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Artificial Intelligence-Based Power System Stability Analysis

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Abstract. Power system stability analysis is a key factor in ensuring the safe operation of the power system. With the deepening integration of renewable energy sources and the escalating structural complexity of modern power grids, fast and accurate stability prediction has become particularly important. Traditional model-based methods have the advantage of physical interpretability, but they face limitations such as high computational complexity and insufficient generalization when dealing with high-dimensional and imbalanced data. This study develops a fusion approach that integrates LightGBM and CatBoost. In the data preprocessing stage, categorical variables are transformed through one-hot encoding, and the SMOTE technique is applied to mitigate the class imbalance problem. Subsequently, LightGBM and CatBoost models are trained separately, and their prediction outputs are fed into a logistic regression model as a meta-learner to build the final fusion classifier. Case study findings indicate that the proposed fusion model delivers improved accuracy and F1-score on the training as well as the testing sets, compared with individual GBDT models. Among them, the combination of LightGBM and CatBoost performs best, enabling efficient and accurate identification of transient stability states in power systems.

Keywords: power system stability analysis, artificial intelligence, gbdt, stacking ensemble

1. Introduction

Grid stability analysis is of paramount importance for safeguarding the reliable operation of increasingly complex power systems. With the widespread integration of renewable energy and the growing diversity of load demands, its significance has become ever more pronounced. The integration of renewable energy sources ranging from wind and solar to hydroelectric power into the grid has brought about significant challenges due to their intermittent nature. These energy sources fluctuate, complicating the stabilization of a consistent supply-demand equilibrium in electrical systems. Ineffective stability analysis methods may lead to system instability, large-scale blackouts, or even severe accidents. Literature [1] points out that combining traditional static analysis and dynamic simulations with machine learning methods can enhance the accuracy of transient stability assessments and reduce prediction errors. Therefore, employing accurate models for power system stability analysis is vital for ensuring the secure operation of power systems.

Current methods for power grid stability analysis can be divided into two primary types: modeling and data-centric methods. Model-based methods offer clear advantages in terms of physical interpretability and theoretical maturity. However, they often face limitations such as high

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computational complexity and weak model generalization capabilities when dealing with high-dimensional, strongly nonlinear, and highly uncertain operating conditions. Literature [2] utilizes a method based on Lyapunov theory to construct dynamic equations for transient stability analysis and evaluation. Literature [3] discusses a simplified analysis method for multi-machine systems based on the Extended Equal Area Criterion (EEAC). Literature [4] provides a systematic review of the applicability limitations of direct methods (such as Lyapunov and EEAC) in modern power systems. Literature [5] introduces the TEF (Transient Energy Function) + CNN method, which corrects misjudgment errors inherent in purely model-driven methods through a hybrid model. Literature [6] proposes a model-based robust control method that effectively ensures system stability in complex power systems, particularly when dealing with parameter uncertainty. This method significantly improves robustness against disturbances and fluctuating operating conditions, which are prevalent in renewable energy-based grids.

In the data-driven domain, researchers typically rely on real-time operational measurements or simulation data, combined with machine learning techniques, to identify the transient stability state of the system. This method has resulted in notable enhancements in both effectiveness and generalization. Research [7] merges support vector machines (SVM) with ensemble strategies to swiftly categorize transient stability conditions in power systems. Literature [8] integrates synchronized phasor measurement unit (PMU) data with random forest algorithms to enhance the accuracy and response speed of stability predictions. Literature [9] employs transfer learning and multi-task learning algorithms to improve model adaptability and generalization. Literature [10] proposes an online TSA framework based on graph neural networks and multi-task learning, achieving rapid fault machine identification and stability prediction. Literature [11] uses manifold learning for dimensionality reduction followed by SVM, achieving precise classification in high-dimensional PMU data. Literature [12] introduces a deep reinforcement learning-based stability prediction method, which improves system prediction accuracy and response speed through the fusion and processing of multiple data sources. These advancements not only improve the efficiency of stability assessments but also offer the potential for real-time, adaptive decision-making, which is critical as power systems become more complex and increasingly reliant on renewable energy sources.

2. GBDT-based prediction model

Maintaining the stability of the power system is crucial for the safe and reliable functioning of the grid, especially as the integration of renewable energy sources rises and the intricacy of power networks expands. With the global shift towards a low-carbon future, renewable energy, including wind, solar, and hydroelectric power, is being interconnected with the power grid in record volumes. This transition, while crucial for reducing greenhouse gas emissions, introduces challenges due to the intermittent nature of renewable generation. Unlike traditional fossil fuel-based generation, which provides a constant power output, renewable energy sources can be unpredictable and fluctuating, resulting in power imbalances that can threaten the stability of the grid. Additionally, the increasing complexity of power systems, characterized by decentralized generation and more dynamic demand responses, further exacerbates the difficulty of maintaining stability.

Under such conditions, the ability to rapidly and accurately assess system stability becomes ever more critical. The performance of the power grid depends on how effectively it can respond to disturbances, such as sudden changes in load, generation, or frequency. Traditionally, power system stability analysis relies on physical modeling and numerical simulations, which are computationally intensive and often suffer from delayed responses. This makes traditional methods unsuitable for

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real-time control needs where swift and accurate decisions must be made to prevent cascading failures. As a result, researchers are making growing use of machine learning methods, which offer the potential to perform real-time predictions with high speed and accuracy. Machine learning-based models can handle large volumes of data and extract meaningful insights from them in a fraction of the processing time relative to conventional methods, rendering them well-suited for real-time implementation in power system stability analysis [13].

In this study, the power system stability problem is formulated as a binary classification task. This approach is motivated by the fact that, at its core, stability assessment is a question of whether the system can recover to a steady state or not. From a system dynamics perspective, when a power system is subjected to disturbances such as power fluctuations, price adjustments, or user behavior responses, it is considered "stable" if it can return to its steady operating point; conversely, if the system exhibits sustained oscillations, frequency deviations, or node instabilities, it is deemed "unstable." This binary classification problem simplifies the stability assessment by treating the stability state as a clearly defined outcome—stable = 1, unstable = 0. This allows for the utilization of machine learning techniques, which are particularly well-suited for classification tasks, to learn the patterns that differentiate stable from unstable states.

To enable machine learning models to model the system's dynamic behavior, three key features are selected: tau[x], p[x], and g[x]. These features represent the critical factors that influence the behavior of power systems under disturbances.

tau[x] represents the individual response time, which reflects the behavioral delay of users or producers in responding to changes in the system. The response time is a critical factor because it dictates how quickly the system can react to fluctuations, whether they are caused by changes in generation, load, or system parameters. A longer response time implies that the system is slower to adjust, which could lead to instability. This parameter ranges from 0.5 to10 seconds, capturing a range of different system behaviors. On the other hand, p[x] represents the nominal power at the node. Positive values of p[x] indicate power generation, while negative values represent power consumption or load. The power level at a given node is a direct indicator of whether the system is in generation surplus or deficit, which plays a key role in system stability. Lastly, g[x] represents the price elasticity coefficient, which indicates the degree of responsiveness to price variations. This coefficient captures how users or generators respond to price signals in the market, with higher values indicating greater responsiveness. The values of g[x] range from 0.05 to 1 s^{-1}, denoted as g1 on the producer side. These features are integral to understanding how the system behaves in response to external disturbances and assist in depicting the overall dynamic stability of the system [14].

For the stability prediction task, which is fundamentally a binary classification problem, this study adopts a fusion approach based on boosting algorithms. Boosting refers to an ensemble approach that integrates several weak learners into a single strong learner, thereby improving both the overall prediction accuracy and the robustness of the model across diverse and complex datasets. In particular, this paper integrates LightGBM, CatBoost, SMOTE oversampling, and a stacking strategy. Each of these methods contributes unique advantages, and their synergistic combination aims to optimize predictive performance in the presence of high-dimensional, imbalanced, and noisy data, thus improving both efficiency and accuracy. This approach ensures that the model is well-suited for real-time stability analysis in power systems, where dynamic adjustments and high adaptability are critical.

Gradient Boosting Decision Trees (GBDT) is a well-established ensemble learning algorithm that sequentially constructs multiple weak learners (decision trees), where each subsequent tree is

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designed to reduce the errors of the preceding one. The gradient descent update rule employed in GBDT can be mathematically expressed as:

$$f^{t}(x) = f^{(t-1)}(x) + \eta \bullet h_t(x) \tag{1}$$

Where $f^{(t)}(x)$ is the prediction output at iteration t, $h_t(x)$ is the output of the t-th decision tree, and η is the learning rate. The learning rate, set to 0.01 in this case, controls the extent to which the model is updated at each iteration. By iteratively adding decision trees, GBDT builds a powerful model capable of making accurate predictions for complex, high-dimensional data.

LightGBM, a high-performance realization of the Gradient Boosting Decision Trees (GBDT) method, leverages histogram-based decision tree training, which significantly improves computational speed while reducing memory consumption, thereby making it particularly suitable for large-scale data applications [15]. This efficiency is of critical importance in power system stability analysis, where real-time requirements demand rapid model training and prediction. The principal hyperparameters of GBDT—namely the learning rate, number of estimators, and maximum tree depth—must be carefully optimized through techniques such as cross-validation or grid search to mitigate overfitting and enhance model generalization. In parallel, CatBoost represents another gradient boosting framework that not only improves training stability but also provides advanced mechanisms for categorical feature handling, effectively reducing overfitting and improving predictive robustness [16].

In power system stability datasets, unstable samples often outnumber stable samples, resulting in a class imbalance. Class imbalance can cause models to tend to favor predictions of the majority class (unstable), leading to poor performance on the minority class (stable). To mitigate this problem, the SMOTE (Synthetic Minority Over-sampling Technique) algorithm is applied. SMOTE produces artificial instances for the minority category through interpolation between current minority samples, thus equalizing the dataset and enhancing the model's capacity to identify the minority class. The SMOTE formula is given by:

$$X_{new} = X_i + \lambda \bullet (X_j - X_i) \tag{2}$$

where λ is a random value between [0, 1], and $x_i$and x_j are samples from the minority class. Through the creation of artificial instances, SMOTE enhances the diversity of the minority class, thereby improving model performance on imbalanced datasets.

Building on this, LightGBM and CatBoost are integrated using a stacking framework. Stacking combines the predictions of multiple base models in order to generate a stronger, more resilient model. The predictions of LightGBM and CatBoost serve as new features that are input into a logistic regression model, which acts as the meta-learner and builds the final fusion model. During the testing phase, test set data are first passed through LightGBM and CatBoost to obtain prediction probabilities. These probabilities are then input into the trained logistic regression model, which produces the final classification. The stacking strategy not only improves prediction accuracy but also enhances generalization across both training and testing sets.

To measure the model's performance, several commonly used performance metrics are adopted, including Accuracy, Precision, Recall, F1 Score, and Error Rate. These metrics offer an extensive view regarding the model's effectiveness in predicting both stable and unstable states of the power

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system. The significance of these metrics becomes even more critical in power systems, where accurate and timely predictions can prevent blackouts and avoid system failures.

Accuracy calculates the fraction of correct predictions (both stable and unstable) out of all predictions. In power system stability analysis, accuracy offers a holistic assessment of the model's effectiveness. However, due to class imbalance, where unstable states dominate, accuracy may not fully capture the model's capacity to detect rare stable states. A high accuracy can be misleading if the model predominantly predicts the majority class (unstable).

Precision focuses on the positive predictions made by the model, calculated as the proportion of true positives relative to all predicted positives. In power systems, precision is critical when false positives are costly, as incorrectly predicting stability can lead to unnecessary corrective actions or operational adjustments, increasing costs and downtime.

Recall assesses the model's capacity to identify all pertinent instances, focusing on the true positive rate. In a power grid context, recall ensures that critical unstable states are detected on time, preventing system failures or cascading outages. High recall ensures even rare unstable conditions are flagged, enabling early intervention.

The F1 Score denotes the harmonic mean of precision and recall, reflecting the trade-off between the two. In settings where both false positives and false negatives carry significant risks, the F1 Score helps ensure that neither precision nor recall is unduly compromised. This balance is important when assessing a system's readiness to respond to instabilities and stability predictions.

Error Rate measures the proportion of incorrect predictions. In power systems, error rate quantifies the failure rate of the model. A lower error rate indicates fewer mistakes, which is critical in real-time applications where misclassification can lead to catastrophic consequences such as power outages or instability propagation.

By incorporating these metrics, the model's performance can be assessed from multiple perspectives, ensuring robustness in predicting both stable and unstable states. The integration of data preprocessing, model training, and evaluation is shown in Figure 1.

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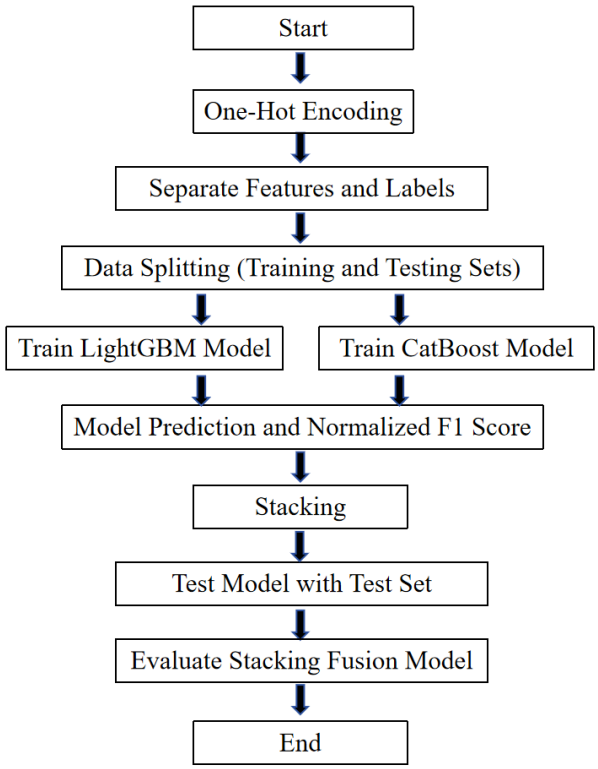

Figure 1. Algorithm framework of the fusion model of LightGBM and CatBoost for power grid stability analysis

3. Case study analysis

The dataset determines system stability based on the features tau, p, and g, comprising a total of 10,000 samples, including 3,620 stable samples and 6,380 unstable samples. The detailed statistics of the sample data are presented in Table 1.

Table 1. Distribution of sample data

Class	Training Set Count	Test Set Count
False	4466	1276
True	2534	724

In Table 1, stab represents the stability index obtained from power system dynamic calculations, with the formula defined as:

$$stab = f(\tau i, pi, gi) \tag{3}$$

Stabf is the discretized version of stab, forming a binary classification label: a value greater than zero indicates stability, while a value less than zero indicates instability.

During data preprocessing, stabf was first subjected to one-hot encoding to generate several new binary features, after which the original stab and stabf columns were removed. The final dataset thus consisted of the encoded features, with the column stable indicating whether the power system is

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stable, serving as the label. All feature columns were used for model training, while the label column stable was separated from the features for supervised learning.

The dataset was partitioned in the following manner: 64% for the training set, 16% for the validation set, and 20% for the test set. To address class imbalance, the SMOTE oversampling method was applied to the training set, ensuring balanced class distribution.

The main hyperparameters include a learning rate of 0.01, a maximum of 1500 training iterations, and an early stopping round of 50.

For model evaluation, several commonly used classification performance metrics were adopted, including Accuracy, Precision, Recall, F1 Score, and Error Rate. These metrics provide insights regarding the ratio of correctly classified samples, the proportion of true positives among predicted positives, the proportion of actual positives correctly identified, and the trade-off between precision and recall.

Within this research, multiple machine learning models were employed and tuned with appropriate hyperparameters, including logistic regression, SVM, CatBoost, LightGBM, XGBoost, Transformer, and CNN.



Figure 2. Training set performance comparison of models



Figure 3. Test set performance comparison of models

In Figure 2 and Figure 3, it can be observed that CatBoost, LightGBM, and XGBoost perform very well, with nearly perfect performance on the training set. In contrast, logistic regression, SVM, and Transformer show weaker performance. CNN also demonstrates strong results on both the training and test sets; however, its training time is significantly higher than that of ensemble learning methods. Therefore, this paper adopts GBDT to construct the model.

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To further improve model performance, an ensemble learning approach is employed by integrating the prediction results of multiple models. The outcomes are reported in Table 2 and Table 3.

Table 2. Comparison of training set results between fusion model and individual model

Model	Accuracy	F1 Score
CatBoost	0.9791	0.9706
LightGBM	0.9994	0.9992
LightGBM+CatBoost (Fusion)	0.9999	0.9998

Table 3. Comparison of test set results between fusion model and individual model

Model	Accuracy	F1 Score
CatBoost	0.9415	0.9164
LightGBM	0.9335	0.9057
LightGBM+CatBoost (Fusion)	0.9490	0.9291

Table 2 and Table 3 demonstrate that, compared with individual GBDT models, the proposed fusion model achieves consistently better performance on both the training and test sets, with noticeable improvements in accuracy and F1-score. These results highlight the effectiveness of integrating multiple boosting models through stacking to enhance predictive accuracy.

Table 4. Test set performance of integrated models with different combinations

Combination types	Accuracy	F1 Score
LightGBM + CatBoost	0.9480	0.9280
CatBoost + XGBoost	0.9460	0.9250
XGBoost + LightGBM	0.9405	0.9191

In Table 4, by integrating any two of the three GBDT models, a comparison of the test set results with respect to accuracy and F1-score shows that the fusion of LightGBM and CatBoost achieves the best performance.

4. Conclusion

This research presents an integrated method utilizing LightGBM and CatBoost for power system stability analysis. The approach leverages efficient gradient boosting models within the GBDT framework and enhances classification performance through a stacking-based integration strategy.

In the implementation process, the raw data were first preprocessed, including feature discretization, one-hot encoding, and SMOTE oversampling to alleviate class imbalance. Subsequently, LightGBM and CatBoost models were trained independently, and their prediction results were fed into a logistic regression model as new features to construct the final fused classifier. Finally, case studies were conducted to evaluate the capability of individual models relative to the fusion model.

The findings from the case studies demonstrate that the developed fusion model achieves significant improvements over standalone LightGBM and CatBoost on both training and test sets.

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Among various ensemble strategies, the combination of LightGBM and CatBoost proved to be the most effective. This method effectively improves the accuracy of power grid stability prediction and enables efficient identification of transient stability states, thereby providing strong support for the secure operation of power systems.

References

[1] Ali, J.S., Qiblawey, Y., Alassi, A., Massoud, A.M., Muyeen, S.M. and Abu-Rub, H. (2025) Power System Stability With High Penetration of Renewable Energy Sources: Challenges, Assessment, and Mitigation Strategies. IEEE Access, 13, 39912–39934.
[2] Qiu, Z., Duan, C., Yao, W., Zeng, P. and Jiang, L. (2022) Adaptive Lyapunov Function Method for Power System Transient Stability Analysis. IEEE Transactions on Power Systems, 37(2), 1631–1644.
[3] Bahmanyar, A., Ernst, D., Vanaubel, Y., Gemine, Q., Pache, C. and Panciatici, P. (2021) Extended Equal Area Criterion Revisited: A Direct Method for Fast Transient Stability Analysis. Energies, 14(21), 7259.
[4] Wu, H., Li, J. and Yang, H. (2024) Research Methods for Transient Stability Analysis of Power Systems under Large Disturbances. Energies, 17(17), 4330.
[5] Mo, T., Liu, J., Liu, J., Wang, G., Li, Y. and Lin, K. (2024) Power System Transient Stability Assessment Based on Intelligent Enhanced Transient Energy Function Method. Energies, 17(23), 5864.
[6] Zhang, Y., Li, X. and Chen, S. (2020) Robust control-based method for power grid stability under parametric uncertainty. Journal of Power Systems, 35(3), 1235–1246.
[7] Ao, Y., Chen, J., Cai, D., Liu, H. and Chen, R. (2023) Power System Transient Stability Prediction Based on GWO-SVM and Boosting Method. In: Yang, Q., Li, J., Xie, K. and Hu, J. (eds.) Proceedings of the 17th Annual Conference of China Electrotechnical Society. Singapore: Springer Nature Singapore, 268–276.
[8] Wang, H. and Chen, H. (2022) Transient Stability Assessment of Power System Based on Improved Random Forest. Science & Technology and Engineering, 22(13), 4367–4374.
[9] Fang, J. and Liu, C. (2024) Artificial Intelligence Techniques for Stability Analysis in Modern Power Systems. iEnergy, 3(4), 194–215.
[10] Liu, Z., Ding, Z., Huang, X. and Zhang, P. (2023) An Online Power System Transient Stability Assessment Method Based on Graph Neural Network and Central Moment Discrepancy. Frontiers in Energy Research, 11, 1187512.
[11] Sarajcev, P. and Lovric, D. (2023) Manifold Learning in Electric Power System Transient Stability Analysis. Energies, 16(23), 7810.
[12] Wang, L., Liu, P. and Zhao, Z. (2021) Transient stability prediction of power systems based on deep reinforcement learning. IEEE Transactions on Power Systems, 36(2), 2552–2564.
[13] Milano, F. (2013) A Python-based Software Tool for Power System Analysis. IEEE Power and Energy Society General Meeting, 2013, 1–5.
[14] Roozbehani, M., Dahleh, M.A. and Mitter, S.K. (2012) Volatility of Power Grids Under Real-Time Pricing. IEEE Transactions on Power Systems, 27(4), 1926–1940.
[15] Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q. and Liu, T.Y. (2017) LightGBM: A Highly Efficient Gradient Boosting Decision Tree. Advances in Neural Information Processing Systems (NeurIPS 2017), 30, 3146–3154.
[16] Chawla, N.V., Bowyer, K.W., Hall, L.O. and Kegelmeyer, W.P. (2002) SMOTE: Synthetic Minority Over-Sampling Technique. Journal of Artificial Intelligence Research, 16, 321–357.