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Post-Disturbance Transient Stability Assessment of Power Systems by a Self-Adaptive Intelligent System

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Abstract—Intelligent system (IS) using synchronous phasor measurements for transient stability assessment (TSA) has received continuous interests recently. For post-disturbance TSA, one pivotal concern is the response time. It is reported that the response time of existing models is a fixed value ranging from 4 cycles to 3s after fault clearance. Because transient instability can develop very fast, there is a pressing need to further reduce the response time. This paper first reviews the state-of-the-art of this area and then develops a novel IS to balance the response speed and accuracy requirements. A set of classifiers are sequentially organized, each classifier is an ensemble of extreme learning machines (ELMs), whose inputs are post-disturbance generator voltage trajectories and outputs are the classification on the stable/unstable status of the post-disturbance system and an evaluation of the credibility of the classification. A self-adaptive TSA decision-making mechanism is proposed to progressively adjust the response time, such that the IS can do the classification faster, thereby allowing more time for emergency control actions. The ELM ensemble classifiers can also be on-line updated by on-line pre-disturbance TSA results with its very fast learning speed. Case studies using the New England system and IEEE 50-machine system are given to validate the efficiency and accuracy of the IS.

I. INTRODUCTION

Transient stability is referred to as the ability of a power system to maintain synchronism when subjected to a large disturbance [1]. Mathematically, the transient stability corresponds to a high-dimensional non-linear differential-algebraic equation (DAE) set. The problem of transient stability assessment (TSA) can be divided into two categories according to different timings: *pre-disturbance* TSA evaluates the stability condition of the power system with respect to a set of anticipated but not yet occurred disturbances, and the assessment results are associated with *preventive control* actions such as generation rescheduling which aim to preventively modify the system operating condition to withstand those harmful disturbances should they really occur. The pre-disturbance TSA can be performed *on-line* or *off-line* depending on practical needs. By contrast, *post-disturbance* TSA predicts the system stability status under an ongoing disturbance, and the assessment results are used to trigger *emergency control* actions such as fast valving, generator tripping, load shedding and controlled islanding, etc., which aim to impede the propagation of the instability. As such, the post-disturbance TSA must be performed in *real-time* to allow timely emergency controls.

The traditional TSA method is time-domain (T-D) simulation. A major limitation of this method is the need for full and accurate information of system model, operating condition as well as the disturbance, and heavy computational burden. For pre-disturbance TSA, parallel computing can be applied to accelerate the TSA speed for on-line use [28]. Direct methods such as transient energy function (TEF) approach [29] and single machine equivalent (SIME) [30] can also be used for on-line pre-disturbance TSA. While

for post-disturbance power systems, since the instability can occur very fast (say, within few cycles), the TSA must be performed faster than real-time. Based on the increase availability of synchronous measurements provided by phasor measurement units (PMUs), real-time post-disturbance TSA becomes feasible. In the literature, the piecewise constant-current load equivalent (PCCLE) method has been developed to speed-up the T-D of the post-disturbance system dynamics [31]. Another possible approach is the E-SIME [30], which uses real-time measurements of multi-machine angles to derive a one-machine-infinite-bus (OMIB) equivalent. Based on the OMIB, the transient stability status can be predicted and the emergency control can be determined accordingly. Furthermore, the *Lyapunov* exponent-based method can also be used by exploiting the coupling relationship between rotor angle stability and maximal *Lyapunov* exponent [32]. Although effective, these methods may still suffer from insufficiently fast decision-making speed for post-disturbance TSA.

In recent years, the intelligent system (IS) strategy has also been identified as an alternative yet promising approach for much faster TSA of power systems [2],[3]. By learning from a transient stability database, the IS can capture the mapping relationship between the system's synchronous measurements (input) and the corresponding stability condition (output). For on-line application, once the required input is available, the output can be determined instantaneously. Compared with traditional analytical methods, the advantages of the IS-based approach are much faster TSA speed, less data requirement, stronger generalization capacity, and the ability to discover useful knowledge for relevant decision-support such as dynamic secure/insecure regions for preventive control [33],[34]. The IS strategy can be used for either pre-disturbance or post-disturbance TSA. For the former case, the model inputs are usually system's steady-state operating variables (such as generation outputs, loads, voltage magnitudes, etc.); for the latter case, the models inputs are usually system's post-disturbance dynamic variables (such as machine angle, angular speed, etc.). A comprehensive review and comparison of IS-based TSA models can be found in [3] and [4], as reviewed therein, previous research emphasis has mainly been put on the generating training and testing data sets, selecting appropriate inputs, developing the learning algorithms and improving the accuracy [5]-[16].

For IS-based pre-disturbance TSA, despite best efforts, due to the usually imperfect model fitting and/or insufficient prior information in the training data, the IS can still suffer from classification/prediction errors leading to inaccurate TSA results [5]-[7]. To mitigate this problem, a reliable IS for pre-disturbance TSA has been proposed by the authors previously [8]. The IS is able to identify the potentially inaccurate (incredible) TSA results that should not be adopted by the operators, and for such incredible decisions, the T-D simulation can be performed to verify the case. In such a way, a reliable real-time TSA mechanism can be achieved. A most recent reference [35] proposes a new index called transient stability estimation index (TSEI) to monitor system stability for different networks without any training requirement, which is promising for on-line pre-disturbance TSA.

This paper focuses on IS-based *post-disturbance TSA* [9]-[16], for which, in addition to the accuracy, a pivotal concern is the response time. The response time is the length of the time window that the IS should wait (to observe the system dynamic behavior) before making a classification on the system's stability status. To be effective, the response time should be as short as possible to allow timely emergency control actions. On the other hand, it is usually the case that the longer the response time, the more system dynamic information the classifier can obtain and hence the more accurate the TSA result tends to be. Consequently, there is a trade-off between reducing the response time and maintaining a satisfactory TSA accuracy. In the literature, the response time of existing models is between 4 cycles to 3s [9]-[16]. It is clear that the shorter response time the IS requires, the longer time can be left to counteract the propagation of the instability. In this aspect, there is a pressing need to further reduce the response time. Besides, it is also observed in the literature that the response time is always a fixed value which means that all the disturbances are classified after a pre-selected constant time window [9]-[16]. In fact, for different disturbances with different severity degrees, the instability

may arise at different times; therefore it is inefficient to make the decision at one constant time. In this regard, a most recent reference [36] has reported a novel model that has a range of strategically determined response times (time windows) to allow early classification of system vulnerability status (considering three short-term stability phenomena). Moreover, since the pre-disturbance TSA is also performed on-line, it is sensible to make use of such pre-disturbance TSA results to update/enrich the IS, which is however not well achieved in the literature due to the insufficiently fast learning/tuning speed of the learning algorithms [9]-[16].

The contribution of this paper consists of addressing the above discussed problems by developing a novel IS for more efficient post-disturbance TSA. Compared with existing models, the novelty of the IS lies in its self-adaptive decision-making mechanism, which means it can progressively adjust the response time to make the right TSA decision at an appropriately earlier time. Besides, the IS has a very fast learning speed to allow on-line updating with pre-disturbance TSA results for performance enhancement. The remaining of this paper is organized as follows. Section II describes the key problems in developing an IS for post-disturbance TSA with a concise yet comprehensive review and discussion of the literature. Section III introduces briefly the learning algorithm used in this paper. Section IV develops the TSA classifier for the IS and the learning and decision-making rules. Section V proposes the self-adaptive decision-making mechanism. Section VI numerically tests on the New England 39-bus and IEEE 50-machine systems to verify the developed IS. Section VII concludes the whole paper and envisions some future works.

II. PROBLEM DESCRIPTION AND LITERATURE REVIEW

A. Principle

Conventional emergency controls against transient instability are based on special protection systems (SPSs). To implement a SPS, pre-disturbance TSA is performed with respect to a set of pre-defined contingencies. For unstable contingencies, corresponding remedial control actions are pre-determined and stored in a decision table. During the on-line operating stage, once a pre-defined unstable contingency is detected, the pre-determined controls will be indexed and triggered immediately. Such protections are *event-based*, although they are relatively fast, their implementation can be extremely complex, cumbersome and expensive [17]. Besides, due to the even-based nature, they can only cover a limited number of pre-defined contingencies.

In recent years, with the gradual deployment of wide-area measurement system (WAMS) in modern power systems, wide-area protection and control (WAPaC) has gained increased attention [17]. Such protection schemes are *response-based*, being much simpler and more accurate over the traditional event-based SPSs. To implement a response-based protection scheme, post-disturbance TSA needs to be performed to predict whether the system is going to loss synchronism following an ongoing disturbance. As illustrated in Fig.1, after the fault clearance, the system dynamic behavior is observed for a certain time window and the prediction on the stability status for future time window is made. Once the system is predicted to lose stability in the near future, emergency controls such as generator tripping, load shedding and controlled islanding, etc. will be triggered immediately to prevent the system against losing stability.

Fig.1 Concept of post-disturbance TSA (the trajectories are obtained by simulating a short-circuit fault on the IEEE 50-machine system)

For a fast and accurate post-disturbance TSA, in addition to the abovementioned analytical methods (i.e., PCCLE, E-SIME, Lyapunov exponent, etc.), an IS can be built to extract the mapping knowledge between the post-disturbance variables and the stability status, then the TSA is converted to a very fast functional mapping procedure: $y = f(\mathbf{X})$, where $\mathbf{X}$ is the input vector corresponding to the time-series of power system dynamic variables (called features), y is the stability status and f is the extracted mapping knowledge.

An illustration of such an IS is given in Fig.2, which has n sets of input vector, each set consists of T_m variables and each variable is the value of that input at a given time point. For instance, $\mathbf{X}_n(T_m)$ is the value of the n -th input at time T_m , y is usually a binary index, e.g., 1 and -1, denoting stable and unstable status of the system. For practical application, once the input is available, the output can be determined instantaneously. Compared with the abovementioned analytical methods, the advantages of such an IS are much faster decision-making speed, less data requirement, and higher adaptability for different network topologies and fault scenarios, making it an ideal approach to allow WAPaC.

Fig.2 Illustration of an IS for post-disturbance TSA

B. Response Time

It is clear that a high decision-making speed is essentially needed for post-disturbance TSA. The TSA speed is measured by the response time, which is the elapsed time (after the fault clearance) before the IS can make a TSA classification, i.e., the time length

of the observation window in Fig.1 and T_m in Fig. 2. The response time is an essential concern since it determines the available time for the emergency controls to act.

Table I reviews the response time reported in the literature.

TABLE I REPORTED RESPONSE TIME IN PREVIOUS LITERATURE

Reference	Response time
[10]	2 to 3s
[11]	1 or 2s
[12]	150 and 300ms
[9]	8 cycles
[13],[15]	6 cycles
[14]	5 cycles
[16]	4 cycles

It can be seen that the reported response time varies from 4 cycles to 3s. It is usually the case that the longer the response time, the more system dynamic information the classifier can obtain and hence the more accurate the TSA result tends to be. However, since the transient instability can occur very faster (the first-swing instability can occur as short as in 2 cycles), if the response time is too long, the emergence controls cannot be timely activated and thus fail to prevent the system against the instability. Consequently, there is pressing need to further reduce the response time. Besides, it is also noted that the response time is always a fixed value in previous works. However, it is clear that given different disturbances, the time when instability occurs can vary significantly due to different severity degrees of the disturbances. Therefore, it can be inefficient to fix the response time for all disturbances.

A most recent reference [36] has reported a novel model that has a set of strategically established response times (time windows) depending on the Monte Carlo statistics of the relay tripping times and wide-area time delay. The reported time windows are 0.12s to 3.5s on a small test system and 0.3s to 9s on a mid-sized test system [36]. In this paper, a novel IS will be developed to be self-adaptive in response time, which means the right TSA decision can be made at an appropriately early time.

C. Feature Selection/Extraction

The input vector $\mathbf{X}$ (called features) is the synchronous time-varying variables of the power system during the post-disturbance period, sampled by PMUs. In previous works, rotor angle and angular speed have been predominantly employed [9]-[14]. However, these mechanical variables cannot be directly measured by the PMUs [18]. They need to be calculated after the phasor measurement signals are transferred to the control center, hence incur certain time-delay and potential conversion errors.

Rather than directly use the PMU measured variables, feature extraction and selection techniques can be used to extract and/or select an important set of features as the model inputs. A comprehensive study and comparison of feature selection methods for pre-disturbance TSA is reported in [37]. While for post-disturbance dynamic variables, short-term Fourier transformation (STFT) [10]-[12] and empirical orthogonal functions (EOFs) [36] have been applied to extract composite features. The selected/extracted features can result in a lower input dimension which, on one hand, can significantly increase the training efficiency during the off-line training state and, on the other hand, requires less PMU installations for real-time application. Moreover, it can contribute to improve the accuracy and allows the recognition of hidden patterns for system's stability characteristics [37].

Moreover, it is worth mentioning that when using the generator dynamic variables as the model inputs, it is assumed that the PMUs are available at all generators' terminal buses. This is an ideal yet reasonable assumption because the price of PMUs are

becoming cheaper and cheaper. To be more practical, ref. [38] considers rational PMU locations based on maximum observability of slow and fast system dynamics. Using a probabilistic-based method [39], the best PMU monitoring locations are selected and coherent areas are defined, then, a support vector machine (SVM) model is trained to predict the area-based center of inertia (COI)-referred rotor angles using the selected PMU measurements. The COI-referred rotor angles are then used to determine the stability status.

While the feature extraction requires certain processing time and is relatively more complex, the authors in [15] proposed to directly use the post-disturbance generator voltage trajectories sampled by the PMUs as the input. As they pointed out, due to the machine inertia, the generator rotor speeds and angles require longer periods of time to show a considerable deviation from their pre-disturbance steady-state values. By contrast, the generator voltage magnitudes can response much faster than that of the rotor values to a fault. Simulation results in [15] have verified the effectiveness of the voltage trajectories in accurately predicting transient stability. More recently, the stronger predicting capability of generator voltage trajectories over the mechanical variables (rotor angle and angular speed) are further demonstrated through extensive tests in [16]. Following this, this paper selects the generator voltage trajectories as the input. **However, it should be indicated that the composite features such as WASIs and EOF scores can also be used for the proposed IS in this paper.**

D. Learning Algorithms

In terms of extracting the mapping relationship, artificial neural network (ANN), decision tree (DT), SVM classifiers/regressors, and fuzzy logic are among the most popular learning algorithms. Table II reviews the usage of these algorithms in the literature.

TABLE II PREVAILING LEARNING ALGORITHMS IN THE LITERATURE

Reference	Learning algorithm
[5],[10],[13],[14]	ANN
[9],[11],[12],[35]	DT
[6],[15],[16],[36],[38]	SVM
[10],[11],[15]	Fuzzy logic

It is widely known that, some of the algorithms often suffer from excessive training/tuning time, for example, it is explicitly indicated in [16] that the tuning of a SVM classifier could cost more than 14 hours. This is because such traditional learning algorithms are based on time-consuming solutions of an optimization model or iteratively adjusting network parameters. This could impair their practical applicability. On the other hand, due to the imperfect fitting and/or insufficient prior information in the training data, most of them can suffer from classification errors leading to inaccurate TSA results, which should not be used directly, especially in post-disturbance environment. In this paper, an increasingly recognized learning technology called extreme learning machine (ELM) is applied for extracting the mapping knowledge. Based on its unique learning mechanism, an ensemble-based classifier is designed for improved classification accuracy and estimating the credibility of the classification results. Besides, with its very fast learning speed, the IS can be on-line updated using pre-disturbance TSA results that can be continuously obtained on-line.

III. EXTREME LEARNING MACHINE

ELM [19] is a generalized single-hidden layer feed-forward network (SLFN) as shown in Fig.3.

Fig.3 Structure of a SLFN

Given a training data set with N instances in total, $\mathcal{S}_N = \{(\mathbf{x}_j, \mathbf{t}_j) | \mathbf{x}_j \in R^n, \mathbf{t}_j \in R^m\}_{j=1}^N$, where $\mathbf{x}_j$ is the $n \times 1$ input vector and $\mathbf{t}_j$ is a $m \times 1$ target vector, the output function of the SLFN is

$$f_{\tilde{N}}(\mathbf{x}_j) = \sum_{i=1}^{\tilde{N}} \beta_i \cdot \mathcal{G}(\mathbf{w}_i \cdot \mathbf{x}_j + b_i) = \mathbf{t}_j, \quad j = 1, 2, \dots, N \quad (1)$$

where $\tilde{N}$ is the number of hidden nodes, $\mathcal{G}$ is the activation function, $\mathbf{w}_i$ is the weight vector connecting the i -th hidden node and the input nodes, β_i is the weight vector connecting the i -th hidden node and the output nodes, and b_i is the bias of the i -th hidden node, $\mathbf{w}_i \cdot \mathbf{x}_j$ denotes the inner product of $\mathbf{w}_i$ and $\mathbf{x}_j$.

Unlike traditional ANNs which are based on iterative learning algorithm, ELM learns a dataset via randomly selecting the input weights and biases for hidden nodes $\mathbf{w}$ and b , and analytically determining the output weights β via direct matrix calculations [19]: equation (1) can be rewritten into a compact format as

$$\mathbf{H}\beta = \mathbf{T} \quad (2)$$

where $\mathbf{H}$ is called the hidden layer output matrix of the network. And the ELM learning process can be briefly summarized as three major steps:

Step 1) Randomly generate the input weights $\mathbf{w}_i$ and b_i , for $i = 1, \dots, \tilde{N}$;

Step 2) Calculate the hidden layer output matrix $\mathbf{H}$; and

Step 3) Calculate output weights matrix $\beta = \mathbf{H}^\dagger \mathbf{T}$.

where $\mathbf{H}^\dagger$ is the *Moor-Penrose (MP) generalized inverse* of $\mathbf{H}$, and can be calculated by *singular value decomposition* for better generalization performance [19],[20].

ELM has been widely demonstrated on a number of benchmark datasets and engineering problems, showing much faster training speed and higher generalization capacity [19]-[21]. In our previous works, we have successfully applied ELM algorithm for pre-disturbance TSA problems, and obtained numerical results have verified much faster learning speed and competitive accuracy over ANN, SVM, and DT [7]. It is also worth mentioning that ELM and its variants have also been employed for other power engineering problems such as non-technical loss analysis [22], electricity price [23] and load forecasting [24], etc., showing satisfactory performance.

IV. EXTREME LEARNING MACHINE-BASED ENSEMBLE CLASSIFIER

In the statistical learning area, it has been widely demonstrated that *ensemble learning* is an effective strategy to increase the accuracy of a single learning algorithm [25]. For ensemble learning, a set of single learners are individually trained and then combined together to make a plurality decision [25]-[27]. In doing so, the single learners can compensate for each others, and the whole can reduce aggregated variance and tend to increase accuracy over the individuals [25]-[27].

Recently, a well-known ensemble classifier called random forest (RF), which is an ensemble of DTs, has been used for post-disturbance TSA, and very satisfactory accuracy is obtained [12]. With its stochastic nature, ELM can be another ideal candidate for ensemble learning. More recently, the authors have proposed an ELM-based ensemble learning scheme, which aims at not only improving accuracy but also estimating the credibility of the classification/prediction results [8]. Based on the proposed ELM ensemble learning scheme, potentially inaccurate assessment results can be identified which can then be treated by T-D simulation, and a reliable real-time power system stability assessment can be achieved.

Encouraged by the results obtained in our previous works [8], this paper develops a novel IS based on ELM ensemble classifiers for more efficiently post-disturbance transient stability prediction of power systems. The structure of the classifier is described in Fig.4. According to Fig.4, there are totally E ELMs in parallel, whose input are the time-series of generator post-disturbance voltage magnitudes.

Fig.4 Structure of the ELM ensemble classifier

A. Learning Rule

During the training stage, each ELM not only selects random input weights and bias (i.e., $\mathbf{w}$ and b) but also randomly selects a subset of the training data, a hidden node number and a candidate activation function (i.e., $\mathcal{G}$). In doing so, the randomness of ELM is generalized and diversity of the ensemble is greatly extended. The specific learning rule is as follows.

ELM Ensemble Learning

Given E single ELMs and a database of D instances,

For $i=1$ to E :

- 1) Randomly sample d instances out of the database, $1 \leq d \leq D$.
 - 2) Randomly assign this ELM h hidden nodes and a candidate activation function, h is within the optimal range $[h_{\min}, h_{\max}]$ which is subject to a pre-tuning step.
 - 3) Randomly select a candidate activation function $\mathcal{G}$, $\mathcal{G} \in [\mathcal{G}_1, \dots, \mathcal{G}_i, \dots, \mathcal{G}_n]$, where $\mathcal{G}_i$ is a pre-defined candidate activation function subject to a pre-tuning step.
-

4) Train this ELM and return.
End

B. Classification Rule

The classification process consists of single classifications performed by each ELM and ensemble classification based on a tailored ensemble decision-making rule.

For single classification, each individual ELM exports an output about whether the classification is credible or not, for a credible classification, it is then classified stable or unstable. The specific single classification rule is as follows. Note that the thresholds are determined based on empirical studies in our previous works [8].

Rule for ELM Single Classification

Suppose the classifier consists of E individual ELMs, two decision boundaries are defined for the “stable” (represented by +1) and “unstable” (represented by -1) classes as $[0.6, 2]$ and $[-0.6, -2]$, respectively. The classification rule and credibility estimation for each single ELM is

$$\begin{aligned} \text{If } & \begin{cases} 0.6 < y_i < 2 \rightarrow y_i = 1 \\ -2 < y_i < -0.6 \rightarrow y_i = -1 \end{cases} \quad (\text{credible sub-output}) \\ \text{If } & \begin{cases} -0.6 < y_i < 0.6 \\ 2 < y_i \text{ or } y_i < -2 \end{cases} \rightarrow y_i = 0 \quad (\text{incredible sub-output}) \end{aligned} \quad (3)$$

where y_i is the sub-output of the i -th ELM unit in the ensemble classifier,
 $i=1,2,\dots,E$.

Given all the single classification results, the ensemble classification determines the final classification result on the stability status and evaluates the credibility of the classification result. The credibility is measured by the “*consistence*” of the individual ELMs. If majority of the ELMs report a credible sub-output, the whole ensemble is considered credible for classifying an instance. The specific ensemble decision-making rule is as follows.

Rule for ELM Ensemble Classification

Given E single ELMs, which give totally m “0” sub-outputs, s “+1” sub-outputs and u “-1” sub-outputs, ($s+u+n=E$):

$$\text{If } m \geq r \rightarrow \text{this classification is incredible} \quad (4)$$

$$\text{Else if } \begin{cases} s > u \rightarrow Y = \text{"stabel"} \\ s \leq u \rightarrow Y = \text{"unstable"} \end{cases} \quad (5)$$

End

where r ($r \leq E$) is an user-defined threshold to evaluate the credibility of the final classification result Y .

With the ensemble learning rule, the ensemble classifier can increase accuracy to a higher level due to the boosting effect, and with the ensemble decision-making rule, the classifier is able to identify the incredible classification results that should not be adopted [8].

V. SELF-ADAPTIVE DECISION-MAKING MECHANISM

As already discussed in Section II.B, existing models in the literature all fix the response time, which can be less efficient against very fast rotor angle instability developments. In this paper, we develop a self-adaptive IS in order to better balance the trade-off between TSA speed and accuracy. The IS organizes a series of ELM-based ensemble classifiers that have different response times. The post-disturbance TSA decision can be right made at an appropriately early time. In the meantime, based on the very high learning efficiency of ELMs, the developed IS can also be on-line updated using pre-disturbance TSA results which can be obtained

from T-D simulation.

A. Structure

The structure of the IS is described in Fig.5. There are a series of individual ELM ensemble classifiers, each performing the TSA at a different response time (note that each classifier is trained using the corresponding input vector of a response time). After the fault clearance, along the evolution of the time-varying system post-fault voltage trajectories, the classification on stability status will be made consecutively by the classifiers at each time point: if the classification at time T is evaluated credible, the IS will deliver the TSA result at T ; otherwise, the classification will continue at time $T+1$, this procedure proceeds until a credible classification output is obtained or the maximum allowable decision-making time is reached (in practical implementation, it should be defined a max allowable decision-making time, e.g., $T_m=2s$, which means the IS must deliver a classification result when 2s is reached). Based on such TSA mechanism, the IS can save much of unnecessary waiting time, in turn leaving more reaction time for emergency controls.

Fig. 5 Structure of the developed self-adaptive IS for post-disturbance TSA

B. On-line Updating/Enriching

Due to the very fast training speed of the ELM, the TSA model can be on-line updated for performance enhancement. The updating can be done periodically, e.g., hourly or half-daily, depending on practical needs. The data for updating can be obtained from T-D simulation-based on-line pre-disturbance TSA results. On-line pre-disturbance TSA is performed in the control center and can cover a broad range of operating condition and fault scenarios, the simulation results (including trajectories and corresponding stability status) can be saved as new training data. Such new training data can be used as a new set or attached to the initial training database to retrain the post-disturbance TSA model – see Fig. 6.

Fig. 6 Schematic description of on-line updating/enriching of the post-disturbance TSA model

VI. NUMERICAL RESULTS

The developed IS is tested on two popular benchmark systems: New England 10-machine 39-bus system [16] and IEEE 50-machine system which comprises 145 buses and 453 branches [5]. The numerical test is conducted on a 64-bit PC with 3.1 GHz CPU and 4.0 GB RAM. The T-D simulation is performed using commercial software PSS/E [27], and the proposed algorithms are realized in the MATLAB platform.

A. Dataset Generation

For each test system, 2000 instances are generated. During the dataset generation, the system generation/load patterns are randomly varied within 80%~120% level of the initial operating condition. The corresponding operating points are obtained by running optimal power flow program. More details on the dataset generation procedure can be found in [7].

For each generated operating point, a fault location and fault clearing time are randomly selected. To consider the probable protection delays in practice, the fault clearing time is randomly generated within 0.1s~0.3s after the fault inception. T-D simulation is performed to simulate the dynamics of the system, where the simulation time is 5s and the simulation step is 0.01s. For each operating point, the simulated generator voltage trajectories and rotor angles are saved. The generator voltage trajectories will serve as the input to the IS and the rotor angles are used to calculate the transient stability index (TSI):

$$TSI = \frac{360 - |\Delta\delta_{\max}|}{360 + |\Delta\delta_{\max}|} \times 100 \quad (6)$$

where $\Delta\delta_{\max}$ is the maximum angle separation (degree) of any two generators during the transient period. For each operating point, if the TSI is positive, the system is stable and its class label is tagged as 1; otherwise, the system is unstable and its class label is tagged as -1. The generated instances for the two test systems are summarized in Table III.

TABLE III GENERATED INSTANCES

Test system	Stable instance	Unstable instances
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New England	1313	687
IEEE 50-machine	1350	650

For each test system, the generated instances are then randomly divided into two sets, one serves as training set while the other as testing set, where training set occupies 75% and testing set occupies 25% of all the instances.

A. Model Training

To train the IS, some parameters should be properly selected, including the total ELM number E , the candidate ELM activation function $\mathcal{G}_i$, the optimal range of hidden node number $[h_{\min}, h_{\max}]$, and the credibility evaluation parameter r .

According to [8], E and d can be empirically set to a certain large value and r should be set a value no smaller than 20% of E . In this test, E is set as 200, i.e., there are 200 individual ELMs in an ensemble, d is set as 90% of the total number of training instances, and r is set as 60. $\mathcal{G}_i$ and $[h_{\min}, h_{\max}]$ can be optimally determined by a pre-tuning procedure, where the training set is divided into two subsets, one for training and the other for validation, and the optimal hidden node range can be selected as the range which achieves highest validation accuracy. Note that there are 5 initial candidate activation functions for an ELM: “*sigmoidal*”, “*sine*”, “*hardlim*”, “*triangular basis*”, and “*radial basis*”. The tuning of $\mathcal{G}_i$ is to select the best ones from them.

In this test, it is assumed that the voltage phasor measurements are sampled at a rate of one sample per cycle (0.02s). So we train one ELM ensemble classifier for each post-disturbance cycle, and the maximum allowable response time is considered as 10 cycles (0.2s), hence an IS has a total of 10 ELM ensemble classifiers trained.

The training of the IS is very fast since the ELM learning process is very computationally efficient (see Section III). Table IV shows the model training time for 1500 training instances during the test. Note that since each single ELM and ELM ensemble may have different hidden node number and input number, the training time for them is varied.

TABLE IV TRAINING TIME

Model	New England system	IEEE 50-machine system
A single ELM	0.11~0.16s	0.18~0.24s
An ELM ensemble	24.7~30.8s	34.7~43.2s
The whole IS	256.8s	415.5s

According to Table IV, the developed IS has a very high training efficiency, which allows it to be on-line updated by the pre-disturbance TSA results for performance enhancement.

B. Test Results

The test dataset is used to examine the trained IS. Following the post-disturbance TSA process of the developed IS (see Fig.5), at each decision cycle, the pending (i.e., unclassified) test instances are classified by the ELM ensemble using the rules (3)-(5). For the credible classifications, the TSA results are exported, while for the incredible classifications, the test instances remain pending and move to the next decision cycle. Note that at the last decision cycle (in this test, it is 10 cycles), all the pending instances have to be classified, in this case, only the classification rules (3) and (5) are used.

The test results for the two systems are presented in Table V and VI, respectively, where: T_i is the i th decision cycle (each cycle corresponds to 0.02s after the fault clearance); $U(T)$ is total number of unclassified instances *until* the current decision cycle; $C(T_i)$ and $C(T)$ are total number of classified instances *at* and *until* the current decision cycle, respectively; $M(T_i)$ and $M(T)$ are total number of misclassified instances *at* and *until* the current decision cycle, respectively; $A(T_i)$ and $A(T)$ are current and accumulative TSA accuracy which correspond to the classification accuracy *at* and *until* the current decision cycle, respectively, calculated as:

$$A(T_i) = [C(T_i) - M(T_i)] / C(T_i) \quad (7)$$

$$A(T) = [C(T) - M(T)] / C(T) \quad (8)$$

TABLE V TEST RESULTS ON THE NEW ENGLAND 39-BUS SYSTEM

T_i	$U(T)$	$C(T_i)$	$C(T)$	$M(T_i)$	$M(T)$	$A(T_i)$	$A(T)$
0	500	-	-	-	-	-	-
1	45	455	455	3	3	99.3%	99.3%
2	37	8	463	1	4	87.5%	99.1%
3	27	10	473	0	4	100%	99.2%
4	23	4	477	0	4	100%	99.2%
5	18	5	482	0	4	100%	99.2%
6	12	6	488	1	5	83.3%	99.0%
7	10	2	490	0	5	100%	99.0%
8	10	0	490	0	5	N/A	99.0%
9	7	3	493	0	5	100%	99.0%
10	0	7	500	1	6	85.7%	98.8%

TABLE VI TEST RESULTS ON THE IEEE 50-MACHINE SYSTEM

T_i	$U(T)$	$C(T_i)$	$C(T)$	$M(T_i)$	$M(T)$	$A(T_i)$	$A(T)$
0	500	-	-	-	-	-	-
1	161	339	339	0	0	100%	100%
2	159	2	341	0	0	100%	100%
3	148	11	352	0	0	100%	100%
4	141	7	359	0	0	100%	100%
5	120	21	380	0	0	100%	100%
6	57	63	443	1	1	98.4%	99.8%
7	49	8	451	0	1	100%	99.8%
8	44	5	456	0	1	100%	99.8%
9	25	19	475	3	4	84.2%	99.2%
10	0	25	500	3	7	88.0%	98.6%

According to Table V and VI, it can be seen that the test instances can be classified at an earlier time with a high accuracy. Taking the New England system test for example, 455 out of 500 instances are classified at the 1st post-disturbance cycle, and the accuracy is as high as 99.3%, the remaining 45 unclassified instances move to the 2nd cycle, where 8 of them got classified with the accuracy of 87.5% (i.e., 1 instance is misclassified), then the remaining 37 pending instances move the 3rd cycle, where 10 of them got classified with the accuracy of 100%, this proceeds until the maximum allowable response time (10 cycles) reaches, when all of the instances have been classified. To better illustrate the self-adaptive TSA process of the developed IS, the accumulative classification rate, calculated as $C(T)/500$, where 500 is the total number of test instances, and accumulative TSA accuracy $A(T)$ are plotted in Fig. 7, where the bar chart shows the percentage of the instances that have been classified until the corresponding decision cycle and the line chart shows the corresponding TSA accuracy.

Fig.7 Plot of accumulative classification rate and accumulative TSA accuracy

For a general estimation of the response speed and accuracy of the developed IS, the average response time (ART) and average TSA accuracy (ATA) can be calculated as follows:

$$ART = \sum_{i=1}^m [T_i \times C(T_i)] / \sum_{i=1}^m C(T_i) \quad (9)$$

$$ATA = \sum_{i=1}^m [A(T)] / m \quad (10)$$

where m is the total number of the maximum allowable decision cycles, which is 10 in this test.

The results are given in Table VII, where it can be seen that the decision speed of the developed IS is generally much faster than that reported in the literature (see Table I) and the TSA accuracy is very high. Consequently, it can allow more time for taking the remedial control actions against transient instability.

TABLE VII AVERAGE RESPONSE TIME AND ACCURACY FOR THE TEST

Test system	ART	ATA
New England	1.4cycles (0.028s)	99.1%
IEEE 50-machine	2.8cycles (0.056s)	99.7%

C. Updating for Performance Enhancement

The benefit of model updating/enriching is demonstrated in this section. In general, the more training data the model has seen, the better generalization capacity can be expected, this has already been observed in the numerical tests conducted in [7]. Here, we randomly generate another 500 instances for the two test systems using the same procedure as in Section VI.A. The newly generated data sets are attached to the initial training datasets to retrain the IS. The updated/enriched IS is then tested on the same testing dataset as in Section VI. B. The test results are given in Table VIII.

TABLE VIII AVERAGE RESPONSE TIME AND ACCURACY FOR THE TEST AFTER MODEL UPDATING/ENRICHING

Test system	ART	ATA
New England	1.3cycles (0.026s)	99.4%

IEEE 50-machine	2.5cycles (0.05s)	99.9%
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Comparing Table VIII and VII, it can be seen that after the model updating/enriching, the performance has been improved in both terms of average response time and TSA accuracy.

VII. CONCLUSION AND FUTURE WORK

This paper develops a novel IS for balancing the response speed and accuracy in PMU-based power system post-disturbance TSA problems. The IS is based on the ELM algorithm and ensemble learning techniques with strategically designed learning and decision-making rules. Compared with existing models, it is self-adaptive in making the right TSA decision at an appropriate earlier time, hence allowing more time to take the remedial control actions. Simulation results on the New England 39-bus system and IEEE 50-machine system show that the developed IS makes the TSA decisions much faster while maintaining a high accuracy. In the meantime, the IS has a very high learning speed which allows it to be on-line updated for performance enhancement. The developed IS can be used for more efficiently predicting the transient stability status of the post-disturbance power systems and triggering emergency controls to protect the system against catastrophic blackout.

An interesting comparison can be made between the proposed self-adaptive IS and the model developed in [36] which also has a set of different response times (time windows). In [36], the reported time windows are 0.12s to 3.5s on the WSCC 9-bus system and 0.3s to 9s on the New England 39-bus system. While these time windows are established depending on the Monte Carlo statistics of the relay tripping times and wide-area time delay, the response time of the proposed IS in this paper is self-adaptive, depending on the credibility evaluation of the individual ELM ensemble classifiers. The different training and testing databases as well as different stability concerns in the two works do not allow a direct comparison on the accuracy performance. Nevertheless, the testing classification accuracies in the two works are both encouragingly high, e.g., on the New England 39-bus system, the complete accuracy is 99.77% in [36] and the average accuracy is 99.4% in this paper.

Future efforts will be devoted to following aspects. First, it is assumed that the PMU measurements are available at all the generators' terminal buses. For a more realistic situation, it will be interesting to consider limited PMU locations and/or missing measurements for the proposed model. In this regard, the methodology proposed in [38] and [39] can be applied to identify coherent areas and best PMU locations. Second, the thresholds of the ensemble ELM model are determined based on empirical simulation studies performed in our previous work [8]. In the future, it is worth employing some optimization algorithm to optimally tune such thresholds. Third, this paper uses the generator voltage trajectories as the model input, in the future, composite features such as WASIs [10]-[12] and EOFs [36] can be considered. Last but not least, this paper only considers the transient stability criterion, in the future, other short-term stability criteria such as voltage and frequency stability can also be incorporated into the self-adaptive decision-making framework. In this connection, the overall vulnerability [36] of the system can be assessed.

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