IET Generation, Transmission & Distribution

Research Article

Hybrid method for power system transient stability prediction based on two-stage computing resources

ISSN 1751-8687
Received on 29th July 2017
Accepted on 8th October 2017
E-First on 5th March 2018
doi: 10.1049/iet-gtd.2017.1168
www.ietdl.org

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Abstract: Accurate and prompt transient stability prediction is one of the effective ways to reduce the risk of blackout or cascading failures. In an effort to achieve improvements in time efficiency and prediction accuracy, a new transient stability prediction method combining trajectory fitting (TF) and extreme learning machine (ELM) based on two-stage process, named hybrid method, is proposed here. ELM-based method is implemented in central station to ensure the time efficiency, while TF-based method is adopted in local station to guarantee the accuracy. Furthermore, data corruption is taken into consideration to assure the robustness of the proposed algorithm. The hybrid method is validated with the New England 39-bus test system and the simulation results indicate its effectiveness and reliability.

1 Introduction

In modern power systems, the occurrence of disturbances is more likely to enlarge and contribute to severe stability problems due to expanding of grid structure and increasing diversity of generation types such as wind and solar power. This challenge involved with operation requires more efficient methodologies for stability prediction [1]. Meanwhile, with the construction of smart grid, the advanced measurement, communication, and computation techniques are available for implementation of online stability prediction [2].

Transient stability described by rotor angle stability with large disturbance is focused in this paper [3]. Methodologies for transient stability prediction include two categories: model-based and model-free methods. Time simulation and transient energy function (TEF) methods are representatives of model-based methods, which are reviewed as follows:

i. Time domain simulation is accurate but time-consuming when applied in a large-scale power system [4–6].
ii. TEF methods avoid cumbersome integrating steps and predict transient stability status directly based on Lyapunov stability principle [7–9]. The key to TEF methods lies in constructing reasonable energy function and calculating critical energy level for certain scenario. However, it is usually hard to calculate the controlling unstable equilibrium point in a practical power system. The time-consuming feature of time simulation and event-driven feature of TEF methods limit their online performance. For breaking these restrictions, data mining model-based methodologies, which leave out power system physical model, have been proposed as the model-free methods. Curve fitting measures and machine learning techniques are representative for these methodologies [10–25], which are reviewed below.
iii. Curve fitting-based methods extract the stability characteristics of a power system from off-line simulated prior data or post-disturbance phasor measurement unit (PMU) data (usually 0.2–0.4 s) and predict with real-time measurement. The fitting model consisting of reasonable fitting functions is kernel of this method. While in [11], fitting model is substituted with pre-processed trajectory pattern database for improvements in accuracy.
iv. Machine learning techniques are concerned in power system due to advantages in obtaining non-linear mapping relationship between the input and output data [13, 14]. Their applications in power system transient security assessment and control have demonstrated promising performance, e.g. artificial neural network [15–17], decision tree [18–20], support vector machine (SVM) [21, 22], core vector machine [23], and extreme learning machine (ELM) [24, 25]. The two main predict objects of these methods are transient stability degree (e.g. critical clearing time) with regression function and transient stability state with classification function. Prediction reliability and practical implementation efficiency are concerned in most studies. In [21], power system stability state is predicted with credibility by SVM-based classifiers and a hierarchical scheme with multiple response time is set up for higher accuracy. In [17], feature reduction is taken to reduce the training time cost and the classification accuracy is not affected. In [24], ELM-based classifier for transient stability analysis can be updated with online instance, which enables it to follow the changes of power system operation in practical use. For machine learning techniques-based methods, physical behaviour of actual power system is ignored, which makes these methods unreliable in certain cases.

Increased installation of wide-area measurements in power system promotes implementation of these data mining-based methods. Curve fitting-based methods need to compute post-disturbance PMU measurement, which consumes a certain time and therefore reduces available time for stability control. In contrast, machine learning-based methods can figure out predict outcomes more rapidly. Nevertheless, without support from high-quality samples, machine learning-based methods will encounter difficulty in extracting effective prior knowledge and their prediction accuracy will be affected.

Therefore, the main objective of this paper is to propose a hybrid online transient stability prediction method with high efficiency and accuracy. With integrating of both local and central computing resources, curving fitting and machine learning-based methods are combined to maximise the benefits of model-free methods. Furthermore, with high requirements of data measurement and transmission in close to real-time stability prediction, potential risk of data missing is also considered.

The remaining of this paper is organised as follows. In Section 2, implementation of curve fitting and machine learning-based prediction method is introduced in detail. The newly proposed two-stage method is presented in Section 3. The implementing structure and process of transient stability prediction is explained in this section. Case studies and conclusion are presented in Sections 4 and 5, respectively.

2 Problem description and algorithm preliminaries

For power system transient stability prediction, the accuracy and the efficiency are usually in conflict. As studied in a recent work [26], the increase in accuracy is usually at the cost of sacrificing the efficiency. Therefore, how to achieve a balanced accuracy–efficiency performance is a core problem.

This paper proposes a hybrid method combining curve fitting and machine learning-based methods to improve both accuracy and efficiency simultaneously. Besides, the proposed method also considers data missing issues, and therefore can improve the prediction robustness. The trajectory fitting (TF) method introduced in [11] is adopted due to its significant advantage in accuracy. In this study, ELM-based method is chosen for its superiority in training speed and sample dependency characteristic among various machine learning techniques [24, 27, 28].

2.1 Mathematical model of multi-machine power system transient stability

Conventionally, power flow algebraic equations for transmission network and differential equations of generators are concerned for transient stability analysis of a multi-machine power system. For the ith generator, rotator dynamics equation can be represented as below:

$$\frac{\mathrm{d}\delta_i}{\mathrm{d}t} = \omega_i \tag{1}$$

$$\frac{\mathrm{d}\omega_i}{\mathrm{d}t} = \frac{1}{M_i} \cdot (P_{mi} - P_{ei} - D_i\omega_i) \tag{2}$$

where δ_i is the rotor angle, ω_i the rotor rotating speed, M_i the generator's moment of inertia, $P_{\mathrm{m}i}$ the mechanical power, and D_i the system damping constant. $P_{\mathrm{e}i}$ is the electromagnetic power and can be determined with the equation below:

$$P_{\mathrm{e}i} = \sum_{k \in N_i} B_{ik} U_i U_k \sin(\delta_{ik}) \tag{3}$$

where N_i is the set of neighbouring buses of the ith generator, B_{ik} the transfer susceptance of buses i and j in the reduced admittance matrix of the system, U_i and U_k are the voltage of buses i and k, and δ_{ik} is the rotor angle difference between buses i and k.

From rotor dynamic equations and electromagnetic power calculating equation, it can be inferred that the rotor angle variation is related to the rotor rotating speed, which is affected by the moment of inertia, mechanical power, electromagnetic power, and the damping constant. In most cases, mechanical power is regarded as a constant considering the limited time-scale. Hence, electromagnetic power is an important parameter affecting the rotor dynamics. Moreover, the electromagnetic power varies with transfer susceptance, the generator voltage level, and rotor difference.

Apparently, the voltage variation, the rotor angle variation, rotor rotating speed variation, and voltage variation are basic features for transient stability assessment. The fault duration is also included to take the influence of transfer susceptance into consideration. Further, power flow is also concerned as a feature to consider the influence of operation condition.

2.2 TF-based prediction method

TF-based prediction method assumes that parameter dynamics in power system transient process always manifests similarities under similar operation conditions. This method consists of generating trajectory pattern database in offline and matching characteristic trajectories with PMU measurement in online. This paper refers to the perturbed trajectory standard pattern database generating method and extends the implementation scenarios in [11]. For a certain generator, trajectories in knowledge base are categorised with hierarchical clustering algorithm and it can be represented by the following optimisation model

$$\begin{aligned} J = {} & \min\{M\} \\ s.t. \quad & f_{ij}(x) \le e \end{aligned} \tag{4}$$

where M is the number of pattern in the trajectory pattern database, $f_{ij}(x)$ the Euclidean distance between the jth trajectory and the characteristic trajectory in the ith standard pattern represented by (2), and e the error threshold value calculated through Euclidean distance

$$f_{ij}(x) = \sqrt{\sum_{t=1}^{T_s} (X_{ijt} - M_{it})^2} \tag{5}$$

where T_s is the length of total simulation time, X_{ijt} the value at time t of the jth trajectory in the ith standard pattern, and M_{it} the value at time t of the characteristic trajectory in the ith standard pattern.

For a certain trajectory pattern database, each characteristic trajectory is labelled with operation information, including fault type, fault location, fault duration, load level, and initial angle. With this additional information, the substitution scheme can be carried out when measurement failure is encountered.

When TF-based prediction method is implemented, the similarity between PMU measurement and characteristic trajectories in trajectory pattern database is calculated, and the most similar characteristic trajectory in database is selected as the predict outcome. The similarity can be calculated from the equation below

$$D_i = \sqrt{\sum_{t=1}^{T_m} (x_t - M_{it})^2} \tag{6}$$

where D_i is the value of similarity calculation, T_m the measurement sample length, x_t the measurement value at time t, and M_{it} the value at time t of the characteristic trajectory in the ith standard pattern.

2.3 ELM-based prediction method

ELM is an emerging fast single-hidden layer feedforward neural network (SLF-NN) algorithm [27, 28]. Compared with other SLF-NN algorithms, the strength of ELM is determining parameters of hidden nodes with random value instead of time-consuming iterative computations when the activation functions in the hidden layer are infinitely differentiable. The output weight value can be figured out directly after parameters and neuron number of hidden layer are set. In such a way, its training speed can be thousands times faster than conventional gradient-based learning algorithms.

Fig. 1 shows the structure of an SLF-NN. For power system transient stability prediction, $x_1, x_2, \ldots, x_n$ is selected power system features in transient process and o is the prediction outcome of transient stability status.

Hence, for a power system, transient stability knowledge base with N samples, $S_N = \{(X_i, t_i) | X_i \in R^n, t_i \in R^m\}$, where $X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^{\mathrm{T}} \in R^n$ and $t_i = [\text{stable, unstable}]^{\mathrm{T}}$. The stable and unstable symbols are known and quantified as 0 and 1, respectively, when training.

The training process for this knowledge can be described as a mathematical model. That is, determine β_i, W_i, and b_i, such that:

$$\begin{cases} \sum_{i=1}^{L} \beta_i \vartheta(W_i \cdot X_j + b_i) = o_j, \quad j = 1, 2, \ldots, N \\ \sum_{j=1}^{N} \| o_j - t_j \| = 0 \end{cases} \tag{7}$$

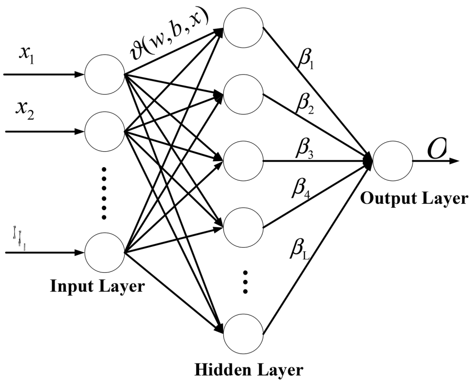

Fig. 1 *Structure of an SLF-NN*

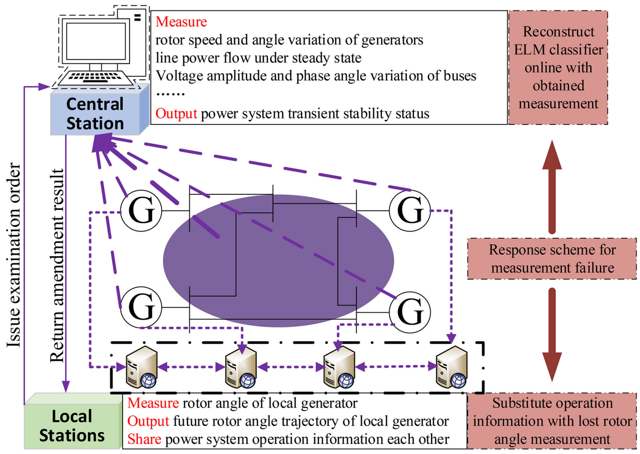

Fig. 2 *Implementing structure of hybrid prediction method*

where $\vartheta(x)$ is the activation function, β_i the output weight value, $W_i = [\omega_{i1},\omega_{i2},\dots,\omega_{in}]$ the input weight value, b_i the bias of hidden node i, and $W_i{\cdot}X_j$ represents the inner product of W_i and X_j.

Hence, the training process is to determine β_i, W_i, and b_i. For ELM training algorithm, the parameter W_i and b_i is fixed before training with random values. β_i is the only undetermined parameter. If the number of hidden neurons is equal to the number of training samples, β_i can be calculated easily [27]. While the number of hidden neurons is less than the number of training samples generally, precise β_i, W_i, and b_i, may not be exist. The mathematical model can be transformed to minimising the cost function shown below, where $\widetilde{\beta}_i, \widetilde{W}_i, \widetilde{b}_i$ (optimal approximate solution) is to be determined

$$E = \sum_{j=1}^{N}\left(\sum_{i=1}^{L}\widetilde{\beta}_i\vartheta(\widetilde{W}_i\cdot X_j + \widetilde{b}_i) - t_j\right)^2 \tag{8}$$

For fixed $\widetilde{W}_i, \widetilde{b}_i, \widetilde{\beta}_i$ can also be figured out easily as the approximate solution [27].

In this paper, the activation function is set as RBF kernel considering its strength in extracting non-linear features. In training process, the W_i and b_i are fixed and β_i is the only parameter to be determined, which becomes a linear calculation problem [27].

The implementing framework of ELM-based prediction method is offline training and online application. Before training, feature selection of knowledge base is necessary for identifying significant features as training inputs. The candidate features in this paper include rotor speed variation of generators, voltage amplitude and phase angle variation, injection power variation, line power flow under steady state, rotor angle variation of generators, and fault duration. In [24], a fast feature selection method based on Fisher discrimination is put forward to evaluate the discrimination capability of a single feature and shows great performance in computing speed. This paper takes this feature selection method for reference. However, other feature selection methods [29] can also be used for the proposed method.

In this paper, ELM is trained with the selected features and prior knowledge about power system transient stability. ELM-based classifier is constructed with training and it is the kernel of online stability prediction method based on ELM. ELM-based classifier takes the global information as input and outputs future power system transient stability status in a very short time delay. The ELM-based classifier enables reconstruction online through fast feature reselection and retraining when it comes to measurement or communication failure.

Table 1 Information source of TF-based and ELM-based prediction method

Method type	Data scale	Resource
TF-based prediction method	single	local
ELM-based prediction method	vast	global

3 Hybrid transient stability prediction method

TF-based prediction method determines transient stability status through rotor angle trajectory tendency of each generator. ELM-based prediction method infers transient stability status directly from PMU measurement. In Table 1, information source of both methods are summarised.

It can be inferred that ELM-based method is suitable for central computing considering its large-scale data processing. While TF-based method can be implemented in local with area computing resources.

Furthermore, reducing misclassification risk of ELM-based prediction method can be realised by examining problematic output [24]. TF-based prediction method is the appropriate tool to examine and modify predict outcomes of ELM-based prediction method on account of its superior performance in prediction accuracy [11].

3.1 Hybrid model for transient stability prediction

Given the complementary advantages of TF and ELM methods, this paper proposes a hybrid model which consists of a two-stage transient stability prediction process, and the structure of the proposed model is shown in Fig. 2. It aims to predict post-disturbance transient stability status in a very short time delay. The essence of the two-stage prediction process is the coordination between ELM-based and TF-based prediction method, and central computing resource and local computing resources.

In the central stage, the central stations are responsible for collecting global measurement and provide inputs for ELM-based prediction method. At the local stage, TF-based prediction method implements with local rotor angle measurement.

Fig. 2 shows the implementation frame of two-stage coordination-based transient stability prediction method. The proposed prediction method is capable of improving the accuracy of ELM-based method in central station with results verification process implemented by local stations. Moreover, in order to guarantee the online implementation effect, measurement failure scenario, which leads to inadequacy inputs for prediction method, is also discussed below.

3.1.1 Normal scenario: In normal scenario, central station capture global measurements for ELM-based method inputs and local stations takes local rotor angle measurement as TF-based methods inputs. These methods calculate and figure out future transient stability status concurrently. For each predict calculation, the output of ELM-based method is compared with a fixed threshold value which is determined by (6) and then suspect region is set up

$$C_E = \min\{A_{\rm Mis}, A_{\rm Cor}\} + |A_{\rm Cor} - A_{\rm Mis}|\cdot\delta \tag{9}$$

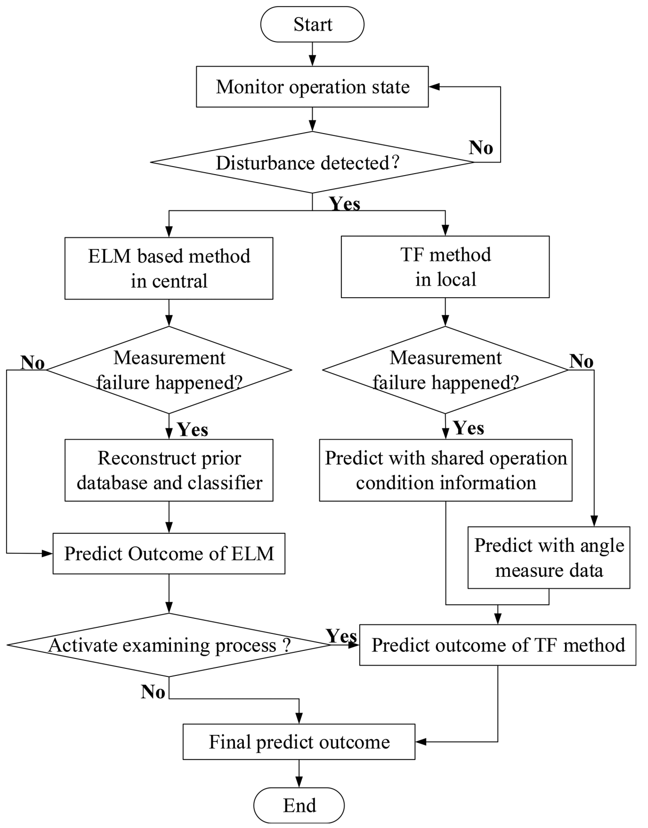

Fig. 3 *Implementation process of hybrid transient stability prediction method*

where C_E is the threshold value, A_{Mis} and A_{Cor} are the average value of ELM-based method outputs in misclassification and correct classification cases after constantly tests, and δ the discrimination weight value. For a determined C_E, if A_{Mis} is not larger than A_{Cor}, the suspect region can be $[0, C_E]$; otherwise, it can be $[C_E, +\infty]$.

If the output value of ELM-based method belongs to the suspect region, the examining process is activated which means predict outcome of central station is proofread with local prediction outcomes. The summarised local predict outcomes are used to judge power system transient stability status for final predict result decision.

3.1.2 Measurement failure scenario: Considering the condition that online transient stability prediction requires high standards of real-time PMU measure, it is rare but possible that central or local stations fail to obtain PMU measurement data timely. In local stage, advanced communication techniques enable local stations to exchange information to support each other in this scenario. While ELM-based method in central station can reconstruct a classifier with obtained PMU measurement data to fit this measurement failure scenario.

Response strategies of local and central stage for measurement failure scenario are summarised below.

i. If any local station fails to obtain rotor angle measurement, the operation information inferred from nearby (in electrical distance) generator's prediction result is shared and the shared operation information is used as search label to carry out TF-based method where measurement failure happens. The operation information includes fault type, fault location, fault duration, load level, and initial angle data.

   In operation information-based search scheme, characteristic trajectories in trajectory pattern database whose fault type and location match the actual operation information are chosen to constitute primary set. The predict trajectory is picked up from the primary set which shares the most similar operation condition with actual operation information in aspects of fault duration, load level, and initial angle data.

ii. If central station fails to obtain global measurement, the transient stability prediction result is judged by predict outcomes from local stage. Meanwhile, a new ELM-based classifier suitable for practical scenario is constructed with available PMU measurement data.

Table 2 Initial information requirements

Notation	Description
δ_i	rotor angle variation of generator i
ω_i	rotor speed variation of generator i
V_i, θ_i	voltage amplitude and phase angle variation of bus i
P_{Ii}, Q_{Ii}	active and reactive power injection variation of bus i
P_{Li}, Q_{Li}	active and reactive power flow of line i
t	fault duration

The classifier reconstruction process contains three steps. (i) The knowledge base is modified with collected measurements. (ii) Feature selection process is implemented to determine features for training inputs. (iii) The initial training process is activated to reconstruct ELM-based classifier. The reconstructed ELM-based classifier is applied for prediction until measurement failure is recovered.

3.2 Implementation process of hybrid method

The implementation process of hybrid rotor angle stability prediction method is shown in Fig. 3 and detail steps are as follows:

Step 1: Start predict program after disturbance is detected.
Step 2: Judge whether the global measurement is enough for ELM-based prediction method inputs. If measurement is not enough, actions are taken to refresh knowledge base, reselect features, and retrain ELM-based classifier.
Step 3: Judge whether examination and amendment is necessary according to ELM output value. If examination and amendment process is taken, go to step 4, else go to step 6.
Step 4: TF-based prediction method is implemented at the same time with step 2. If rotor angle measurement is absent, the shared operation information is used as substitution input, else rotor angle measurement is the input.
Step 5: The prediction result of TF-based method is recognised as final predict result, if the outcome of TF-based and ELM-based prediction method is conflict.
Step 6: The prediction result of ELM-based prediction method is recognised as final prediction result.
Step 7: Prediction program ends and go to next round.

4 Case study

The proposed hybrid transient stability prediction method is tested in New England 39-bus test system. For TF-based method, it assumes that PMU measurement continues for 200 ms on 20 ms cycle and 10 sets of data are acquired for prediction. As mentioned in Section 2.1, initial features for ELM-based method are listed in Table 2, which consists of 269 sets.

Notation: These features are numbered from 1 to 269 with sequence of δ_i, ω_i, V_i, θ_i, P_{Ii}, Q_{Ii}, P_{Li}, Q_{Li}, and t.

It assumes that power system is not stable in transient process if rotor angle difference between one generator and reference generator beyond 180°, and vice versa. Fig. 4 illustrates the stable state and unstable state of power system transient process.

4.1 Sample generation method

Samples are created by Monte Carlo sampling method based on Matlab PSTv3.0 software. Critical operation parameters are

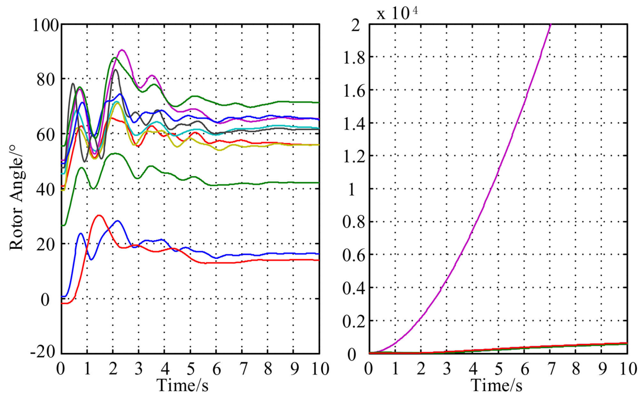

Fig. 4 *Rotor angle trajectories under stable and unstable condition for power system transient process*

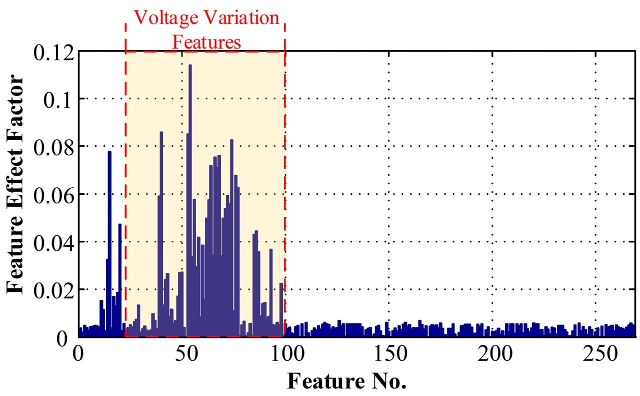

Fig. 5 *Comparison in effect factor value of each feature*

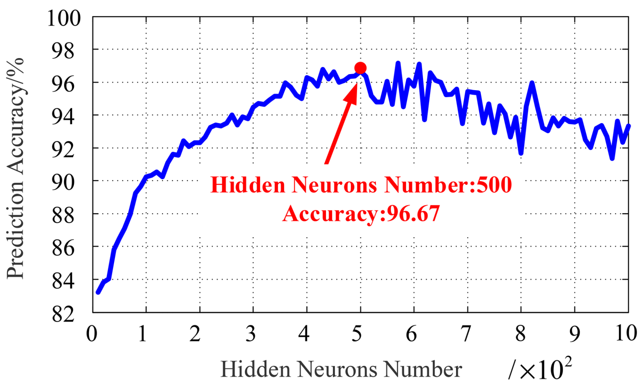

Fig. 6 *Variation trend of prediction accuracy with hidden neurons number*

assumed to follow a certain probability distribution. The load level of each bus ranges from 80 to 110% of base load. The injection power of bus is subject to normal distribution whose expectation is the base injection power and the standard deviation is $\pm 3\%$ of the base injection power. Five types of fault are applied including three-phase short-circuit fault, single-phase ground fault, double-phase ground fault, phase fault, and load loss. Fault happens on lines spread over the whole system following hypodispersion. Fault duration is assumed to follow normal distribution, of which the expectation is 0.1 and standard deviation is 0.01.

The simulation is carried out by a computer with Inter® Core i5-5200U and 4G cache. It consumes ~8 s per simulation. In order to provide enough training samples for ELM and lessen calculative burden, 10,000 sets of samples are created which costs ~23 h in total. Ninety per cent of them are used to construct rotor angle trajectory pattern database and train ELM-based classifier. The rest are applied for testing.

Table 3 Performance with different error threshold value

Error threshold value	Pattern numbers in database	Computing time, s	Misclassification [*A*, *B*]
120	79	0.0474	[48, 0]
50	140	0.0402	[1, 0]
5	2968	0.3502	[0, 0]

4.2 Verification for TF-based prediction method

For TF-based prediction method, the undetermined parameter is error threshold value which has a connection with prediction accuracy. The performances in prediction accuracy with different error threshold value configuration are summarised and shown in Table 3.

Notation: *A* represents the number of stable samples being misjudged as unstable, *B* represents the number of unstable samples being misjudged as stable. The total number of unstable samples for testing is 168.

Few misclassification happens when error threshold value is set as 50 and 5. Further, performances in measurement failure scenario are carried out based on both values and they are compared to configure actual error threshold value.

When error threshold value is set as 5, the performance of TF-based method in measurement failure scenario is still reliable and no more misclassification case appears. While in condition of error threshold value 50, misclassification cases increase sharply to 26, which misjudges unstable cases as stable cases. In order to guarantee the prediction reliability in measurement failure scenario, the error threshold value is determined to be 5 for further implementation.

Moreover, the computing time in measurement failure scenario increases to 0.7562 s. It can be explained that only if one local station output predict trajectory with operation information, the station with measurement failure can starts to compute.

4.3 Verification for ELM-based prediction method

4.3.1 Feature selection: With modified Fisher discriminant method, the relevance between each feature and transient process condition is evaluated quantitatively, shown in Fig. 5.

It is obvious in Fig. 5 that features with high effect factor value concentrate on voltage variation features and rotor angle variation features come next. The rest features show similar effect factor in numerical magnitude, which indicates that their contribution for correctly classification is limited.

According to effect factor, 100 significant features are selected as inputs for classifier. The rest features are reserved for substitution in measurement failure scenario, named backup features.

4.3.2 Hidden neuron nodes determination: Hidden neurons number is an important undetermined network parameter for ELM-based classifier. Ten-fold cross-validation is used to test the performance of ELM-based prediction method. Variation trend of prediction accuracy with the number of hidden neurons is presented in Fig. 6.

Fig. 6 shows that the prediction accuracy climbs up at first and then decline, i.e. there exists an optimal number of hidden neurons making best performance in prediction accuracy.

Hence, the optimal hidden neurons number is set as 500 in this case for classifier construction and the prediction accuracy can reach 96.67%. The training time and computing time are 1.2813 and 0.0391 s separately.

4.3.3 Performance in measurement failure scenario: The inputs of ELM-based classifier can be divided into six parts, including rotor angle variation, rotor speed variation, voltage amplitude and phase angle variation, injection power variation, power flow variation, and fault duration. The effect of each feature sets on classification accuracy in measurement failure scenario is tested and summarised in Table 4.

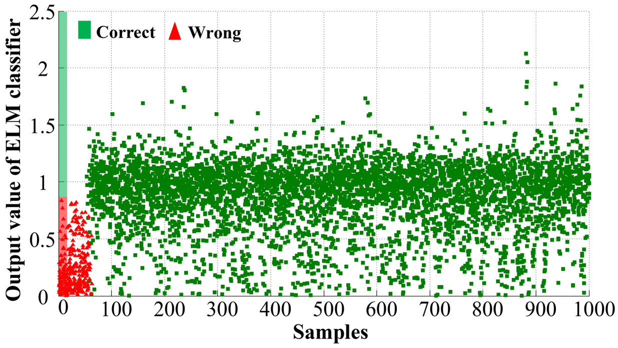

Fig. 7 *ELM output value of all investigated instances*

Table 4 Effect of feature sets on prediction accuracy

Ignored feature sets	Classification accuracy, %
none	96.67
rotor angle variation	93.43
rotor speed variation	93.54
voltage amplitude and phase angle variation	85.89
injection power variation	94.82
power flow variation	94.52
fault duration	93.68

Table 5 Comparison of different prediction methods in performance

Method type		Expected computing time, s	Prediction accuracy, %
SVM		0.195	92.5
trajectory fitting		0.843	100
ELM		0.0413	94.1
hybrid method	[0–0.8]	0.342	100
	[0–0.5]	0.184	99.1

Notation: [0–0.8] and [0–0.5] represent suspect region of ELM output value. The expected computing time are calculated by multiple simulation.

Table 6 Predict result analysis

Actual result	Suspect region [0–0.8]		suspect region [0–0.5]	
	Prediction result		Prediction result	
	Stable	Unstable	Stable	Unstable
stable	832	0	831	1
unstable	0	168	8	160

Table 7 Performance of hybrid prediction method with measurement failure

Suspect region	Expected computing time, s	Prediction accuracy, %
[0–0.8]	0.374	99.6
[0–0.5]	0.210	98.9

Notation: [0–0.8] and [0–0.5] represent suspect region of ELM output value. The expected computing time are calculated by multiple simulation.

Table 8 Predict result analysis

Actual result	Suspect region [0–0.8]		Suspect region [0–0.5]	
	Prediction result		Prediction result	
	Steady	Unsteady	Steady	Unsteady
steady	831	1	830	2
unsteady	3	165	9	159

It can be inferred from Table 4 that the loss of voltage amplitude and phase angle variation causes the largest accuracy rate drop, which is correspond to the effect factor value distribution in Fig. 5. The rotor angle and speed variation show relatively important effect on classification accuracy. Hence, it can include that measurement failure happening in feature sets of voltage amplitude and phase angle variation will make serious negative effect.

4.3.4 Accuracy analysis: Misclassification instances of ELM-based prediction method are investigated for hybrid method implementation. All instances in multiple tests are shown in Fig. 7 in which the ELM output values are presented.

In misclassified instances, ELM output value is bent on region from 0 to 0.8 and most of them are in region from 0 to 0.5, which provides a screening measure to determine instance with doubtful prediction outcome.

4.4 Verification for hybrid prediction method

About 1000 sets of samples are tested on TF-based, ELM-based, and hybrid method, respectively. Moreover, prediction method based on SVM with quadratic kernel is implemented for comparison. Results are recorded in Table 5.

From Table 5, ELM-based method shows better performance in computing time cost and prediction accuracy compared with SVM-based method. The hybrid prediction method combines the advantages of TF-based and ELM-based prediction method and its prediction achieves 100% with suspect region [0–0.8]. The expected computing time is reduced compared with TF-based prediction method and the prediction accuracy increases observably compared with ELM-based prediction method due to the effect of examination and amendment process. When the suspect region is set to [0–0.8], the examination process is activated 355 times. While the suspect region is set as [0–0.5], the activation times reduce to 169.

The detail predict result of hybrid method is summarised in Table 6. It shows that misclassification samples increase to 9 when the suspect region is set to [0–0.5], which is worse than the condition when the suspect region is [0–0.8].

In measurement failure condition, the local measurement is lost and only one generator's rotor angle data can be captured in power system. For central station, 50% of selected significant features are assumed to be lost and substituted with candidate features. The performance of the hybrid prediction method is recorded in Tables 7 and 8.

It can be inferred from Table 6 that the performance of two-stage prediction method becomes a little worse both in computing time and prediction accuracy due to the effect of measurement failure.

According to detailed analysis in Table 8, when the suspect region comes to [0–0.8], the predict outcomes of ELM-based method are examined by TF-based method for 393 times and 53 of them is corrected. It shows that there are four misclassifications in test samples.

Meanwhile, when the suspect region comes to [0–0.5], the examination and amendment process carried by TF-based method reaches 200 times and 52 times, respectively. The misclassification samples increase to 11 which is worse than the condition when the suspect region is [0–0.8].

4.5 Online implementation process analysis

In this section, it aims to illustrate online implementation process of the proposed two-stage prediction method. Take three unstable cases for example, case 1 is predicted through ELM-based method with output value 1.0251. Cases 2 and 3 are amended with TF-based method after processed by ELM-based method. The difference of cases 2 and 3 is that predict result of ELM-based method is modified by TF-based method in case 3.

From Fig. 8, it indicates that the proposed two-stage prediction method enables to foresee the unstable condition of transient process. Generally, the most serious measurement failure scenario

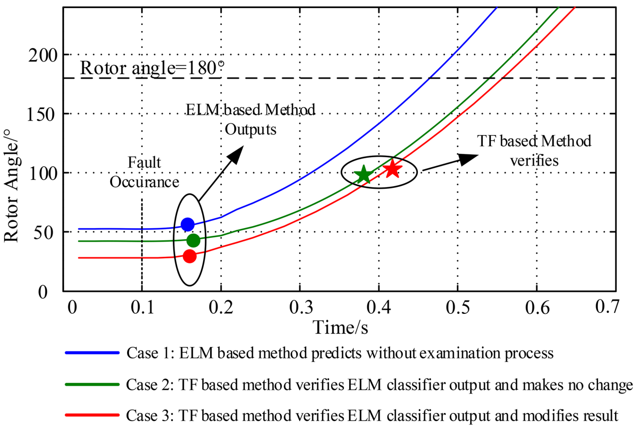

Fig. 8 *Online implementation process in three typical cases*

is that measurement failure happens in local station, it will cost ∼0.4–0.6 s for computing considering middle-scale pattern database. The time consuming can also be reduced by other high performance computing techniques in practical use.

5 Conclusion

In this paper, a hybrid transient stability prediction model consisting of a two-stage process is developed. It achieves coordination between TF-based and ELM-based prediction method in predict outcome determination and computing resources configuration. In implementation, TF-based and ELM-based prediction methods are allocated with local and central computing resources, respectively. When the output value of ELM is in a suspect region, the final predict outcome is judged by examination and amendment process. The measurement failure is also considered and response schemes are made for it. The hybrid method is examined on New England test system. The performance of the hybrid prediction method is compared with TF-only based and ELM-only based prediction method. Obtained results confirm the manifest improvement of two-stage prediction method in time efficiency, prediction accuracy, and implementing reliability.

6 Acknowledgments

This work was supported by National Natural Science Foundation of China (Grant no. 51577030) and Projects of International Cooperation and Exchanges NSFC (Grant no. 51561145011).

7 References

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