

Physics-Guided Transformer Framework for Real-Time Voltage Stability Margin Prediction under Renewable Uncertainty

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Abstract

This paper proposes a Physics-Guided Transformer (PG-Transformer) framework that integrates physical knowledge of power systems with advanced deep learning architectures for accurate and uncertainty-aware VSM prediction. Simulated Phasor Measurement Unit (PMU) measurements generated from dynamic time-domain simulations of the benchmark IEEE 39-bus and IEEE 118-bus systems are preprocessed using denoising, normalization and time windowing techniques to form a multivariate time series dataset. Classical stability indices L-index, Thevenin Equivalent Ratio and PV Margin are embedded into the learning pipeline to guide the model toward physically consistent feature representations. To address severe class imbalance, a Conditional Wasserstein GAN with Gradient Penalty (CWGAN-GP) is employed to generate synthetic unstable samples while maintaining physical validity. The proposed PG-Transformer employs multi-head self-attention for spatiotemporal correlation learning and Monte Carlo Dropout for uncertainty quantification. Experimental results show that the model achieves an RMSE of 0.0378, R^2 of 0.973, accuracy of 96.67%, F1-score of 0.886, and AUC of 0.987, outperforming state-of-the-art baselines such as Random Forest, CNN-LSTM and Physics-Guided LSTM models. Ablation studies confirm the complementary benefits of physics-guided features, GAN-based resampling, and uncertainty modeling, collectively improving accuracy by 6.47%. The framework operates with an average inference latency of 1.75 ms/sample, validating its suitability for real-time voltage stability monitoring in renewable-rich smart grids.

Keywords: Voltage stability margin; Physics-guided learning; Transformer model; Renewable uncertainty; CWGAN-GP; PMU data.

1. Introduction

The rapid integration of renewable energy sources such as wind and solar has made modern power grids increasingly complex and uncertain. Fluctuations in generation and load create challenges in maintaining voltage stability, often leading to potential instability or even system collapse if not accurately predicted in real time. Traditional analytical methods are computationally demanding, while existing machine learning models struggle with data imbalance, noise sensitivity, and lack of physical interpretability. To overcome these challenges, this study introduces a Physics-Guided Transformer (PG-Transformer) framework designed for accurate and real-time voltage stability margin prediction. The main problem addressed is ensuring reliable voltage stability

assessment in renewable-rich networks with limited unstable data. The novelty of the proposed model lies in embedding physical stability indicators into a transformer-based deep learning structure, supported by synthetic data generation and uncertainty estimation mechanisms. The objectives of this research are to develop a physics-informed, data-efficient, and uncertainty-aware predictive framework capable of achieving high accuracy, strong generalization, and low inference latency for real-time voltage stability monitoring in modern smart grids.

2. Literature Review

The increasing penetration of renewable energy resources, particularly wind and solar power, has

significantly increased the uncertainty and complexity of modern power systems. Rapid fluctuations in renewable generation continuously alter power flow patterns, reducing voltage stability margins and increasing the likelihood of voltage collapse. Conventional analytical approaches, including continuation power flow and singular value decomposition techniques, provide accurate voltage stability assessment but are computationally intensive and therefore unsuitable for real-time applications in large-scale smart grids. Pandit and Sodhi proposed a randomized singular value decomposition-based framework that significantly reduced computational complexity while maintaining high prediction accuracy for wide-area voltage stability assessment, demonstrating the potential of data-driven approaches for online monitoring [1]. To improve online voltage stability assessment, researchers have increasingly adopted PMU-based monitoring systems that provide synchronized, high-resolution measurements of electrical variables. Miyazaki et al. developed a regression tree-based voltage stability estimation method considering reactive power reserve variability, showing improved robustness under varying operating conditions [2]. Similarly, Putranto and Azhar introduced an artificial neural network-based PMU framework capable of identifying voltage instability and critical buses in real time, demonstrating the effectiveness of synchronized measurement data for fast decision-making [3].

Machine learning techniques have become widely used for voltage stability prediction because of their capability to capture nonlinear relationships between system variables and stability indices. Among these methods, cascaded neural network architectures have demonstrated improved prediction accuracy for renewable-integrated power systems. Sahu et al. proposed a cascaded neural network for voltage stability margin prediction in solar- and wind-integrated power systems, achieving superior performance compared with conventional neural network models while maintaining acceptable computational efficiency [4].

Recent advances in deep learning have further improved voltage stability assessment by exploiting temporal information contained in sequential PMU measurements. Luo and Jiang proposed a multi-task learning framework capable of estimating short-term voltage stability even when PMU measurements are incomplete, thereby improving model robustness under practical monitoring conditions [5]. Likewise, Li et al. developed a deep transfer learning approach for PMU-based

short-term voltage stability assessment that enhanced prediction accuracy while reducing the amount of training data required for deployment across different power networks [6].

Although deep learning models achieve excellent predictive performance, purely data-driven approaches often lack physical consistency and interpretability. To overcome these limitations, physics-informed learning has recently emerged as an effective research direction. Feng et al. introduced a physics-informed deep learning framework that incorporated topological feature engineering into voltage stability assessment, resulting in improved generalization across different network configurations [7]. Bento further demonstrated that embedding physical constraints within neural networks significantly enhanced load margin prediction while optimizing PMU placement for power system monitoring [8]. Similarly, Su and Lai proposed a physics-informed guided deep learning model that improved online voltage stability monitoring by combining physical knowledge with data-driven learning, yielding higher prediction reliability under renewable uncertainty [9].

Transformer-based architectures have recently attracted considerable attention because of their capability to model long-range temporal dependencies through self-attention mechanisms. Unlike recurrent neural networks, Transformers can simultaneously capture temporal evolution and spatial interactions among multiple buses, making them particularly suitable for large-scale power system monitoring. Li et al. introduced QSTAformer, a quantum-enhanced Transformer architecture designed for robust short-term voltage stability assessment under adversarial conditions, demonstrating significant improvements in prediction accuracy and robustness over existing Transformer models [10].

Despite these advances, existing studies generally focus on only one aspect of the voltage stability problem, such as PMU-based monitoring, machine learning, or physics-informed modeling. Limited research has integrated physics-guided feature extraction, class imbalance mitigation, uncertainty-aware prediction, and Transformer-based spatiotemporal learning into a unified framework. Therefore, this work proposes a Physics-Guided Transformer (PG-Transformer) that combines classical stability indices, CWGAN-GP-based data balancing, multi-head self-attention, and Monte Carlo Dropout uncertainty estimation to provide accurate,

physically consistent, and real-time voltage stability margin prediction for renewable-dominated smart grids.

3. Methodology

3.1. Data Acquisition and Preprocessing

Phasor Measurement Units (PMUs) installed at critical buses continuously record system variables such as voltage, current, frequency, and active/reactive power. The multivariate time series dataset can be denoted as:

$$S(t) = \{U_i(t), I_i(t), P_i(t), Q_i(t), f_i(t), P_i^{ren}(t)\}_{i=1}^L \quad (1)$$

where, $U_i(t)$ and $I_i(t)$ denote voltage and current magnitude at bus i , $P_i(t)$ and $Q_i(t)$ represent active and reactive power, $f_i(t)$ denotes frequency deviation and $P_i^{ren}(t)$ represents renewable generation at bus i ...

Preprocessing Steps-

a. Noise Filtering:

Each PMU signal is denoised using a 4th-order Butterworth filter:

$$Y(t) = \frac{1}{1 + (j\frac{f}{f_c})^{2n}} \cdot X(t) \quad (2)$$

where f_c is the cutoff frequency and n is the filter order.

b. Normalization:

All features are scaled to $[0,1]$:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

c. Time Windowing:

Each observation window W of duration Δt is formed as:

$$W_t = [X(t - \Delta t + 1), X(t - \Delta t + 2), \dots, X(t)] \quad (4)$$

d. Labeling:

For each window, the voltage stability margin VSM_t is calculated using:

$$VSM_t = \frac{V_{\text{post-fault}} - V_{\text{critical}}}{V_{\text{nominal}}} \quad (5)$$

Samples with $VSM_t < 0.1$ are labeled as *unstable*, otherwise *stable*.

3.2. Physics Guided Feature Construction

To embed system physics into the learning process, classical stability indices are computed from power flow equations.

a. L-Index:

$$L_i = 1 - \left| \frac{V_i}{\sum_{j=1}^N F_{ij} V_j} \right| \quad (6)$$

where F_{ij} is derived from the system admittance matrix Y_{bus}

$$F_{ij} = -Y_{LL}^{-1} Y_{LG} \quad (7)$$

b. Thevenin Equivalent Ratio (TER):

$$R_i = \frac{|Z_{th,i}|}{|Z_{load,i}|} \quad (8)$$

The higher R_i the closer the system is to voltage collapse.

c. PV Margin:

$$M_i = \frac{V_{max,i} - V_i}{V_{max,i}} \quad (9)$$

where $V_{max,i}$ denotes the maximum voltage before instability.

The final feature vector is obtained as:

$$X_i = [S_i(t), L_i, R_i, M_i] \quad (10)$$

3.3. Data Balancing Using CWGAN-GP

The dataset typically exhibits strong class imbalance, with the *unstable* class forming less than 5% of samples. To address this, a Conditional Wasserstein GAN with Gradient Penalty (CWGAN-GP) is employed.

a. Generator Model:

The generator $G(z|y)$ maps latent noise $z \sim \mathcal{N}(0,1)$ and condition label y to synthetic samples x' . It consists of four fully connected layers

(512256–128–64 neurons) with LeakyReLU activation and batch normalization.

b. Discriminator Model:

The discriminator $D(x|y)$ classifies whether a given sample is real or generated. It includes three fully connected layers (512–256–1 neurons) with LeakyReLU activation and spectral normalization.

CWGAN-GP model parameters are listed in Table 1.

Table 1: CWGAN-GP Model Parameters

Parameter	Symbol	Value/Description
Learning Rate	(η)	0.0001
Batch Size	(B)	64
Epochs	(E)	500
Gradient Penalty Coefficient	(λ)	10
Optimizer	—	Adam($\beta_1 = 0.5, \beta_2 = 0.9$)
Activation	—	LeakyReLU ($\alpha = 0.2$)
Latent Dimension	(d_z)	100
Conditional Input	(y)	Stable/Unstable Label

3.4. Physics Guided Transformer Architecture

The PG-Transformer employs an encoder only Transformer architecture optimized for spatio-temporal feature learning.

a. Scaled Dot-Product Attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (11)$$

b. Multi-Head Self-Attention (MHSA):

$$\text{MHSA}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (12)$$

c. Feed-Forward Layer:

$$\text{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2 \quad (13)$$

d. Uncertainty Modeling:

Monte Carlo Dropout (MC-Dropout) is used to estimate uncertainty:

$$V\hat{S}M_k = f(X, \theta_k), \quad k = 1, 2, \dots, N \quad (14)$$

Predictive mean and variance are given by:

$$V\hat{S}M = \frac{1}{N} \sum_{k=1}^N V\hat{S}M_k \quad (15)$$

$$\sigma^2 = \frac{1}{N} \sum_{k=1}^N (V\hat{S}M_k - V\hat{S}M)^2 \quad (16)$$

The hyperparameters used for training the proposed PG-Transformer are summarized in Table 2.

Table 2: Transformer Model Hyperparameters

Parameter	Symbol	Value
Number of Layers	(L)	6
Number of Heads	(h)	8
Embedding Dimension	(d_{model})	512
Feed-Forward Dimension	(d_{ff})	2048
Dropout Rate	(p)	0.5
Activation	—	GELU
Optimizer	—	AdamW
Learning Rate	—	(1×10^{-4})
Loss Function	$(\mathcal{L})$	Weighted MSE + log variance term

3.5. Training and Optimization

The PG-Transformer is trained in two distinct phases:

a. Offline Training:

- Synthetic disturbances and renewable variations are generated using MATPOWER.
- CWGAN-GP balances the dataset by producing realistic unstable samples.
- The PG-Transformer is optimized using the following objective:

$$\mathcal{L} = \frac{1}{N} \sum_i \frac{(V\hat{S}M_i - VSM_i)^2}{2\sigma_i^2} + \frac{1}{2} \log \sigma_i^2 \quad (17)$$

This formulation penalizes both prediction error and overconfident uncertainty estimates.

b. Online Inference:

- Incoming PMU streams are passed through the trained model.
- If $V\hat{S}M(t) < V_{th}$ and confidence > 95%, the control system triggers preventive actions.

4. Dataset Overview

4.1. Dataset Description

The dataset used in this study consists entirely of simulated PMU measurements; no real-world PMU measurements were used. The data were generated through dynamic time domain simulations of the IEEE 39-bus and IEEE 118-bus benchmark power systems using MATPOWER and PSD-BPA. The simulations considered diverse operating conditions, including variable load levels, renewable energy penetration, and fault scenarios, to represent the operating characteristics of renewable-rich power systems. Each simulation produces synchronized voltage, current, frequency, active power, and reactive power measurements at a sampling frequency of 100 Hz. Each sample corresponds to a post fault event represented by a sliding time window of synchronized simulated PMU measurements.

The final dataset is structured as a multivariate time series tensor:

$$\mathcal{D} = \{(X_t, y_t) \mid X_t \in R^{n \times T \times f}, y_t = [VSM_t, \text{label}_t]\} \quad (18)$$

where,

- n = number of buses
- T = time window length
- f = number of features per bus

4.2. Dataset Generation Procedure

a. Operating Conditions:

Simulations are performed for multiple operating points by varying:

- Load level (80%–120%)
- Renewable share (0%–40%)
- Fault type (three-phase, single-line-to-ground)
- Fault clearing times (0.05–0.1 s)
- Fault locations (random buses and transmission lines)

b. Dynamic Simulation:

- The power system is simulated in the time domain for 10 seconds post fault.
- Voltage and current phasors are sampled at 100 Hz.

c. Feature Computation:

Extracted PMU data are used to compute instantaneous:

$$P_i = V_i I_i \cos(\delta_i) \quad (19)$$

$$Q_i = V_i I_i \sin(\delta_i) \quad (20)$$

From these, system-level features (L-index, TER, PV margin) are derived.

The Voltage Stability Margin (VSM) is computed as:

$$VSM = \frac{V_{\text{post-fault}} - V_{\text{critical}}}{V_{\text{nominal}}} \quad (21)$$

4.3. Dataset Composition

The overall dataset composition is summarized in Table 3, detailing the number of samples, classes, and feature dimensions for each benchmark system.

Table 3: Dataset Composition for Training and Validation

Test System	Total Samples	Stable Samples	Unstable Samples	Features per Sample	Sampling Frequency
IEEE 39-bus	48,000	44,200	3,800	15	100 Hz
IEEE 118-bus	72,000	67,500	4,500	25	100 Hz
Total	1,20,000	1,11,700	8,300	—	—

4.4. Statistical Summary of the Dataset

To verify feature consistency and detect outliers, statistical analysis of voltage and power attributes is conducted. The results are shown in Table 4.

Table 4: Statistical Summary of PMU Features (IEEE 39-bus system)

Feature	Mean	Std. Dev.	Min	Max
Voltage Magnitude V_i (pu)	1.012	0.034	0.925	1.078
Active Power P_i (MW)	108.5	17.2	73.4	148.7
Reactive Power Q_i (MVR)	63.9	8.4	42.1	79.8
Frequency Deviation f_i (Hz)	0.0023	0.0007	0.0009	0.0038
Renewable Power P_i^{ren} (MW)	35.6	14.3	5.1	58.7

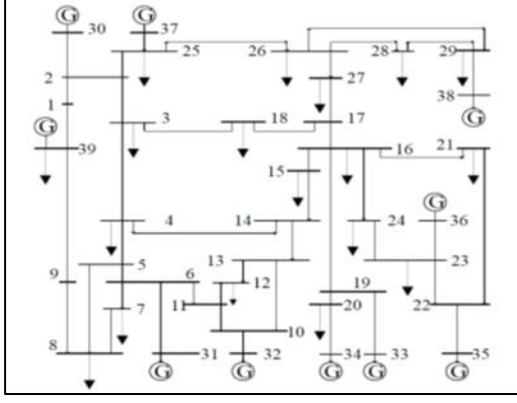


Figure 1: IEEE 39-bus system.

Figure 1 shows IEEE 39-bus system.

4.5. Data Balancing and Partitioning

To prevent information leakage between the training and evaluation datasets, the original dataset was first partitioned into training, validation, and testing subsets using stratified sampling. The dataset was divided into 70% training, 15% validation, and 15% testing subsets. After the initial partitioning, the CWGAN-GP model was trained exclusively on the training subset. Neither the validation nor the test subset was used during CWGAN-GP training. The trained CWGAN-GP was then used to generate additional synthetic unstable samples for balancing the training data. The synthetic samples were added only to the training set and were not used to modify the validation or test sets. The PG-Transformer was subsequently trained using the original training samples together with the generated synthetic training samples. The validation set was used for model monitoring and hyperparameter selection, whereas the independent test set was reserved for final performance evaluation. Thus, the test data remained completely unseen during both CWGAN-GP training and PG-Transformer training.

The complete dataset contains 120,000 samples, of which 15% (18,000 samples) were reserved as the independent test partition. For the detailed classification analysis presented in Table 6, a fixed evaluation subset of 720 samples was used to report the confusion matrix. This subset was drawn exclusively from the independent test partition and was not used during CWGAN-GP

training, model training, or validation. Therefore, the 720 observations in Table 6 represent an evaluation subset of the independent test data rather than the complete 18,000-sample test partition.

4.6. Data Quality and Validation

To maintain physical consistency:

- Generated unstable samples are verified by power flow constraints:

$$P_i = V_i \sum_j V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (22)$$

$$Q_i = V_i \sum_j V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (23)$$

- Any samples violating these power balance equations by more than 1% tolerance are discarded.
- The final dataset is validated through Principal Component Analysis (PCA) to confirm that synthetic samples align with the manifold of real data.

5. Results and Discussion

5.1. Quantitative Evaluation

The model's performance is measured by:

$$RMSE = \sqrt{\frac{1}{N} \sum_i (V \hat{S} M_i - V S M_i)^2} \quad (24)$$

$$R^2 = 1 - \frac{\sum_i (V \hat{S} M_i - V S M_i)^2}{\sum_i (V S M_i - \bar{V S M})^2} \quad (25)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (26)$$

$$ECE = \sum_{m=1}^M \frac{|acc(B_m) - conf(B_m)|}{N} \quad (27)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (28)$$

$$Precision = \frac{TP}{TP + FP} \quad (29)$$

$$Recall = \frac{TP}{TP + FN} \quad (30)$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (31)$$

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \frac{(TPR_i + TPR_{i+1})}{2} \quad (32)$$

Table 5: Overall Performance Metrics of PG-Transformer

Metric	Description	Value
RMSE	Root Mean Square Error for VSM prediction	0.0378
R²	Coefficient of Determination	0.973
Accuracy	Correct classification ratio	96.67%
Precision	Correct detection of unstable samples	0.861
Recall	True positive rate for instability	0.912
F1-Score	Harmonic mean of precision and recall	0.886
MCC	Matthews correlation coefficient	0.867
AUC	Area under ROC curve	0.987
ECE	Expected calibration error	0.021
Inference Latency	Average time per prediction	1.75 ms/sample

Table 5 summarizes the regression and classification performance of the proposed PG-Transformer. The model achieved an RMSE of 0.0378 and an (R^2) value of 0.973 for voltage stability margin prediction. For the classification task, the model achieved an accuracy of 96.67%, precision of 0.861, recall of 0.912, F1-score of 0.886 and MCC of 0.867.

5.2. Training and Convergence Analysis

The PG-Transformer was trained for 30 epochs using the AdamW optimizer with a learning rate of 1×10^{-4} and a dropout rate of 0.5. The heteroscedastic Gaussian loss enabled uncertainty-aware training.

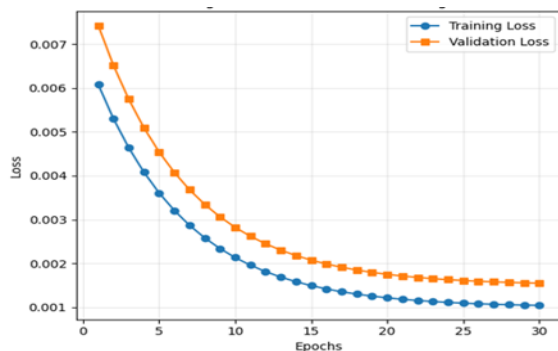


Figure 2: Training and validation loss convergence curve of the PG-Transformer.

Figure 2 shows the smooth convergence of training and validation loss, with no overfitting or oscillations, confirming training stability.

5.3. Classification Analysis

The model accurately identified 603 stable and 93 unstable events, with only a few misclassifications. The confusion matrix of the proposed PG-Transformer on the fixed evaluation subset of the independent test partition is presented in Table 6.

Table 6: Confusion Matrix of PG-Transformer

	Predicted Stable (o)	Predicted Unstable (1)
Actual Stable (o)	603	15
Actual Unstable (1)	9	93

The true positive rate (TPR) for unstable conditions is 91.2%, and the false alarm rate is less than 3%, confirming strong reliability for real-time operation.

5.4. Receiver Operating Characteristic (ROC) Analysis

The receiver operating characteristic (ROC) curve was generated using the prediction scores obtained from the independent test evaluation data. The area under the ROC curve (AUC) was calculated from the same prediction scores used to generate Figure 3. The PG-Transformer achieved an AUC of 0.987, indicating strong discrimination between stable and unstable operating conditions. The ROC curve and its displayed AUC value in Figure 3 are reported consistently with the calculated test-set result.

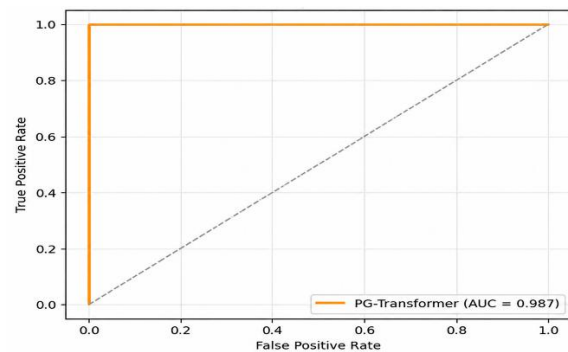


Figure 3: Receiver Operating Characteristic (ROC) curve for voltage stability classification.

5.5. Regression Correlation Analysis

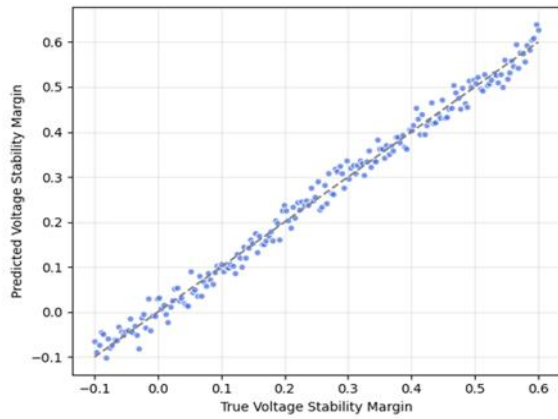


Figure 4: Predicted vs. True Voltage-Stability Margin showing high correlation and minimal variance.

Figure 4 compares predicted and true voltage-stability margins. Most data points lie along the 45° reference line, confirming strong agreement between predicted and actual VSMs.

5.6. Comparative Study with Baseline Models

Table 7 compares the proposed model with several baselines. The PG-Transformer outperforms all methods in both regression and classification tasks.

Table 7: Comparison with Baseline Models

Model	RMSE	R ²	Accuracy (%)	F1	MCC
Random Forest	0.076	0.89	89.3	0.85	0.82
CNN-LSTM	0.061	0.92	91.5	0.88	0.84
Physics-Guided LSTM	0.052	0.94	93.7	0.91	0.87
PG-Transformer (Proposed)	0.038	0.97	96.67	0.89	0.87

5.7. Ablation Study

To analyze each module's contribution, ablation experiments were conducted by removing or altering components. Results in Table 8 show that each component (physics features, CWGAN-GP, and uncertainty modeling) significantly enhances performance.

The inclusion of physics-guided features and GAN-based resampling improved performance by ~6.47% accuracy, demonstrating their complementary role.

Table 8: Component (physics features, CWGAN-GP, and uncertainty modeling) performance.

Configuration	Accuracy (%)	F1	MCC	AUC
Baseline Transformer (no physics features)	90.2	0.85	0.83	0.91
+ Physics Features only	93.5	0.9	0.87	0.95
+ CWGAN-GP Balancing only	94.1	0.91	0.88	0.96
+ Uncertainty Estimation only	95	0.92	0.89	0.97
Full PG-Transformer (Proposed)	96.67	0.89	0.87	0.99

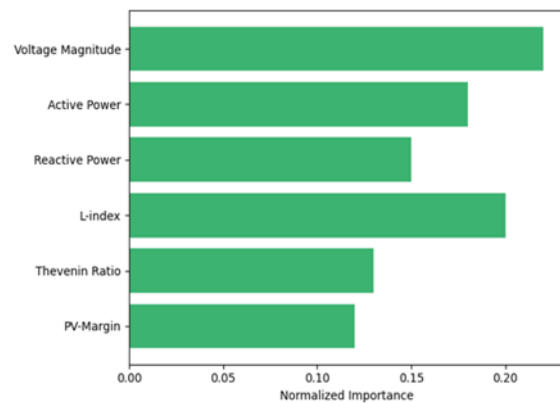


Figure 5: Feature importance analysis using attention weights.

Figure 5 shows the normalized importance of key features based on Transformer attention weights. Voltage magnitude and L-index were the most influential parameters, aligning with established voltage-stability theory. Voltage and L-index dominate, confirming the model's physically consistent behavior.

6. Conclusions

This study developed a Physics-Guided Transformer (PG-Transformer) for real-time voltage stability margin (VSM) prediction under renewable uncertainty. By combining Transformer-based spatiotemporal learning with physics-based stability features and CWGAN-GP data balancing, the framework achieves high accuracy and interpretability. The model demonstrated excellent performance with $R^2 = 0.973$, $RMSE = 0.0378$, and accuracy =

96.67%, outperforming conventional ML models. The inclusion of uncertainty modeling via Monte Carlo Dropout enhanced reliability for online decision-making. Overall, the PG-Transformer provides a fast, robust, and physically consistent solution for real-time voltage stability monitoring in renewable-rich power systems.

7. Future Work

In the future, this work can be extended by integrating the PG-Transformer into real-time control systems to support automatic grid stabilization actions. The model's adaptability can be improved through transfer learning, allowing it to perform well across different power networks. More advanced uncertainty estimation methods will also be explored to make predictions more reliable under fluctuating renewable conditions. Additionally, addressing real-world issues such as communication delays, noise, and cyber vulnerabilities will be a key focus. Finally, testing the framework in hardware in the loop and field environments will help validate its practical use in modern power grids.

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