Evaluation and Intelligent Enhancement of Transient Rotor Angle Stability Index for Power-Electronics-based Power System

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***Abstract*—This paper introduces a power system stability index, enhanced by neural networks for improved accuracy and interpretability, to improve its adaptability in power-electronics-based systems. An integrated transient rotor angle stability index is focused on, attempting to use neural networks to intelligently enhance the key link in the stability discrimination process. Among various neural network architectures, Long Short-Term Memory (LSTM) networks demonstrate faster and stable convergence rates during training. To improve the generalizability of the index in different cases, Sobol sensitivity analysis is conducted to identify the most influential parameters affecting system stability, which are then used as inputs to construct a hybrid multi-input neural network based on LSTM. Simulation results show that the proposed intelligently enhanced transient rotor angle stability integrated index achieves significant improvements in precision, recall, and timeliness compared to the original index.**

***Index Terms*—transient rotor angle stability, response-driven, Sobol sensitivity, intelligent enhancement**

I. Introduction

With large-scale integration of renewable energy in power systems, the dynamic characteristics of power systems have undergone profound changes, leading to different stability problems. The nonlinearity, time-varying nature, and uncertainty of the power-electronics-based power system pose challenges to existing transient stability analysis methods [1].

Power system stability analysis methods can be divided into model-based and response-based according to data source. Model-based methods rely on accurate models, including direct methods and time-domain simulation. Large-scale and modeling uncertainties of components in power-electronics-based power systems challenge traditional model-based stability analysis methods. Therefore, with construction of wide-area measurement system (WAMS), stability analysis based on measurement has attracted increasing attention. Previous studies have found that among transient angle stability indices, the integrated index based on simplified Branch Transient Transmission capacity(sBTTC) [2] has higher accuracy and timeliness, compared with Transient Stability Index (TSI) and Maximum Lyapunov Exponent [3]. The overall process of the integrated index can be divided into three steps: 1) Key branch screening based on simplified branch transient transmission capacity. 2) Position and amplitude of the vertical voltage and rate of change of phase angle analysis. 3) Dominant stability criterion: phase trajectory analysis. However, the index tends to be overly conservative when applied to systems with high renewable penetration, and its adaptability with step changes and oscillations remains under investigation.

Existing theoretical tools are unable to meet the requirements of timeliness and accuracy for safety and stability control in applications. Therefore, artificial intelligence based methods have been widely studied in recent years. A category of AI-based approaches involves directly applying AI models for stability assessment. Widely used models include Convolutional Neural Network (CNN) [4], Long Short-Term Memory (LSTM) [4], and transfer learning [5]. However, the opacity, unclear parameter meaning, and poor transferability of model limit its further application in power systems. Explainable Artificial Intelligence (XAI [6], [7]) and physical-informed neural network(PINN, [8]–[10]) provide a new solution for the application of deep learning in power systems, of which interpretability and performance are improved. However, the complexity of the calculation and training process is high, and the generalization needs to be further verified.

Aiming at existing problems in application of above stability indices and deep learning methods, this paper proposes an intelligent enhancement framework for the key link of the integrated stability index. The simulation results demonstrate that the proposed intelligent enhancement framework can significantly improve the timeliness and accuracy of the index.

(1)Theoretical analysis and simulation validation are carried out for each criterion in the integrated index, and the dominant stability criterion (phase trajectory) is determined as the intelligent enhancing point of the index.

(2)To improve the generalization of the index, Sobol sensitivity is applied to identify key influencing factors of the system by sensitivity analysis of electrical quantities.

(3)Neural networks are used to enhance the dominant stability criterion of the integrated index, and a hybrid multi-input neural network based on LSTM is constructed with key influencing factors as input.

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II. Comprehensive Evaluation of the Integrated Index and Analysis of Key Link

A. Principles of the Integrated Index

Previous work analyzed the applicability and effectiveness of each link of the integrated index, finding that the dominant stability criterion (phase trajectory) serves as a key factor affecting both the accuracy and timeliness. Therefore, the dominant stability criterion serves as the fundamental basis for intelligent enhancement.

The phase trajectory was first introduced in [11] as a transient stability index. For single-machine infinite-bus systems and multi-machine systems, based on the second-order rotor dynamic equation, different performances of the phase trajectory are derived. As disturbance increases, the trajectory shifts from the stable equilibrium to the unstable equilibrium; meanwhile, convexity transition occurs, as shown in Fig. 1.

In complex networks, multi-machine approximation is generally carried out by finding the inertia center and real-time grouping of units, with convexity and concavity analysis being improved. In the integrated index, the polynomial fitting method is used to evaluate the concavity and convexity of the phase frequency trajectory. The key step is to determine when the fitted quadratic coefficient crosses zero.

B. Key Link for Intelligent Enhancement

The dominant stability criterion in the integrated index adopts a different dimension reduction method compared with the original phase trajectory: simplified Branch Transient Transmission capacity is based on branch response information, reflecting the dynamic characteristics of the system through transient response characteristics of branches.

However, the above improvements keep the index's theoretical foundation (sway equation of synchronous machine) unchanged, so the applicability of the index in power-electronics-based power systems remains underexplored. The dominant stability criterion plays a dominant role in the accuracy and timeliness of the integrated index. Therefore, the key link for intelligent enhancement is selected as the phase trajectory. The obstacles of the original index in terms of timeliness and accuracy mainly lie in the following two points:

1) The polynomial fitting exhibits a temporal lag during positive and negative transitions of the quadratic coefficient.

2)Misjudgments frequently occur near the zero crossing. With dynamic characteristics of power electronic equipment, the concavity and convexity may fluctuate in a short time.

III. Identification of Key Influencing Factors based on Sobol Sensitivity

With response data available, influential parameters are added and identified via Sobol sensitivity analysis to enhance the index's applicability across scenarios.

A. Principles of Sobol Sensitivity

Sobol sensitivity is based on the orthogonal decomposition of a nonlinear function over all subsets of parameters. The decomposition result is shown in (1) [12]. In practice, the calculation of Sobol sensitivity is based on Monte Carlo sampling, with expectation and variance used to approximate the factorization process, as in (2) and (3).

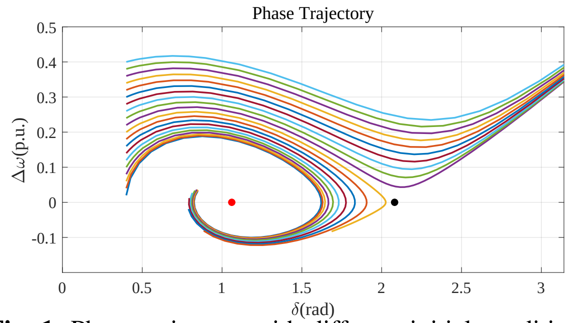

Fig. 1. Phase trajectory with different initial conditions

$$Y = f_0 + \sum_{s=1}^{N} \sum_{i_1<...<i_s}^{N} f_{i_1...i_s}(X_{i_1}, ..., X_{i_s}) \tag{1}$$

$$S_i = \frac{V_i}{Var(Y)} = \frac{Var_{X_i}(E_{X_{\sim i}}(Y|X_i))}{Var(Y)} \tag{2}$$

$$S_{Ti} = \frac{(E_{X_{\sim i}}(Var_{X_i}(Y|X_i))}{Var(Y)} \tag{3}$$

Where: Y is the dependent variable, X_i is the independent variable i. f represents the decomposed contribution of parameters. S_i and S_{Ti} are the first-order and full-order sensitivities corresponding independent variable i, respectively. The subscript "$\sim i$" indicates the exclusion of the i-th variable.

Monte Carlo sampling can lead to errors, so the following two methods are adopted to reduce the error:

1) Replace S_i with S_{Ti}: power system is determined by joint actions of multiple parameters, but S_i adopts a univariate analysis, which causes larger sampling error.

2) Mean centering: sampling error is also related to the constant term f_0, so f_0 can be estimated in advance from Y.

B. Sobol Sensitivity Analysis of System Electrical Quantities

To reflect the stability characteristics of the system, Sobol sensitivity is used to identify factors that influence rotor angle and voltage stability the most. Through Sobol sensitivity analysis of the system parameters with respect to the electric quantities (bus voltage, rotor angle), the influence of each parameter is quantitatively compared. Through theoretical analysis of the transient process in a simple system, the Sobol sensitivity of each system parameter is estimated.

1) Voltage: A binary threshold matrix is used to identify instances where voltages drop below the set limit(a limit of 0.8 p.u. is adopted), and the corresponding integral area A_i quantifies the severity of low-voltage events.

2)Rotor angle: As rotor angle δ_i is in the rotating reference frame, orthogonal decomposition in (1) may introduce errors. Therefore, bilinear transformation is used to map the circular arc of radius π in the complex plane to the interval $[-1, 1]$, as in (4). When rotor angle exceeds $180°$, TSI turns negative.

$$TSI_I = \frac{\pi - \delta_i}{\pi + \delta_i} \tag{4}$$

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Sobol sensitivity of the electrical quantities is estimated from the theoretical point of view, and a two-machine system with load is constructed as shown in Fig. 2. A receiving-sending-end system is constructed, and two wind turbines are connected to both ends. For simplification, the following calculation is based on three assumptions: (1) the wind turbine is considered a power injection model; (2) the DC power flow is used for power flow calculation; (3) the electromagnetic power of generator P_e is considered 0 during a fault. The detailed derivation process can be found in [13].

The two-machine system is equivalent to a single-machine infinite-bus system, and δ satisfies:

$$\frac{d^2\delta}{dt^2} = \frac{\omega_0}{M}(P_m - P_e) \tag{5}$$

where: $M = M_1M_2/(M_1 + M_2)$,M,ω,P_m, and P_e represent inertia, frequency, equivalent mechanical power, and electromagnetic power of generators. 0 in subscript represents the pre-fault steady state.

Assuming that a fault occurs at t_f, the differential equation and the initial value of δ are obtained in (6) and solved in (7)

$$\begin{aligned} \frac{d^2\delta}{dt^2} &= \frac{\omega_0}{M}P_m = \frac{\omega_0}{M}[P_{G1} - \alpha_M(1 - k_{wr}P_L)] \\ \delta|_{t=t_f} &= xP_1 + (x - x_w)P_{w1} + x_wP_{w2} - (x - x_L)P_L \end{aligned} \tag{6}$$

$$\delta(t) = \frac{1}{2}\frac{\omega_0}{M}[P_{G1} - \alpha_M(1 - k_{wr}P_L)](t - t_f)^2 + \delta|_{t=t_f} \tag{7}$$

When the fault is cleared at t_c, with the load injection point as reference ($\delta_L = 0$), the differential equations of rotor angle of two generators can be obtained as in (8), and superscript"c" represents the impedance after fault removal.

$$\begin{aligned} \frac{d^2\delta_1}{dt^2}\frac{M_1}{\omega_0} &= P_{G1} - \frac{\delta_1}{x_L^c} + \frac{x_L - x_w}{x_L^c}P_{w1} \\ \frac{d^2\delta_2}{dt^2}\frac{M_2}{\omega_0} &= P_{G2} - \frac{\delta_2}{x^c - x_L^c} + \frac{x^c - x_L - x_w}{x^c - x_L^c}P_{w2} \end{aligned} \tag{8}$$

Then, by changing ratio of P_{w1} and P_{w2}, k_{wr} and M, rotor angle can be calculated. Furthermore, Sobol sensitivity is calculated to qualitatively analyze the key factors influencing rotor angle stability, and the calculation results are shown in Fig. 3. It can be found that the renewable energy permeability has a greater impact on δ_1, while ratio of P_{w1} and P_{w2} has a greater impact on δ_2.

IV. Deep Learning–based Intelligent Enhancement of the Integrated Index

Based on the analysis results of the key link in the integrated index, neural networks are used to intelligently enhance the key link, thereby improving the comprehensive performance of the index's accuracy and timeliness. The overall enhancement framework is shown in Fig. 4. A neural network is designed to take time series as input and stability result as output, so as to realize the accurate and timely identification of the trajectory's concave-convex transition point.

Furthermore, to improve the adaptability of the enhanced index in different cases and scenarios, based on the identification

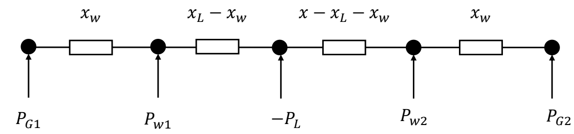

Fig. 2. Two-machine system

P.S. x is the electrical distance between the two generators, and x_w is the electrical distance between wind turbines and generators. P_{w1} and P_{w2} respectively represents power of the wind turbines. P_L is the load power, and $K_{wr} = (P_{w1}+P_{w2})/P_L$ represents the proportion of wind power injected. $\alpha_M = M_1/(M_1+M_2)$quantitatively represents the inertia coefficient distribution of the generator.

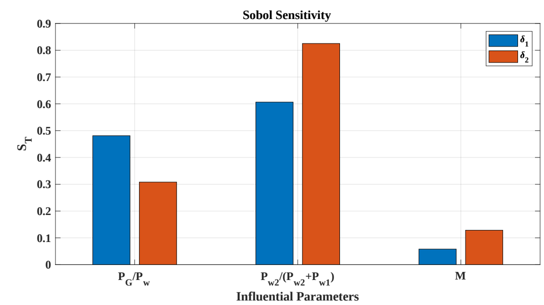

Fig. 3. Sobol sensitivity results based on the theoretical model

of the key influencing factors, parameters with great influence on stability are used as the input of the neural network at the same time. A hybrid multi-parameter input neural network based on neural network is constructed. Models use Adam optimizer, and the loss function is *BCEWithLogitsLoss*.

Aiming at the key link of the integrated index analyzed in II and existing adaptability problems, the sample generation process is designed as follows:

Step 1: Long-term time series samples generation. System parameters are generated using Gaussian distribution and incorporated into modified simulation cases.

Step two: Filter out invalid samples. Data missing due to non-convergence of power flow or system collapse caused by unreasonable parameter setting is excluded.

Step 3: Short-term time series samples generation. All samples are sampled using a fixed-length moving time window.

Step 4: Split training and test sets. All short-term time series samples are split into training (60%) and test (40%) sets.

V. Case Study

CSEE-TAS-173 [14] is used to test and verify the effectiveness of the proposed method. The case is designed based on the actual Chinese power grid and exhibits typical characteristics of power-electronics-based power systems. The simulations are performed using the CloudPSS platform, with a 2.60 GHz 13th Gen Intel(R) Core(TM) i9-13900H processor. The case includes 197 nodes, multiple centralized access points for renewable energy, and 4 DC transmission lines.

The connecting line between receiving and sending areas is subjected to a three-phase permanent-to-ground N-2 fault. The contingency-based control involves cutting off units and

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TABLE I
SYSTEM MODIFIABLE PARAMETERS

No.	Name	Physical Meaning
1	sync_rate	Generator output participation factor
2	WG_rate	Renewable generation distribution ratio in sending- and receiving-end system
3	krate	Wind turbine active power recovery rate
4	DC_type	DC type: HVDC / VSC-HVDC
5	WG_type	Wind turbine type: DFIG / PMSG
6	Inertia_rate	Inertia constant

TABLE II
PERFORMANCE OF ORIGINAL AND ENHANCED INDICES

Metrics	Original Index	RNN	LSTM	CNN	Hybrid Input LSTM
Precision	92.9%	96.2%	93.8%	88.37%	87.33%
Recall	85.7%	98.7%	98.7%	98.7%	98.7%
F1-Score	0.892	0.974	0.962	0.933	0.927
Time(ms)	380	247	245	246	243

loads in receiving area and advancing units at sending area. By modifying operation modes, contingency-based control match and mismatch scenarios can be constructed. The selected parameters are shown in Table. I.

A. Sobol Sensitivity Analysis of Electrical Quantities

Parameters are generated, and time series samples are generated through batch simulation. Sobol sensitivity of rotor angle and voltage relative to system parameters is calculated, as in Fig. 6, which matches Fig. 3.

B. Intelligent Enhancement of the Integrated Index

The procedure of stability evaluation of the integrated index before and after intelligent enhancement is shown in Fig.5, where the intelligent enhancement part is marked with dotted lines. Performance of indices before and after the intelligent enhancement is compared and analyzed by confusion matrix(setting instability as positive and stability as negative). Recall, precision and F1-score are defined in (9)-(11). Recall measures index's ability to identify instability, while precision measures the conservative nature of the index. F1-score provides a comprehensive evaluation of the index's performance.

$$R = \frac{TP}{TP + FN} \tag{9}$$

$$P = \frac{TP}{TP + FP} \tag{10}$$

$$F1 = \frac{TP}{TP + FP} \tag{11}$$

Results before and after enhancement are shown in Table.II. Recall of the enhanced index has increased by 13%, and the average stabilization time has been shortened by 140ms. The stabilization time of the hybrid-input LSTM is relatively low. Correspondingly, the precision of all enhanced models except RNN and LSTM has slightly decreased. Among them, the RNN enhanced index has the highest precision, recall, and F1-score. However, LSTM demonstrates better convergence and stability during the training process. Therefore, LSTM is selected to construct a hybrid-input model.

The hybrid input LSTM model simultaneously takes typical parameters and time series as input, but results in higher conservativeness. For further research, samples are plotted in Fig. 7a. Comparing the original index with the hybrid-input model, the original index is more prone to judgment errors (including misjudgment and missed judgment) near the stable boundary(TSI=0). The enhanced index decreases the omission rate but tends to produce more misclassifications near the boundary. Notably, some misjudged samples belong to the instability caused by low ramping.

The following conclusions can be drawn from Fig. 7:

(1) Identification of instability caused by low damping: In the instability scenario in Fig. 7c, due to insufficient system damping, rotor angle swings with oscillation. The enhanced index can identify instability before rotor angle swings, indicating a certain recognition ability for this type of instability.

(2) Identification of transient instability scenarios: As shown in Fig. 7c, the enhanced index immediately determines instability after the change in convexity of trajectory, while the original index makes a judgment approximately 100ms after transformation, which indicates enhanced timeliness.

VI. CONCLUSION

In response to the applicability issues of response-based stability indices and the interpretability of data-driven stability indices in power systems, this paper realizes the intelligent enhancement of the integrated stability index. Sobol sensitivity is used to quantitatively analyze the major influencing factors, and multiple neural networks are used to intelligently enhance the dominant criterion: phase trajectory. A multi-input framework is developed with both influential parameters and time series. Through simulation validation, the average stabilization speed of the intelligently enhanced index has increased by 140 ms. Among them, recall of the best-performing model has increased by 13%, and precision by 3%. The hybrid-input model demonstrates higher conservation and better timeliness.

The trajectory-based intelligent enhancement index is designed to address possible step changes and oscillations of power electronic devices under large disturbances, providing better applicability in power-electronics-based systems.

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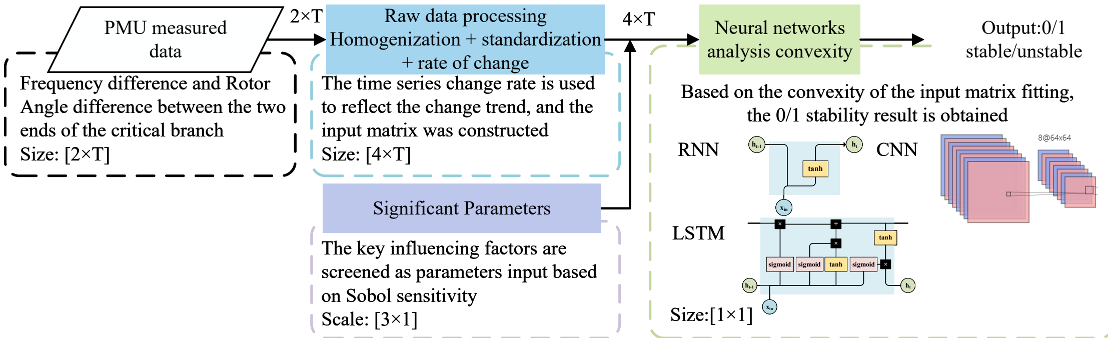


Fig. 4. Intelligent enhancement framework

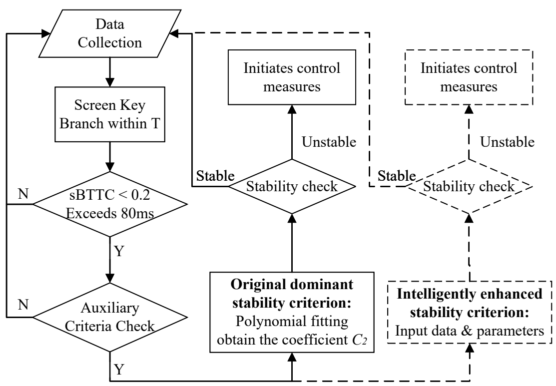


Fig. 5. Stability assessment procedure of the original integrated index and the intelligent enhanced index

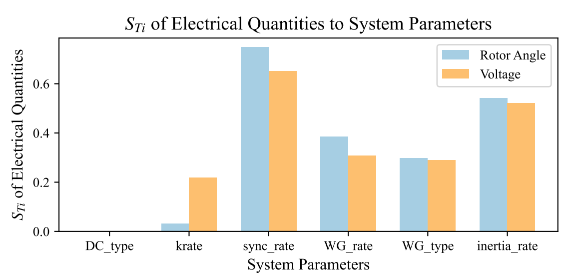
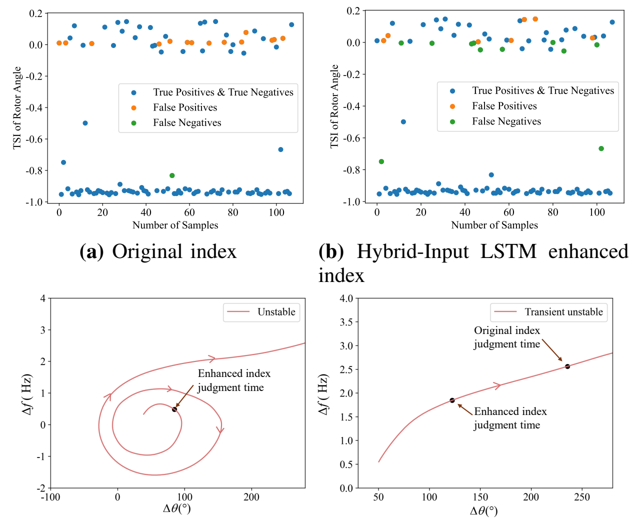


Fig. 6. Results of Sobol sensitivity analysis for rotor angle and voltage



(a) Original index

(b) Hybrid-Input LSTM enhanced index

(c) Phase trajectory in different cases

Fig. 7. Comparison of results before and after the dominant stability criterion enhancement

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