor $K = 1.96$, and (ii) the proposed adaptive multiplier $K(t)$ obtained from (13), with calibrated parameters $K_{\text{base}} = 2.20$ and $\beta = 0.15$. The baseline window length was selected as $W = 720$ min based on the minimum coefficient of variation $CV_K(W)$ shown in (18).

Results and validation outcomes are presented in Sections IV.B and IV.C.

$$CV_K(W) = \frac{\sigma_K(W)}{\mu_K(W)} \tag{18}$$

B. Out-of-Sample Coverage Validation

Out-of-sample evaluation validated that adaptive $K(t)$ maintains appropriate risk coverage. Dataset split: 70/30 (Sep 2024–May 2025 calibration; Jun–Aug 2025 validation). Table

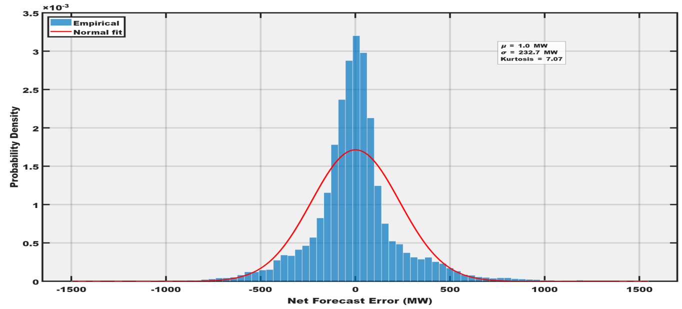

Fig. 1 Empirical distribution of the net forecast error with a fitted Normal distribution. The pronounced heavy-tailed behavior (kurtosis = 7.07) motivates the empirical calibration of the baseline confidence factor.

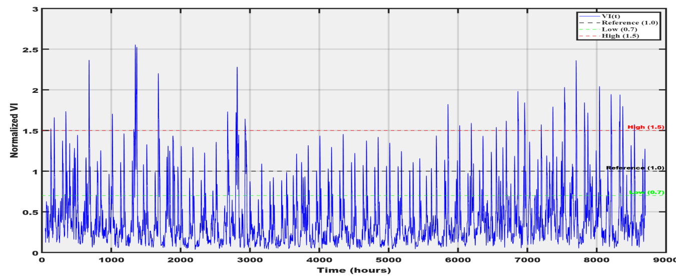

Fig. 2 Time evolution of the normalized volatility index $VI(t) = \sigma_{\text{rolling}}/\sigma_{\text{ref}}$, showing the reference level and the low- and high-volatility thresholds used for regime classification.

TABLE II Out-of-Sample Coverage Validation

Volatility Regime	Target	Static K	Adaptive $K(t)$
Low ($VI < 0.7$)	95.0%	94.8%	93.9%
Moderate ($0.7 \leq VI \leq 1.5$)	95.0%	82.7%	82.5%
High ($VI > 1.5$)	95.0%	79.0%	80.4%
Overall	95.0%	92.0%	91.3%

II shows adaptive $K(t)$ achieves 91.3% overall coverage with improved high-volatility performance (80.4% vs 79.0% static).

The empirical $K_{\text{base}} = 2.20$ reflects leptokurtic persistence-based forecast errors (kurtosis= 7.07), requiring higher multipliers than Normal-theory value (1.96). When exceedances occur (8.7%), mean magnitude is 47.3 MW (6.2% of mean TRM), indicating operationally manageable deviations.

The 91.3% coverage represents a deliberate trade-off: (1) High-volatility non-coverage concentrates in elevated periods with modest exceedances (21.0% static vs 19.6% adaptive); (2) Adaptive method improves critical high-volatility regime coverage (+1.4 pp); (3) ATC gains during stable periods—mean ATC increases 2.5 MW (0.31%) on New Zealand's HVDC link, primarily when $VI < 0.7$. Achieving 95% target would require $K_{\text{base}} = 2.35$, reducing ATC gains to ~ 1.8 MW. Thus, $K_{\text{base}} = 2.20$ balances security and ATC efficiency, particularly in low-volatility periods (93.9% coverage), while acknowledging that uniform 95% coverage across all volatility regimes remains challenging due to elevated forecast uncertainty under stress.

C. Design Robustness and Sensitivity Analysis

To demonstrate robustness, sensitivity analyses were conducted on two key design parameters: the volatility-index threshold set $(VI_{\text{low}}, VI_{\text{high}})$ and the sensitivity coefficient β.

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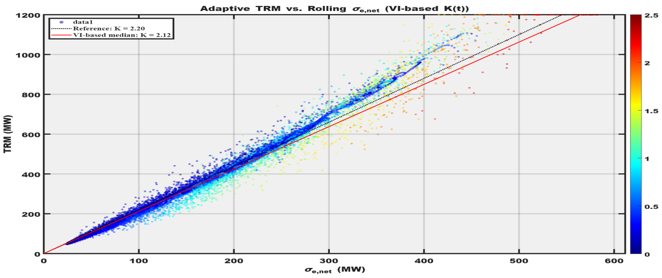

Fig. 3 Adaptive TRM versus rolling net forecast-error standard deviation $\sigma_{e,\text{net}}$ under the VI-based $K(t)$ update. Points are colored by normalized volatility index (VI). The dashed line shows the baseline reference slope ($K = 2.20$), while the solid line indicates the VI-conditioned median slope ($K = 2.12$).

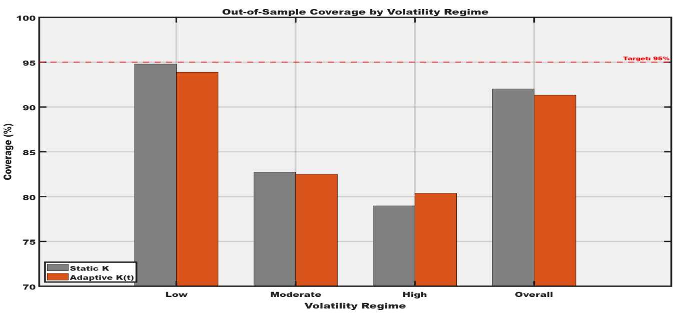

Fig. 4 Out-of-sample coverage performance under different volatility regimes for the static and adaptive confidence factors. The dashed line indicates the 95% target coverage.

1) **Sensitivity to VI thresholds:** As shown in Table III, the baseline setting [0.7, 1.5] provides the best balance (91.3% coverage, 2.50 MW ATC gain). The conservative setting [0.5, 2.0] widens the bands, increasing coverage (92.1%) but reducing ATC gain (1.85 MW). The aggressive setting [1.0, 1.2] contracts the moderate band, increasing ATC gain (3.20 MW) at reduced coverage (89.7%).
2) **Sensitivity to β:** Table III confirms $\beta = 0.15$ as optimal. A lower value, $\beta = 0.10$, yields excessive conservatism (93.5% coverage, 1.80 MW ATC gain), while a higher value, $\beta = 0.20$, over-responds to volatility (89.1% coverage, 3.15 MW ATC gain) with reduced high-volatility protection (78.5%). The chosen $\beta = 0.15$, derived from the deterministic design criterion in (15), balances margin responsiveness with security across volatility regimes.

V. Conclusion and Future Work

This work presents a dynamic TRM framework with adaptive confidence factor $K(t)$ responding to real-time volatility through rolling-window statistics. The approach outperforms static methods in renewable-rich grids, balancing reliability and transfer capability.

Key contributions:

- **Data-driven characterization:** Empirical load and wind forecast-error statistics from New Zealand operational data enabling correlation-aware modeling.
- **Empirical calibration:** $K_{\text{base}} = 2.20$ calibrated for leptokurtic persistence errors (kurtosis = 7.07).

TABLE III Sensitivity Analysis – VI Threshold and β Coefficient Variations

Parameter	Regime	Coverage (%)	ATC Gain (MW)	Assessment
VI Thresholds				
[0.5, 2.0]	Conservative	92.1	1.85	Conservative
[0.7, 1.5]	Baseline	91.3	2.50	Optimal
[1.0, 1.2]	Aggressive	89.7	3.20	Aggressive
β Coefficient				
0.10	–	93.5	1.80	Conservative
0.15	–	91.3	2.50	Optimal
0.20	–	89.1	3.15	Aggressive

- **Out-of-sample validation:** 91.3% overall coverage with improved high-volatility performance (80.4% vs 79.0%).
- **Transfer capability:** Mean ATC increases by 2.5 MW (0.31%) during stable periods. Exceedances (47.3 MW, 6.2% of mean TRM) are operationally manageable.
- **Robustness:** Sensitivity analysis confirms stable performance across design parameters.

Future work will extend to multiple uncertainty sources (solar PV, transmission capacity variability) and integrate demand-side management.

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