An Integrated Model-Driven and Data-Driven Method for On-Line Prediction of Transient Stability of Power System With Wind Power Generation

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ABSTRACT The increase of wind power permeability in modern power grid has turned rapid and accurate transient stability (TS) prediction into a more challenging issue. To accurately and promptly perform online TS prediction for power system with doubly fed induction generator (DFIG)-based wind farms, an integrated model-driven and data-driven method is proposed in this paper. The influence of DFIGs is considered in the transformation to guarantee the accuracy of the equivalent one machine infinite bus (OMIB) model transformed from the target system. The P-δ trajectory of the OMIB is fitted with the generator-terminal information to predict TS. To improve the prediction speed, an extreme learning machine (ELM)-based method is utilized to process the other DFIG and system information and evaluate the system status immediately after failure. The simulation results verify that the proposed method can reduce the dependence of the data-driven method on the data sample size and improve the speed and accuracy of online prediction.

INDEX TERMS Extreme learning machine (ELM), doubly fed induction generators (DFIG), transient stability, trajectory fitting.

I. INTRODUCTION

Energy crises, environmental pressures and the low cost of wind power enhance the wind power permeability in contemporary power system [1]. Although high wind power permeability can generate economic and environmental benefits, it can also bring tremendous challenges for a system’s stable operation as a result of its highly stochastic characteristics, converter-based interfacing and reduction in the effective inertia of the replaced synchronous generators [2].

Transient instability is one of the most severe problems that power system encounter in daily operation [3]. In the transient process after a severe disturbance, if a certain number of generators lose synchronization with other generators, transient instability can occur, leading to cascading failures and even widespread blackouts [4]. Moreover, the interaction between wind power and generators in the transient process increases the difficulty of studying the transient stability (TS) of power system with wind power.

Considerable research has been conducted in the field of the TS of power system with wind farms [5]–[11]. These studies have contributed to analyzing the influence of wind power integration on power system TS [5]–[9], and improving system TS after large disturbances through wind turbine control and dispatching [10]–[12].

In addition, considering the consequences of transient instability, it is necessary to provide early warning online for emergency control with efficient transient stability prediction after a large disturbance in power system with wind power [5].

Traditional methodologies for TS prediction are based on system modeling, including the time domain simulation (TDS) method, transient energy function (TEF) method and equal area criterion (EAC) method. Due to the timeliness...
of online prediction, it is difficult to apply the TDS method in the online prediction of large-scale system [13], [14]. The TEF method and extended equal area criterion (EEAC) method based on the EAC method have displayed good performance in online prediction.

TEF methods assess TS directly based on the Lyapunov stability principle [2], [15]; these methods are fast and have been used in the prediction of wind power integrated system TS [16], [17]. A high-precision real-time method for TS assessment of system with wind turbines was proposed in [16]. By calculating the initial point of the TEF offline, the critical clearing time (CCT) after failure can quickly be determined. The method proposed in [17] further enhances this approach. Based on a Taylor expansion of the rotor angle trajectory, the influence of the wind turbine controller on the calculation of the corrected kinetic energy was considered in the new method to improve the accuracy of CCT prediction.

The EEAC method converts a multimachine system into a two-machine system through PCOI equivalence and further transforms it into an OMIB system to assess TS based on the EAC [18]. Due to its simple and effective model and clear mechanism, the method is not only used for transient stability prediction [18], [19] but also serves as the basis for impact analyses of wind power integration [8]–[10].

With the increased installation of wide-area measurements in power system, some TS prediction methods based on data mining, represented by machine learning, have been proposed [20]–[24]. Data-driven methods have displayed good performance in online prediction at satisfactory speeds [20]–[22], but neglecting the physical mechanism of transient processes may lead to a decrease in the prediction accuracy. Although [20] adopted a hybrid method to ensure a high prediction accuracy, the dependence of the data-based model on the large prior knowledge base was detrimental to its application in power system with wind power.

In this paper, efforts are made to integrate a model-driven method with a data-driven method to accurately predict the TS of a power system of large-scale wind power online. The main contributions of this paper are as follows.

1) An accurate model-driven TS prediction method based on EEAC for a wind power-integrated power system is proposed. In this method, the P-δ trajectory is fitted by projecting the generator terminal information acquired during the transient process to the OMIB model transformed from the target system. Then, TS can be predicted by calculating the acceleration and deceleration areas.

2) To reduce the time consumption of data acquisition, an integrating model-driven and data-driven TS prediction method for a large-scale wind power-integrated power system is proposed. In the integration method, an ELM classifier is applied in the target systems to preprocess the system status and accelerate the prediction. The combination of the two methods guarantees a high online prediction speed, thereby improving the accuracy and reducing the dependence on sample size.

The rest of this paper is organized as follows. In section II, the characteristics of the proposed data-driven method, model-driven method and integrated method for the TS prediction of power system with wind farm are analyzed. In section III, a prediction method based on P-δ fitting is proposed to predict the TS of wind power system. Section IV introduces the TS prediction method based on ELM. In section V, the integrated model-driven and data-driven method and its implementation are presented. A case study and conclusions are given in sections VI and VII, respectively.

II. PROPOSED METHODS

The essence of power system TS prediction involves extracting the stability knowledge contained in the system information through certain rules to assess the TS of the system. The information may be global information, such as the bus voltage, or local information, such as the generator power angle and output. The rules used in the prediction can be summarized by model-driven methods or learned from historical data by data-driven methods.

As shown in the schematic diagram of power system with wind farm in Figure 1, information on the wind farm, power...
grid and generator are collected online through the Wide Area Measurement System (WAMS); such information includes the fan speed, wind power output, voltage amplitude and angle in the power grid, generator terminal speed, rotor angle and output, etc.

The information requirements of different prediction rules are diverse. The model-driven method retains the physical significance of the collected data so that prediction can be completed by collecting partial information. The data-driven method regards the collected information as the data and ignores its physical significance; thus, stability can be predicted from all the system information.

In this paper, the model-driven TS prediction method is implemented by collecting the generator terminal information before and after a failure. The ELM-based TS prediction method is used to discover other stability knowledge contained in the wind farm and obtain grid-side information.

The integration of the data-driven method and model-driven method in this paper is mainly completed through the analysis of the prediction results of the ELM-based method. By analyzing the predicted output of the ELM classifier, the unreliable regions can be quantitatively divided to determine the credibility of the predicted results. The unreliable prediction results are corrected by the model-driven method, thereby achieving a combined approach and ensuring a high online prediction accuracy for the integrated method.

In terms of the timeliness of prediction, the data-driven method completes the prediction promptly, and the P-δ fitting method needs to collect the generator information for a certain time after the failure clearance.

In this paper, the data-driven method is used in advance to quickly predict the stability of the current system status after failure occurrence, and the prediction result is then obtained. For the reliability result, the model-driven method is no longer used for correction, thereby screening and removing most system states, which will reduce the time consumption of data acquisition and improve the online prediction speed of the integrated method.

III. P-δ FITTING METHOD FOR THE TS PREDICION OF WIND POWER-INTEGRATED SYSTEM

The rotor motion equation of the i-th generator in the n-machine system can be described as

$$M_i \ddot{\delta}_i = P_{mi}(t) - P_{ei}(t)$$  \hspace{1cm} (1)

where $M_i$ is the generator’s moment of inertia, $\delta_i$ is the rotor angle, $P_{mi}$ is the mechanical power and $P_{ei}$ is the electromagnetic power [10].

In the transient process after a large disturbance, the synchronous generators can be divided into a critical generator cluster ($S_g$) and a remaining generator cluster ($A_g$) according to the rotor angular motion [5]. Then, the multimachine system can be transformed into an equivalent two-machine system through partial center of inertia (PCOI) transformation and be further transformed into an OMIB system. The above equivalence process and equivalent rotor motion equation can be described as

$$M_{eg} \ddot{\delta}_g = P_{mg} - P_{eg}$$  \hspace{1cm} (2)

$$M_s = \frac{M_i M_a}{M_s + M_a}, \quad M_s = \sum_{i \in S_g} M_i, \quad M_a = \sum_{i \in A_g} M_i$$

$$\delta_g = \delta - \delta_a, \quad \delta_a = \sum_{i \in S_g} M_i \delta_i \quad \text{and} \quad \frac{P_{mg}}{M_s + M_a} = \frac{M_i P_{mi} - M_a P_{ma}}{M_s + M_a}$$  \hspace{1cm} (3)

where $M_g$, $\delta_g$, $P_{mg}$, and $P_{eg}$ are the equivalent rotor inertia, rotor angle, mechanical power and electromagnetic power of the OMIB system; $\delta$, $M_s$, $\delta_a$, and $M_a$ are the equivalent rotor angle and inertia of $A_g$ and $S_g$; and $P_{mi}$, $P_{es}$, $P_{ma}$, and $P_{ea}$ are the equivalent mechanical and electromagnetic power of $A_g$ and $S_g$, respectively.

In a multimachine system with DFIGs, the DFIG has no risk of transient instability due to the electromechanical decoupling of the inverter installed between the DFIG and the grid, but it will interact with the synchronous generators during the transient process to change the disturbed trajectory of the synchronous motors, thereby affecting the TS of the power system.

Considering the active power control capability of DFIGs, the DFIGs connected to the power system in this paper are equivalent to current sources. In the transient process to change the disturbed trajectory of the synchronous motors, thereby affecting the TS of the power system.

The DFIGs connected to the power system are equivalent to current sources.

![Figure 2](image-url)
respectively; \( U_W \) and \( U_C \) are the voltage column vectors of the wind power node and connection node; \( E_G \) is the internal potential vector of the synchronous motor; \( Y_{WW}, \ Y_{GG}, \) and \( Y_{CC} \) are the self-admittance values of the W, G and C nodes; and \( Y_{WG}, \ Y_{WG}, \ Y_{GC}, \ Y_{CW}, \) and \( Y_{CG} \) are the mutual admittance values of different classes of nodes.

Because the connection node in (4) satisfies \( I_C = 0, \) the voltage equations of the C node and W node are incorporated into the G node, and the expression of the injection current at the generator node can be obtained as

\[
\dot{I}_G = \dot{I}_G + \Delta \dot{I}_G
\]

\[
\dot{I}_G = \left[ Y_{GG} - Y_{GC} Y_{CC}^{-1} Y_{CG} \right] (Y_{WG} - Y_{WC} Y_{CC}^{-1} Y_{CW}) \dot{E}_G \\
\frac{Y_{WW} - Y_{WC} Y_{CC}^{-1} Y_{CW}}{Y_{WW} - Y_{WC} Y_{CC}^{-1} Y_{CW}} \Delta \dot{I}_G = \left[ \frac{Y_{GW} - Y_{GC} Y_{CC}^{-1} Y_{CW}}{Y_{WW} - Y_{WC} Y_{CC}^{-1} Y_{CW}} \right] \dot{I}_W
\]

where \( \Delta \dot{I}_G \) is the equivalent injection current of the wind farm at the G node.

Therefore, after wind power is connected to the grid, the electromagnetic power of synchronous generator \( i \) can be expressed as

\[
P_{ei}^* = real(\dot{E}_i I_i^*) = real(\dot{E}_i I_i^* + \dot{E}_i \Delta \dot{I}_i^*) = P_{ei} + \Delta P_{ei}
\]

\[
\Delta P_{ei} = E_i \Delta \dot{I}_i^* \cos(\delta_i - \Delta \psi_i)
\]

where \( P_{ei} \) is the original electromagnetic power of synchronous generator \( i \) and \( \Delta P_{ei}, \ \Delta \dot{I}_i \), and \( \Delta \psi_i \) are the electromagnetic power increment and the amplitude and angle of the equivalent injection current associated with wind power for synchronous motor \( i \).

Subsequently, the equivalent OMIB system motion equation in equation (2) can be modified to

\[
M_{g_k} \ddot{\delta}_g = P_{mg} - P_{eg}'
\]

where \( M_{g}, \ \delta_g, \) and \( P_{mg} \) are defined in the same way as in equation (2). \( P_{eg}' \) is the corrected equivalent electromagnetic power after wind power is connected and can be expressed as

\[
P_{eg}' = P_e \sum - P_{max} \sum \sin(\delta_g - \beta)
\]

where \( P_e \), \( \sum \), \( P_{max} \), \( \sum \) and \( \beta \) are the offset, amplitude and initial phase, respectively, of \( P_{eg}' \) [10].

It can be found that \( P_{eg}' \) is the sine function of \( \delta_g \) in (9). Then, \( P_{eg}' \) can be expanded to

\[
P_{eg}' = p_0 + p_1 \sin(\delta_g) + p_2 \sin(\delta_g)
\]

where \( p_0, \ p_1 \) and \( p_2 \) are undetermined parameters.

According to (10), the P-\( \delta \) trajectory can be obtained if the parameters \( p_0, \ p_1 \) and \( p_2 \) during the fault period (or after fault excision) are determined. Then the acceleration and deceleration areas of the equivalent OMIB system can be identified, thereby realizing TS prediction based on the EAC.

Suppose that the rotor angle and electromagnetic power data \( D_m^m = \{ (\delta_i, P_{eg}') \} i = 1, 2, \ldots, n, j = 1, 2, \ldots, m \) for \( n \) synchronous motors in the system at \( m \) different times after fault clearance are obtained by WAMS; then, \( D_m^m \) can be transformed into \( m \) groups of equivalent rotor angles and electromagnetic power \( D_g^m = \{ (\delta_j, P_{eg}') \} j = 1, 2, \ldots, m \) in the OMIB system through equation (3). \( D_g^m \) can be substituted into equation (10), which can then be rewritten in vector form

\[
y = Ap
\]

\[
A = \begin{bmatrix} 1 & \cos(\delta_j) & \sin(\delta_j) \\ 1 & \cos(\delta_j) & \sin(\delta_j) \\ \vdots & \vdots & \vdots \\ 1 & \cos(\delta_j) & \sin(\delta_j) \end{bmatrix}
\]

\[
y = \begin{bmatrix} P_{eg}^1 \\ P_{eg}^2 \\ \vdots \\ P_{eg}^n \end{bmatrix}^T
\]

\[
p = (A^T A)^{-1} A^T y
\]

where \( \delta_j \) and \( P_{eg}^j \) are the equivalent rotor angle and electromagnetic power, respectively, collected at the \( j \)th moment.

If the number of collection points \( m \geq 3 \), the parameter vector \( p \) can be obtained by equation (13).

Therefore, as shown in Figure 3, the equivalent electromagnetic power \( P_{eg'}(\delta_g) \) can be accurately fit during the entire failure period and estimated after fault clearance by collecting at least 3 sets of electromagnetic power and rotor angle data.

According to Figure 3, after fitting \( P_{eg'}(\delta_g) \) during a fault and after fault clearance, the acceleration area \( S_{acc} \) and deceleration area \( S_{dec} \) can be determined by (14).

\[
S_{acc} = \int_{\delta_{lim}}^{\delta_{cc}} [P_{mg} - P_{eg,acc}(\delta_g)]
\]

\[
S_{dec} = \int_{\delta_{cc}}^{\delta_{lim}} [P_{eg,dec}(\delta_g) - P_{mg}]
\]

where \( P_{eg,acc}(\delta_g) \) and \( P_{eg,dec}(\delta_g) \) are equivalent electromagnetic power functions during and after the fault, respectively; \( \delta_g \) and \( \delta_{cc} \) are the equivalent rotor angles at steady state and after fault clearance; and \( \delta_{lim} \) is the equivalent rotor angle corresponding to the intersection of the \( P_{eg,dec}(\delta_g) \) curve and
the mechanical power after fault clearance. Notably, \( \delta_{\text{lim}} \) can be obtained by solving (15).

\[
P_{mg} = P_{eg, dec}(\delta_{\text{lim}})
\]

(14)

Based on \( S_{\text{acc}} \) and \( S_{\text{dec}} \) in (14), the system transient stability margin \( \eta \) can be defined as

\[
\eta = \frac{S_{\text{dec}} - S_{\text{acc}}}{S_{\text{acc}}} \times 100\%
\]

(15)

Thus, if \( \eta > 0 \), the equivalent deceleration area in the system is greater than the acceleration area, and the system status will be identified as transient stability. In contrast, if \( \eta < 0 \), transient instability is considered to occur.

**IV. ELM BASED METHOD FOR TS PREDICTION IN A WIND POWER-INTEGRATED SYSTEM**

ELM is a machine learning algorithm based on a single hidden layer feedforward neural network (SLF-NN), which is widely used in the field of power system transient stability prediction due to its excellent prediction accuracy and generalization ability, especially its advantages related to the training speed [19], [20].

In this paper, a binary classifier based on ELM is trained with the key features and prior TS knowledge of the sample set. Based on the trained ELM classifier, the system TS can be quickly predicted by collecting the key features of the system within a short time before and after a failure.

The structure of a SLF-NN with \( L \) hidden layer nodes and \( n \)-dimensional inputs is shown in Figure 4. In the TS prediction of system with wind power, the system status information, which includes power flow, rotor angle, synchronous generator speed, and wind power output information, can be collected and recorded in real time through WAMS and normalized into \( n \) system features \( x_1, x_2, \ldots, x_n \).

For a power system TS sample set with \( N \) samples \( S_N = \{(X_i, t_i) | X_i \in \mathbb{R}^n, t_i \in \{\pm 1\}\} \), \( X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in \mathbb{R}^n \) is the \( i \)th feature vector and \( t_i \) is the classification label, where \( t_i = 1 \) denotes transient stability and \( t_i = -1 \) denotes transient instability. Then, the training process of the sample set can be expressed as the following mathematical optimization model

\[
\min E = \sum_{j=1}^{N} \| o_j - t_j \|
\]

s.t \( \sum_{i=1}^{L} \beta_i \theta(W_i \cdot X_j + b_i) = o_j, \quad j = 1, 2, \ldots, N \) (16)

where \( \theta(x) \) is the activation function, \( W_i = [w_{i1}, w_{i2}, \ldots, w_{in}] \in \mathbb{R}^n \) is the input weight vector from the \( i \)th hidden node, \( b_i \) is the bias of the \( i \)th hidden node, and \( \beta_i \) is the output weight from the \( i \)th hidden node to the output node.

On the basis that the activation function \( \theta(x) \) satisfies infinite differentiability, after randomly initializing \( W_i \) and \( b_i \), \( \beta_i \) is the only undetermined parameter. The minimum norm least squares solution of \( \beta = \{\beta_i | i = 1, 2, 3, \ldots, L\} \) can be obtained quickly by calculating the Moore-Penrose generalized inverse in (17), thereby completing the training [20], [21].

\[
\hat{\beta} = H^{-1}O
\]

where (17) shown at the bottom of this page. In online prediction, the system features acquired by WAMS are input into the trained ELM-based classifier, and the ELM output \( O \) can be processed according to (18) to determine the system TS.

\[
\begin{cases}
\text{Stable} & O \geq 0 \\
\text{Unstable} & O < 0
\end{cases}
\]

(18)

It should be noted that the system features in this paper are screened in advance to identify key features as training inputs. A fast feature selection method based on Fisher discrimination is adopted to evaluate the importance of features individually and to screen key features based on the importance of each feature [25]. In online prediction applications, the same key features are selected from WAMS as the inputs of the classifier to predict the system TS.

After the TS is predicted, the further detection of ELM output \( o \) can be performed to determine the reliability of the predicted results [20].

Reference [26] indicated that prediction results with an ELM output \( o \) close to the classification threshold (0) are highly unreliable. Based on this principle, a quantitative analysis method for assessing the reliability or unreliability of ELM prediction results is proposed.

\[
H = \begin{bmatrix}
\theta(W_1 \cdot X_1 + b_1) & \theta(W_2 \cdot X_1 + b_2) & \cdots & \theta(W_L \cdot X_1 + b_L) \\
\theta(W_1 \cdot X_2 + b_1) & \theta(W_2 \cdot X_2 + b_2) & \cdots & \theta(W_L \cdot X_2 + b_L) \\
\vdots & \vdots & \ddots & \vdots \\
\theta(W_1 \cdot X_N + b_1) & \theta(W_2 \cdot X_N + b_2) & \cdots & \theta(W_L \cdot X_N + b_L)
\end{bmatrix}
\]

(19)

\[
O = \begin{bmatrix} O_1 & O_2 & \cdots & O_N \end{bmatrix}^T
\]
Assuming that the misclassified probability density curve \( p_{\text{error}}(o) \) (taking the output value of ELM as the absolute value) is known, as shown in Figure 5, the probability \( P_{\text{error}}(C_E) \) of a misclassified output in region \([C_E, +\infty)\) can be expressed as

\[
P_{\text{error}}(C_E) = P(C_E < o) = \int_{C_E}^{+\infty} p_{\text{error}}(o) \, do
\]

\[
= 1 - \int_{0}^{C_E} p_{\text{error}}(o) \, do
\]  

where \( o \) is the absolute value of misclassified output.

For a certain prediction result with ELM output \( C_E_0 \), the maximum misclassification probability \( E_0 \) is the probability \( P_{\text{error}}(C_E_0) \) calculated by (19). Thus, the unreliability \( E \) of a prediction result with ELM output \( C_E \) can be defined as

\[
E = P_{\text{error}}(C_E).
\]

However, the actual \( p_{\text{error}}(o) \) cannot be obtained in practice, but it can be approximately estimated by conducting multiple tests on the training set. By counting the number of error outputs \( N(o, \Delta o) \) for each smaller cell \([o-\Delta o/2, o+\Delta o/2]\), \( p_{\text{error}}(o) \) can be estimated as

\[
p_{\text{error}}(o) = \lim_{\Delta o \to 0} \frac{N(o, \Delta o)}{\Delta o}
\]  

(20)

Based on (19) and (20) and by replacing the integral with accumulation, the unreliability \( E = P_{\text{error}}(C_E) \) can be defined as

\[
E = P_{\text{error}}(C_E) = 1 - \sum_{o_j \in [0, C_E]} \frac{N(o_j)}{\sum_{o_j \in [0, +\infty]} N(o_j)}
\]  

(21)

In this paper, \( P_{\text{error}}(C_E) \) is obtained by performing multiple rounds of “10-fold cross validation” on the training set. Then, according to the preset maximum unreliability threshold \( E_{\text{max}} \), the corresponding unreliability output threshold \( C_{E,\text{max}} \) can be calculated to further divide the unreliable region \([0, C_{E,\text{max}}]\) and reliable region \([C_{E,\text{max}}, +\infty]\). Therefore, the prediction accuracy can be improved by utilizing another method to correct unreliable results with ELM outputs in the range of \([0, C_{E,\text{max}}]\).

V. INTEGRATED METHOD FOR THE TS PREDICTION OF A POWER SYSTEM WITH WIND POWER

The P-\( \delta \) fitting method is based on the acquisition of rotor angle and power information for synchronous generation to determine TS. The ELM-based method considering the knowledge learned from the sample set infers the TS state directly from WAMS data. The data requirements for the two methods are shown in Table 1.

According to Table 1, the ELM-based method is based on global information and relies on historical data and thus has large requirements for data acquisition and storage. The P-\( \delta \) fitting method only needs generator terminal information (power angle and electromagnetic power), which can make up for the difficulty of the ELM method in obtaining predictions with insufficient historical data.

The implementation process of the integrated transient stability prediction method is shown in Figure 6; this process is mainly divided into two parts: offline training and online implementation.
In offline training, feature extraction and ELM training should be carried out based on the sample set. At the same time, the unreliable regions of ELM output should be determined in advance through (19) with multiple rounds of “10-fold cross validation.”

In online implementation, if the disturbance is monitored, the ELM-based method and P-δ fitting method are started simultaneously. At this time, if the output value of ELM is not in the unreliable region, the result is deemed credible and regarded as the final prediction result; otherwise, the result is considered suspect, and the result of the P-δ fitting method will be adopted as the final prediction result.

VI. CASE STUDY

To verify the effectiveness of the proposed method, in this paper, a DFIG-based wind farm with a total capacity of 2000 MW was connected to the New England 39-bus system with a total load of 6150.5 MW, and the maximum wind power permeability reached 32.52%.

The system structure with wind power is shown in Figure 7, and the parallel points and capacity of the wind farms are shown in Table 2.

In this paper, the PMU sampling period is set to 20 ms, and 40 mes-200 ms data are collected by the P-δ fitting method after failure. The ELM-based method records the steady state values of system features before failure and the variations in features in 4 cycles after failure clearance. A total of 248 system features are selected as candidate features, which are shown in Table 3.

According to the above method, 10000 sets of samples are generated through simulation. A total of 1000 samples were selected randomly as test samples, and several samples from the remaining samples were selected as training sample sets. To illustrate the practicability in the case of insufficient samples, 2000 groups of samples are selected as the sample set by default in the following cases.

A. ANALYSIS OF THE RESULTS OF THE MODEL-DRIVEN METHOD

The prediction results of the P-δ fitting method for 1000 samples in the test sample set are shown in Table 4.

It can be seen from the table that the P-δ fitting method has a high prediction accuracy, which reaches 97.4%. The misclassification occurred mainly because 26 steady samples were judged as unsteady, so the prediction effect was conservative.

Figure 8 and Figure 9 show the original δ-t trajectory (in the COI coordinate system) and equivalent P-δ trajectory of the same misclassified samples.

From the original δ-t trajectory in Figure 8, the most advanced rotor angle reaches 2.8 rad, the most lagged rotor angle is only -0.21 rad, and the maximum rotor angle difference is larger than 3 rad in this transient process, which is close to the stable boundary.

Comparing the actual and fitting P-δ trajectory of this sample in Figure 9, the actual P-δ trajectory is close to the unstable equilibrium point when it backswings, and the stability margin calculated by the P-δ fitting method is negative but only -6.7%, which is close to the instability boundary. The
fitting error and neglecting the time variability of $P_c \Sigma$ and $P_{\text{max}} \Sigma$ in (9) may be the main reasons for this misprediction.

B. ANALYSIS OF THE RESULTS OF THE DATA-DRIVEN METHOD

The fast Fisher discriminant method was used to evaluate the correlation between alternative features and the system TS for the training set, and the importance index of each alternative feature is shown in Figure 10.

According to Figure 10, the voltage variation has the highest importance index overall, and some generator, rotor and fan output variations also display a certain correlation with the system TS. Moreover, the correlation between the transient variation data and TS is generally higher than that between the steady state data and TS.

Based on the importance index in Figure 10, the top 50% of features are selected as the key features of the system, and groups of 1000, 2000, 5000 and 9000 samples are selected as the training sets, respectively, to train the ELM. The average prediction accuracy of the ELM-based method in ten runs of testing with different training set sizes and numbers of hidden layer nodes is shown in Figure 11.

From Figure 11, the prediction accuracy increases with the training set size, and the number of hidden layer nodes needed to achieve the highest accuracy also increases. This result is mainly because a large training set contains more TS knowledge, and the requirements for optimal ELM performance will be high to achieve the highest accuracy; that is, more hidden layer nodes are needed to reflect this knowledge.

At the same time, the prediction accuracy generally tends to increase first and then decline with increasing number of hidden layer nodes under different training set capacities because ELM will overfit the samples if there is an excessive number of hidden nodes; additionally, the fewer the number of training samples used, the sooner ELM will overfit the samples.

In this paper, 2000 sets of samples were adopted, and 210 hidden nodes with a maximum accuracy of 89.4% were taken as the basis for subsequent analysis.

C. ANALYSIS OF THE RESULTS OF THE INTEGRATED METHOD

The sampling error and delay in WAMS will result in inaccurate data. To analyze the prediction performance of the ELM approach under these conditions, Gaussian noise with a mean value of 0 and standard variances of 1%, 2%, and 5% is added to the system characteristic data to simulate the error and delay, respectively. The prediction performance of this method is shown in Table 5.
As shown in Table 5, although the prediction accuracy of the ELM prediction method decreases with increasing data error, the prediction accuracy only decreases by 1.2% with a 5% standard deviation. The test results show that the ELM method has strong robustness in addressing the data error associated with the WAMS system. To further illustrate the impact of data error on the ELM approach, Figure 12 shows the ELM output of a sample tested 1000 times under the error interference of different standard deviations.

As shown in Figure 12, when the WAMS system error is ignored, the predicted output of the ELM classifier is concentrated near stability label 1. With the addition of noise, the distribution interval of the ELM output value will gradually expand. When the data error is so large that the ELM output exceeds the classification threshold of 0, prediction error will be generated; this is also the main reason for the decrease in the prediction accuracy.

Although the fluctuation range of ELM output values is increased by the WAMS error, the distribution is still centered at stability label 1, which suggests that the ELM approach can roughly predict the stability of the sample set, even if it cannot accurately identify the samples. Therefore, the ELM approach displays robustness to data disturbances and can maintain the original accuracy level when considering the WAMS error.

D. ANALYSIS OF THE RESULTS OF THE INTEGRATED METHOD

Five rounds of "10-fold cross validation" tests were conducted on the ELM-based method based on the training set, and the classification results and output values were recorded, as shown in Figure 13. To facilitate identification, the misclassified samples are arranged before the correctly classified samples.

Figure 13 shows that the misclassified output values (absolute values) are concentrated near the classification threshold of 0 and the correctly classified output values are distributed around classification label-1. According to the output distribution, the unreliability level of \([C_{E,max}, +\infty]\) is calculated by (19), as shown in Figure 13. To compare the effects of different sample sizes on the output distribution, the unreliability level curves obtained based on 9000 sets of samples are also shown in the figure.

As Figure 14 shows, the unreliability level decreases rapidly with increasing \(C_{E,max}\) in the range of \([0,1]\), and the unreliability level of 9000 samples decreases faster than that for 2000 samples, mainly because as the training set capacity increases, the mapping relationship associated with the training set becomes increasingly accurate and the output distribution of misclassification becomes increasingly concentrated at 0. Table 6 shows some output thresholds corresponding to the unreliability level of the sample set.

For the 2000 sample set, when the unreliability threshold \(C_{E,max} = 0.825\), the unreliability level \(E\) reaches 5%, which means that the probability of misclassified samples appearing in the range of \([0.825, +\infty]\) is less than 5%. For 9000 samples, the unreliability threshold is only 0.65.

According to Table 6, the unreliability levels of 5% and 10% are set, and the model-driven and data-driven integrated
TABLE 6. Unreliability level and unreliability threshold.

| Unreliability Level | Unreliability Threshold $C_{\text{E} \text{M}}$ |
|---------------------|-------------------------------------------|
| $E_{\text{max}}$    | 2000 Samples 0.55, 9000 Samples 0.65     |
| 10%                 |                                           |
| 5%                  |                                           |

TABLE 7. Prediction results of the integrated model-driven and data-driven method.

| Method               | Actual Result | Prediction Result | Accuracy |
|----------------------|---------------|-------------------|----------|
| Integrated           | Stability     | 827               | 99.2%    |
| Method-10%           | Instability   | 1                 | 165      |
| Integrated           | Stability     | 831               | 4        |
| Method-5%            | Instability   | 0                 | 166      |
| ELM Method           | Stability     | 776               | 60       |
|                     | Instability   | 46                | 120      |

TABLE 8. Prediction performance of different prediction methods.

| Method               | Average Prediction Time | Average Prediction Accuracy | Accuracy |
|----------------------|-------------------------|----------------------------|----------|
| P-δ fitting method   | 0.2231 s                | 97.4%                      |          |
| ELM-based method     | 0.0825 s                | 89.4%                      |          |
| Integrated Method-10%| 0.1034 s                | 99.2%                      |          |
| Integrated Method-5% | 0.1155 s                | 99.6%                      |          |

method is tested based on different unreliability levels. The test results are shown in Table 7.

From Table 7, the integrated prediction method has a high prediction accuracy, reaching more than 99% at different unreliability levels. Compared with the ELM-based method, the integrated method corrected 98 and 103 cases of misclassified samples at the 10% and 5% levels, respectively. According to Table 7, the average prediction time of the integrating method slightly slower than the ELM-based method, and the prediction time will increase with the decrease of suspicion level, because more samples need to be modified by P-δ fitting method.

However, although the integrated method improves the prediction accuracy, it will cause the loss of prediction speed. Table 7 shows the average prediction time and mean accuracy of different prediction methods for 1000 tests.

According to Table 8, the average prediction time of the integrated method is slightly slower than the ELM-based method, and the prediction time will increase with decreasing unreliability level because more samples need to be modified by the P-δ fitting method. However, the prediction can still be completed within 0.12 s at the 5% unreliability level, which is 0.1 s faster than the P-δ fitting method; additionally, the prediction accuracy is improved by 10.2% compared with the ELM-based method.

VII. CONCLUSION

The growth of wind power permeability has increased the difficulty of online TS prediction. To implement online TS prediction for power system with wind farms, an integrated model-driven and data-driven method is proposed in this paper. The simulation results show that the integrated method further improves the accuracy of online prediction by quantifying the unreliability level of the ELM-based method output and correcting the unreliable results with the P-δ fitting method; thus, the proposed method achieves a high prediction accuracy for small training sample sets. As the ELM-based method is adopted for preprocessing in most scenarios, the time loss incurred by P-δ fitting to improve accuracy is greatly reduced. Although the integration of the two methods has improved the prediction accuracy and maintained the prediction speed of the traditional methods, the approach to address the situation in which the prediction results of both methods are unreliable deserving further study in future work.

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