Reliable Smart Grid Stability Prediction Using Calibrated LightGBM

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Abstract: This paper presents a reliability-focused approach for smart grid stability prediction using calibrated machine learning models. A LightGBM classifier is combined with probability calibration to improve confidence estimation and support more reliable decision-making. The study analyzes prediction behavior through reliability diagrams, risk-coverage analysis, confidence distributions, and accuracy-coverage trade-offs. Results show that calibration significantly improves probability quality by reducing Brier Score and Expected Calibration Error while maintaining prediction accuracy. The proposed framework helps distinguish reliable and uncertain predictions, making it suitable for practical smart grid applications where dependable and interpretable decisions are important.

Keywords: Smart Grid Stability; Reliability-Aware Prediction; Probability Calibration; Confidence Estimation; Risk-Coverage Analysis.

Introduction

Classification The growing integration of renewable energy sources has increased the complexity of modern smart grid systems. Variations in generation and load conditions can affect grid stability and make reliable operation more challenging. Machine learning models are widely used for grid stability prediction because they can learn complex system behavior from data [1-2]. However, most existing approaches mainly focus on improving prediction accuracy and pay less attention to the reliability of model predictions. In practical power system applications, understanding how confident a model is can be as important as the prediction itself. Incorrect but highly confident predictions may lead to unsafe operational decisions. To address this issue, this work presents a reliability-focused prediction framework using a calibrated LightGBM model [3-4]. The study evaluates prediction confidence through calibration analysis, risk-coverage behavior, and confidence distribution patterns. The results show that calibration improves probability reliability while maintaining strong prediction performance, making the framework more suitable for dependable smart grid decision-making.

Related work

Recent studies have shown significant interest in applying machine learning techniques for smart grid stability prediction. Ensemble models such as Random Forest, XGBoost, and LightGBM have demonstrated strong predictive capability due to their ability to capture nonlinear relationships in power system data [5-6]. Several works have reported high classification accuracy for identifying stable and unstable grid conditions. However, most of these approaches mainly evaluate performance using accuracy and F1-score, without examining how reliable the predicted probabilities are [7]. To improve interpretability and decision support, recent research has started exploring confidence estimation and uncertainty-aware learning in power system applications. Calibration methods have been used to align predicted probabilities with actual outcomes, while uncertainty estimation techniques help identify unreliable predictions [8]. Risk-aware prediction and selective decision-making have also gained attention in safety-critical applications. Despite these developments, limited work combines calibration analysis, confidence behavior, and risk-coverage evaluation within a single framework for smart grid stability prediction. This motivates the need for a simple and reliable prediction framework that focuses not only on accuracy but also on prediction trustworthiness.

Methodology

This work uses the Smart Grid Stability dataset containing 60,000 samples with 12 numerical input features and one binary target variable representing stable and unstable grid conditions. The dataset includes time-related, power-related, and control gain parameters collected from smart grid operations. Stratified train-test splitting is used to preserve class balance during model training [9-10].

A LightGBM classifier is first trained to predict the probability of grid instability as shown in Eq. (1).

$$\hat{p}(\, y = 1 \mid x\,) = f_{\mathrm{LGBM}}(x) \tag{1}$$

Since raw probabilities may not accurately represent true confidence, isotonic regression calibration is applied to improve probability reliability is given in Eq. (2).

$$\hat{p}_{cal} = g(\hat{p}) \tag{2}$$

The quality of calibration is evaluated using Brier Score and Expected Calibration Error (ECE) are presented in Eq. (3) and Eq. (4) respectively.

$$Brier = \frac{1}{N}\sum_{i=1}^{N}(\,\hat{p}_i - y_i)^2 \tag{3}$$

$$ECE = \sum_{m=1}^{M}\frac{|B_m|}{N} \mid acc(B_m) - conf(B_m) \mid \tag{4}$$

Further analysis is carried out using reliability diagrams, confidence distribution analysis, accuracy-coverage evaluation, and risk-coverage curves to study the behavior of model confidence and prediction reliability.

Results & Discussion

The proposed reliability-focused framework is evaluated using prediction performance, calibration quality, and confidence-based analysis. Table 1 summarizes the overall performance of the models before and after calibration.

TABLE 1: Table 1. Performance and calibration results of the proposed framework.

Model	Accuracy	F1-Score	Brier Score	ECE
LightGBM (Before Cal.)	0.9379	0.9117	0.0526	0.5797
LightGBM (After Cal.)	0.9379	0.9117	0.0418	0.2646
Random Forest	0.9458	0.9234	—	—

The baseline LightGBM model achieves an accuracy of 0.9379 with an F1-score of 0.9117. After calibration, the classification performance remains unchanged, but the quality of probability estimation improves noticeably. The Brier Score decreases from 0.0526 to 0.0418, while the Expected Calibration Error (ECE) reduces from 0.5797 to 0.2646, indicating better confidence reliability. The Random Forest model achieves slightly higher prediction accuracy, but calibration analysis is mainly focused on the LightGBM model due to its probabilistic output behavior.

The confidence distribution before and after calibration is shown in Figure 1. The calibrated model produces a more balanced confidence spread compared to the original model, reducing overly confident predictions and improving reliability interpretation.

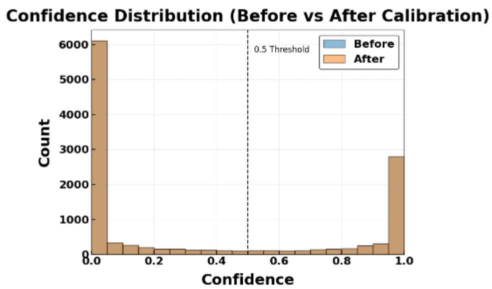

Figure 1. Confidence distribution before and after calibration.

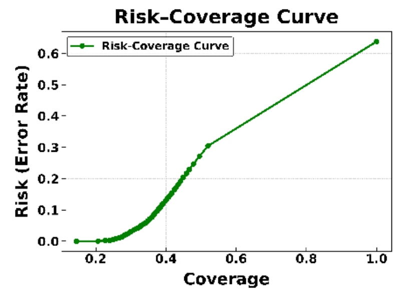

Figure 2. Risk–coverage analysis of the calibrated model.

The reliability behavior of the calibrated model is further analyzed using the risk-coverage curve shown in Figure 2. The results indicate that prediction risk decreases when low-confidence samples are filtered out. At lower coverage levels, the model achieves very low prediction risk, showing that highly confident predictions are generally more reliable.

Figure 3 illustrates the relationship between prediction accuracy and confidence threshold. As the confidence threshold increases, accuracy improves steadily while coverage decreases. This demonstrates the usefulness of selective prediction, where uncertain predictions can be avoided to obtain more dependable decisions.

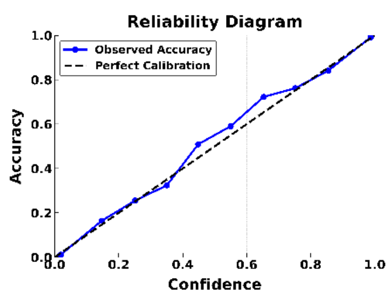

Figure 3. Accuracy variation with confidence threshold.

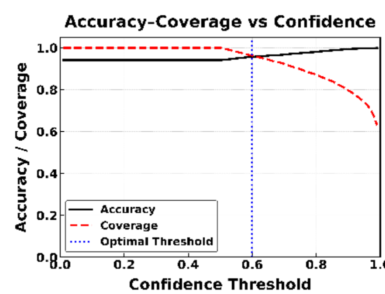

Figure 4. Accuracy–coverage trade-off under different confidence thresholds.

The trade-off between prediction accuracy and coverage is shown in Figure 4. Higher confidence thresholds improve accuracy but reduce the number of accepted predictions. This behavior confirms that model confidence can effectively separate reliable and uncertain predictions.

Overall, the results show that probability calibration improves confidence quality without affecting prediction accuracy. The proposed framework provides a simple and effective way to support reliability-aware smart grid stability prediction through confidence-based decision analysis.

Conclusion

This paper presents a simple reliability-focused framework for smart grid stability prediction using a calibrated LightGBM model. Instead of relying only on prediction accuracy, the study examines how confidence and calibration can improve the trustworthiness of model predictions. The results show that probability calibration significantly improves confidence quality by reducing Brier Score and Expected Calibration Error while maintaining strong classification performance. The reliability diagram, risk-coverage analysis, and accuracy-coverage evaluation further demonstrate that highly confident predictions are more dependable. Overall, the proposed framework provides a practical and interpretable approach for reliability-aware decision-making in modern smart grid systems operating under uncertain conditions.

References

1. Z. Wen, J. Shi, B. He, J. Chen, K. Ramamohanarao and Q. Li, "Exploiting GPUs for Efficient Gradient Boosting Decision Tree Training," in *IEEE Transactions on Parallel and Distributed Systems*, vol. 30, no. 12, pp. 2706-2717, 1 Dec. 2019, doi: 10.1109/TPDS.2019.2920131
2. Niculescu-Mizil, A., and Caruana, R., "Predicting good probabilities with supervised learning," Proceedings of the 22nd International Conference on Machine Learning, pp. 625–632, 2005. https://doi.org/10.1145/1102351.110243
3. S. A. Balanya, J. Maroñas, and D. Ramos, "Adaptive temperature scaling for robust calibration of deep neural networks," Neural Comput. Appl., vol. 36, pp. 8073–8095, 2024. doi: 10.1007/s00521-024-09505-4.
4. . Zhang, M. Sun, J. L. Cremer, N. Zhang, G. Strbac and C. Kang, "A Confidence-Aware Machine Learning Framework for Dynamic Security Assessment," in *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 3907-3920, Sept. 2021, doi: 10.1109/TPWRS.2021.3059197
5. K. Dab *et al*., "Uncertainty Quantification in Load Forecasting for Smart Grids Using Non-Parametric Statistics," in *IEEE Access*, vol. 12, pp. 138000-138017, 2024, doi: 10.1109/ACCESS.2024.3465229.
6. Raju, V. A. G., Mishra, M., Singh, J. G., Nayak, J., and Dash, P. B., "Smart grid stability prediction based on Bayesian-optimised LGBM for smarter energy management," International Journal of Advanced Mechatronic Systems, vol. 11, no. 4, pp. 226–241, 2024. https://doi.org/10.1504/IJAMECHS.2024.143382
7. A. Chhabra, S. K. Singh, S. Kumar, et al., "Improving predictive reliability and automation of smart grids using the StarNet ensemble model," Sci. Rep., vol. 16, p. 9592, 2026. doi: 10.1038/s41598-025-31479-z.
8. A. Alaerjan, R. Jabeur, H. Ben Chikha, M. Karray, and M. Ksantini, "Improvement of smart grid stability based on artificial intelligence with fusion methods," Symmetry, vol. 16, no. 4, p. 459, 2024. doi: 10.3390/sym16040459.
9. DeGroot, M. H., and Fienberg, S. E., "The comparison and evaluation of forecasters," The Statistician, vol. 32, no. 1–2, pp. 12–22, 1983.
10. M. S. Hassan, M. A. Siddique, N. Mohammad and A. I. Ikram, "Performance Analysis of Machine Learning-Based Traditional and Ensemble Techniques for Smart Grid Stability Prediction," 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 2024, pp. 1020-1025, doi: 10.1109/ICEEICT62016.2024.10534560.