Random Forest-Assisted Dynamic TRM Estimation for Improved ATC in Renewable-Rich Power Systems

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***Abstract*—Accurate Available Transfer Capability (ATC) assessment is critical for reliable operation of renewable-rich power systems. Conventional dynamic Transmission Reliability Margin (TRM) methods based on rolling-window statistics mainly react to recent volatility, limiting responsiveness during rapid system changes. This paper proposes a Random Forest (RF)-assisted dynamic TRM framework where a lightweight RF regression model predicts short-term volatility using historical forecast errors and operating-condition features. The predicted volatility is incorporated into an adaptive confidence factor, $K(t)$, enabling anticipatory TRM adjustment while preserving the original probabilistic framework. Validation on the IEEE 24-bus Reliability Test System with integrated wind generation demonstrates improved performance, achieving 97.2% coverage during ramp events compared with 91.7% for the rolling-window approach and 69.4% for the static method. The RF model achieved RMSE = 3.60 MW and R^2 = 0.825 for 3-step-ahead volatility prediction, showing strong potential for renewable-integrated Australasian power systems.**

Keywords-Available transfer capability, transmission reliability margin, machine learning, random forest, renewable energy integration, power system reliability.

I. INTRODUCTION

The accelerating integration of renewable energy sources (RESs) into power grids worldwide is reshaping the operational landscape of modern transmission networks. The Australasian region has witnessed rapid growth in utility-scale renewable deployment, including Australia's large-scale wind and solar farms under the Renewable Energy Target and New Zealand's ambitious 100% renewable electricity goal [1, 2]. However, increasing renewable penetration is unfolding alongside aging transmission infrastructure and limited interconnection capacity, particularly across long inter-area corridors. Under these conditions, ensuring the secure and efficient transfer of renewable power from generation-rich regions to demand centres becomes both critical and challenging.

Available Transfer Capability (ATC) is a key operational metric that quantifies the additional power transfer that can be reliably accommodated by a transmission corridor without violating system security limits [3]. As defined by the North American Electric Reliability Council (NERC), ATC is computed by subtracting Existing Transmission Commitments (ETC), Transmission Reliability Margin (TRM), and Capacity Benefit Margin (CBM) from Total Transfer Capability (TTC). Among these components, TRM plays a particularly important role, as it reserves a portion of transfer capability to accommodate uncertainties arising from load variability, generation intermittency, and transmission outages [4]. Conventional TRM estimation methods apply a fixed confidence factor K to a static standard deviation of system uncertainty, producing a constant TRM value that does not reflect the time-varying nature of renewable-rich grids [5, 6]. Even recent probabilistic approaches that incorporate wind generation uncertainty into day-ahead ATC evaluation maintain a static K throughout the assessment period [7].

Recent advances have introduced dynamic and probabilistic TRM frameworks that adapt the reliability margin in response to observed system conditions. Rolling-window statistical analysis has emerged as an interpretable and computationally efficient approach in which the confidence factor $K(t)$ is updated based on the recent standard deviation of forecast errors within a sliding time window [8-10]. When combined with Latin Hypercube Sampling (LHS) for efficient uncertainty scenario generation, these frameworks provide adaptive TRM estimation that responds to renewable-induced volatility. However, the rolling-window mechanism is primarily retrospective, since the confidence factor is adjusted based on volatility that has already appeared within the observed window. In rapidly evolving system conditions, such as wind ramp events or sudden changes in net load, this response may lag the actual variability, leaving the system temporarily under-protected during critical operating periods. Machine learning (ML) techniques have demonstrated significant potential in power system forecasting and operational decision support, including load and renewable generation prediction, fault detection, and asset risk assessment [11, 12]. Despite this progress, the application of ML to enhance the anticipatory capability of dynamic TRM assessment has received limited attention. This paper addresses this gap by introducing a Random Forest (RF)-assisted volatility prediction layer within the established dynamic TRM framework.

The contributions of this paper are threefold:

1) A lightweight RF regression model is developed to predict short-term system volatility using historical forecast errors, ramping rates, and operating-condition features, thereby providing an early indicator of impending uncertainty.
2) The predicted volatility is integrated into the adaptive confidence factor $K(t)$, extending the dynamic TRM framework from a primarily retrospective rolling-window mechanism to a forecast-informed assessment approach.
3) The proposed framework is evaluated on the IEEE 24-bus Reliability Test System with integrated wind generation and compared with conventional rolling-window TRM estimation using coverage probability, TRM responsiveness, and ATC utilization as performance metrics.

The remainder of this paper is organised as follows. Section II presents the background on dynamic TRM and ATC formulation. Section III describes the proposed RF-assisted framework. Section IV presents the case study setup. Section V discusses the simulation results. Section VI concludes the paper.

II. BACKGROUND ON DYNAMIC TRM AND ATC

A. Standard and Dynamic ATC Formulation

The standard NERC definition of ATC [3] is given by (1).

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

In conventional practice, these quantities are treated as fixed values over the assessment interval. However, in renewable-rich systems, both TTC and TRM vary significantly with time. To reflect this, the dynamic ATC formulation is given by (2).

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

where $TTC(t)$ is determined through AC power flow analysis at each time step, while $TRM(t)$ is dynamically estimated using the adaptive framework described in Sections II.C and III. ETC and CBM are treated as given operational parameters.

B. Probabilistic TRM Estimation

In probabilistic TRM assessment, the reliability margin is expressed by (3).

$$TRM = K \times \sigma_U \tag{3}$$

where K is the confidence factor and σ_U is the standard deviation of uncertainty propagated to transfer capability.

For multiple uncertain parameters, σ_U can be estimated using (4).

$$\sigma_U = \sqrt{\sum_{i=1}^{m} \left(\frac{\partial TTC}{\partial p_i}\right) \sigma^2(p_i)} \tag{4}$$

where p_i represents an uncertain parameter such as load demand or wind generation, $\partial TTC / \partial p_i$ is the sensitivity of TTC to p_i, and $\sigma(p_i)$ is its standard deviation [4]. For dynamic operation, TRM is given by (5).

$$TRM\ (t) = K\ (t) \times \sigma_U(t) \tag{5}$$

where both $K(t)$ and $\sigma_U(t)$ may vary with the operating condition.

C. Rolling-Window Adaptive Confidence Factor

The rolling-window statistics update the adaptive confidence factor $K(t)$, and the updated $K(t)$ is then used to compute the dynamic TRM as shown in (6).

$$K(t) = K_{\text{base}} \left[1 + \beta \frac{\sigma_W(t) - \sigma_{\text{ref}}}{\sigma_{\text{ref}}}\right] \tag{6}$$

where K_{base} is the baseline confidence factor, $\sigma_w(t)$ is the rolling standard deviation of forecast errors, σ_{ref} is the reference standard deviation from historical data, and β controls the responsiveness of $K(t)$ to volatility changes [8]. Because $\sigma_w(t)$ is computed from already-observed errors, the response is mainly retrospective. This motivates the RF-assisted approach proposed in Section III.

III. PROPOSED RF-ASSISTED DYNAMIC TRM FRAMEWORK

A. Overall Architecture

The proposed framework augments the baseline rolling-window dynamic TRM mechanism with a RF-based volatility prediction layer. In the baseline rolling-window approach, $K(t)$ is updated using volatility already observed within the sliding window. In contrast, the proposed RF layer predicts the volatility three steps ahead, equivalent to 15 minutes, $\hat{\sigma}_w(t + \Delta t)$, using recent operating-condition features. The predicted volatility is then used to update $K(t + \Delta t)$, which determines $TRM(t + \Delta t)$. The 24-hour persistence forecast for load and wind is retained as the forecasting baseline; the RF layer modifies only the volatility signal used in the adaptive confidence factor.

B. Feature Engineering

Eight input features are constructed from the operational time series to capture recent volatility, forecast-error behaviour, and system ramping conditions:

1) Current and lagged rolling standard deviations: $\sigma_w(t)$ $\sigma_w(t-1)$, and $\sigma_w(t-2)$.

2) Wind generation ramping rate:

$$\Delta P_W(t) = P_W(t) - P_W(t-1) \tag{7}$$

3) Load demand ramping rate:

$$\Delta P_L(t) = P_L(t) - P_L(t-1). \tag{8}$$

4) Current forecast error, $e(t)$.

5) Hour-of-day index, encoded as *sin*(2πh/24) and *cos*(2πh/24) to preserve cyclic continuity of the diurnal pattern.

6) Net load level: $P_{\text{net}}(t) = P_L(t) - P_W(t)$.

C. Random Forest Volatility Predictor

The RF regression model is trained to map the feature vector x(t) to the 3-step-ahead volatility using (9).

$$\hat{\sigma}_w(t + \Delta t) = f_{\text{RF}}(x(t)) \tag{9}$$

The RF model consists of an ensemble of 150 regression trees; each trained on a bootstrap sample of historical data. The final prediction is obtained by averaging the outputs of all trees, providing robustness and feature-importance scores for interpretability. Hyperparameters are tuned using 5-fold cross-validation.

D. Integration with the Adaptive Confidence Factor

The predicted volatility is substituted into the adaptive confidence factor formulation shown in (10).

$$K(t+\Delta t) = K_{\text{base}} \times \left[1+\beta \frac{\hat{\sigma}_w(t+\Delta t)-\sigma_{\text{ref}}}{\sigma_{\text{ref}}}\right] \tag{10}$$

The next step TRM is then calculated using (11).

$$TRM(t+\Delta t) = K(t+\Delta t) \times \sigma_U(t+\Delta t) \tag{11}$$

where $\sigma_U(t+\Delta t)$ is the transfer capability uncertainty obtained from the probabilistic uncertainty modelling stage. The corresponding forecast-informed ATC is obtained by (12).

$$ATC(t+\Delta t) = TTC(t+\Delta t) - ETC - TRM(t+\Delta t) - CBM \tag{12}$$

The probabilistic structure of the original TRM framework is preserved. LHS remains responsible for uncertainty scenario generation, while the RF model only modifies only the volatility signal used to update the adaptive confidence factor.

IV. CASE STUDIES

The IEEE 24-bus Reliability Test System (RTS) [11] is used for validation. The system comprises two voltage areas: Area 1 (138 kV, Buses 1–10) and Area 2 (230 kV, Buses 11–24) interconnected by five tie-lines that form the inter-area transfer corridor analyzed in this study (see Fig. 1). To represent a renewable-rich operating condition, two 100 MW wind farms are integrated at Buses 13 and 23, modelled using a Weibull distribution with shape parameter k = 2.0 and scale parameter λ = 6.0 m/s.

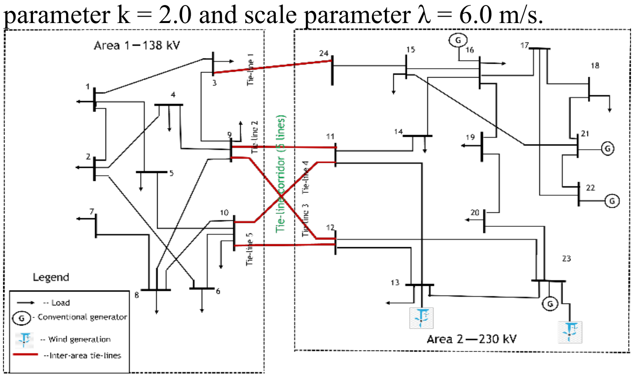

Fig. 1. Modified IEEE 24-bus RTS with two 100 MW wind farms at Buses 13 and 23. Five tie-lines form the inter-area transfer corridor between Area 1 (138 kV) and Area 2 (230 kV).

A 288-step (24-hour) simulation is performed at 5-minute resolution. The LHS generates uncertainty scenarios at each time step. The rolling-window length is 12 steps (1 hour), with K_{base} = 1.645 (95% one-sided coverage), β = 1.5, and σ_{ref} computed from 1-week historical training data.

The RF model is trained using MATLAB's TreeBagger function with 150 regression trees and a minimum leaf size of 5. Training data are constructed from a separate 1-week historical run (2,016 steps), with the feature vector $x(t)$ and target $\sigma_w(t+\Delta t)$ extracted at each step. The prediction horizon is 3 steps (15 minutes). The trained model is then deployed on the 288-step test simulation.

Three TRM estimation methods are compared:

1. Static TRM with fixed K = 1.645, applied uniformly across all time steps.
2. Baseline rolling-window dynamic TRM using lagged observed volatility, $\sigma_w(t-1)$.
3. Proposed RF-assisted dynamic TRM using predicted 3-step-ahead volatility, $\hat{\sigma}_w(t+\Delta t)$.

Three metrics are evaluated: (i) empirical coverage probability, defined as the percentage of time steps in which the realized transfer-capability uncertainty is adequately covered by the estimated $TRM(t)$; (ii) mean ATC utilization, defined as the average available transfer capability achieved while maintaining the target reliability level; and (iii) volatility prediction accuracy, measured using the RMSE between the RF-predicted volatility, $\hat{\sigma}_w(t+\Delta t)$, and the subsequently observed volatility, $\sigma_w(t+\Delta t)$.

V. RESULTS AND DISCUSSION

A. Volatility Prediction Performance

The RF model achieved a test-set RMSE of 3.60 MW for three-step-ahead volatility prediction, with an R^2 value of 0.825. Fig. 2 presents the permutation-based feature-importance scores of the RF volatility prediction model.

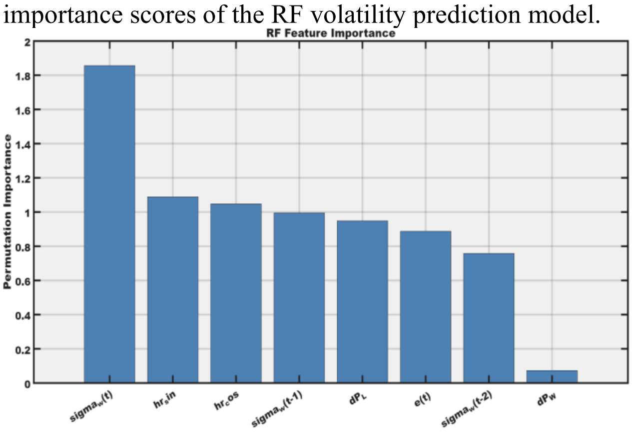

Fig. 2. Random Forest permutation-based feature importance for 3-step-ahead volatility prediction.

Current observed volatility, $\sigma_w(t)$, is the dominant predictor, followed by the hour-of-day features and first-lagged volatility, $\sigma_w(t-1)$. This indicates strong autocorrelation in the volatility process: the most recent observed uncertainty level provides the strongest indication of the uncertainty level three steps ahead. The hour-of-day features capture systematic variation in forecast-error magnitude across the daily load and wind cycle. Load ramping, forecast error, and deeper-lagged volatility also contribute, although with lower relative importance. Wind ramping rate, $\Delta P_W(t)$, shows limited individual importance in this test case, as its effect on volatility is largely captured indirectly through the lagged σ_w features. These results show that the RF model captures physically meaningful relationships rather than arbitrary numerical patterns. Fig. 3 compares the RF-predicted and observed volatility over the 288-step test simulation, showing that the model follows the general volatility trend, including transitions between calm and volatile operating periods.

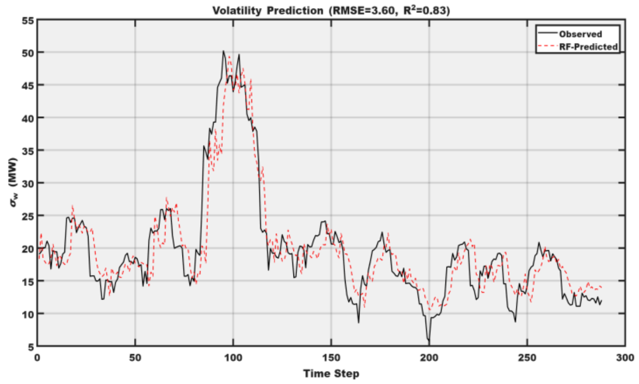

Fig. 3. Three-step-ahead volatility prediction: RF-predicted $\hat{\sigma}_w(t + \Delta t)$ versus observed $\sigma_w(t + \Delta t)$ over the 288-step test simulation.

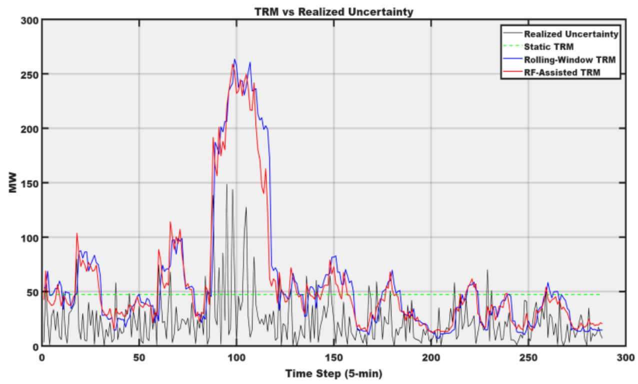

Fig. 4. Reserved TRM for each method compared with the realized uncertainty magnitude across the 288-step simulation.

B. Coverage Probability

Tables I and II compare the three TRM estimation methods under non-ramp and ramp conditions. The static method provides 92.1% coverage during non-ramp periods, but its coverage drops to 69.4% during ramp events, showing its limited ability to respond to time-varying uncertainty

Table I. Overall Comparison of TRMM Methods

Method	Coverage (%)	Mean ATC (MW)	Mean TRM (MW)
Static *K* baseline	89.2	1202.7	47.3
Rolling-window	81.6	1190.9	59.1
RF-assisted proposed	87.2	1193.2	56.8

Table II. Coverage Breakdown Ramp vs. Non-ramp Periods

Method	Non-Ramp (252 steps)	Ramp (36 steps)
Static *K* baseline	92.1%	69.4%
Rolling-window	80.2%	91.7%
RF-assisted proposed	85.7%	97.2%

The baseline rolling-window dynamic TRM improves ramp-period coverage to 91.7% by increasing $K(t)$ after higher volatility is observed. However, its non-ramp coverage of 80.2% reflects margin contraction during stable periods, which improves ATC utilisation but may reduce protection against occasional large forecast errors.

The proposed RF-assisted method achieves the highest ramp-period coverage of 97.2%, giving a 5.5 percentage-point improvement over the rolling-window method. This is because the RF model predicts volatility increases before they are fully captured by the rolling window. Its non-ramp coverage also improves to 85.7%, indicating a better balance between reliability and ATC utilisation.

As shown in Fig. 4, the static TRM (green dashed) remains constant and is exceeded during ramp events, while both dynamic methods adapt, with the RF-assisted method (red) responding earlier than the rolling-window method (blue).

C. Time-Series Behaviour of $K(t)$

Fig. 5 shows the $K(t)$ trajectories for the three methods. The static method keeps $K = 1.645$ throughout the simulation, while the baseline rolling-window method adjusts $K(t)$ only after volatility changes are captured within the observation window. This causes a delayed response during ramp onset. In contrast, the proposed RF-assisted method increases $K(t)$ earlier, typically one to two steps ahead of the rolling-window method, because it predicts short-term volatility from ramp-related features. This anticipatory behaviour allows TRM to expand before the volatility peak is fully realized.

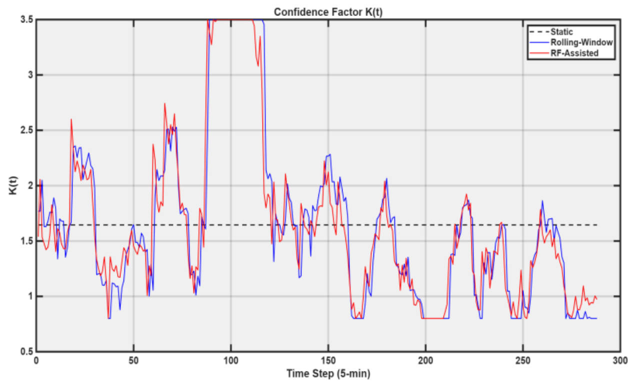

Fig. 5. Adaptive confidence factor $K(t)$ trajectories for the static, rolling-window, and RF-assisted TRM methods.

D. Discussion

The results confirm that introducing a machine-learning-based volatility predictor within the existing real-time TRM framework without altering its probabilistic foundation can improve coverage probability during critical ramp events while maintaining reasonable ATC utilization. While the rolling-window method already provides real-time adaptive $K(t)$ updates from observed volatility, the RF-assisted variant uses predicted 3-step-ahead volatility, enabling earlier margin adjustment. The RF model's interpretability through feature-importance analysis provides practical value, as operators can identify the physical signals driving TRM adjustment. The framework is computationally suitable for real-time deployment, with RF inference at each time step requiring less than 5 ms.

This is particularly relevant for power systems in the Australasian region, where increasing renewable penetration and long transmission corridors may reduce the grid's ability to absorb late corrective actions [1], [2]. By using predicted rather than observed volatility within the real-time TRM update, the proposed method enables earlier margin adjustment, thereby reducing the likelihood of emergency interventions, renewable curtailment, and conservative underutilization of transmission capacity.

VI. CONCLUSION

This paper has presented a RF-assisted dynamic TRM assessment framework for renewable-rich power systems. By predicting 3-step-ahead volatility from operational features and embedding the prediction within the established adaptive confidence factor formulation, the proposed method extends real-time dynamic TRM estimation from an observed-volatility approach to a forecast-informed one.

Validation on the IEEE 24-bus RTS demonstrated that the RF-assisted method achieves 97.2% coverage during ramp events, compared with 91.7% for the rolling-window method and 69.4% for the static method a clear progressive improvement in reliability coverage during the most critical operating periods. Building on the validation already, future work will extend the framework to broader datasets, advanced machine-learning models, and integration with demand-side management for enhanced uncertainty mitigation..

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