

# A Multiple Randomized Learning based Ensemble Model for Power System Dynamic Security Assessment

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**Abstract**—With the deployment of wide-area measurement systems (WAMS), intelligent learning techniques have recently shown their strengths in online power system dynamic security assessment (DSA). This paper proposes a multiple randomized learning based ensemble model for online DSA. Rather than using a single learning algorithm, the proposed model combines multiple randomized learning algorithms, including extreme learning machine (ELM) and random vector functional link networks (RVFL), to obtain more diversified machine learning outcome. Based on such diversified outputs, a credible decision-making process is designed to optimally discriminate credible and incredible DSA results, so a high DSA accuracy can be ensured with a high DSA efficiency. The proposed model is tested on New England 39-bus system, which demonstrates its improved DSA performance over a single learning algorithm.

**Index Terms**—Dynamic security assessment, ensemble learning, extreme learning machine, optimization, random vector functional link network.

## I. INTRODUCTION

With the increasing integration of renewable energy sources and the active demand-side response, more uncertainties are brought to power system operation, which significantly challenged the power system's dynamic security such as transient stability. In this case, more advanced DSA techniques are imperatively needed to accurately and timely evaluate the dynamic security status.

In recent years, WAMS have been widely deployed in modern power systems to support online DSA. Compared to conventional offline analysis paradigm, online DSA can make fast assessment decision based on the real-time power system operating status. In doing so, the uncertainties in power system operation can be timely captured and reflected in DSA results. The conventional DSA methods, such as time-domain (T-D) simulation and energy functions, are too slow to satisfy the online computation needs. Alternatively, intelligent learning techniques have been identified as effective and efficient tools for online DSA, benefiting from their faster computation speed, less data requirement, better generalization capability and improved robustness [1]–[3].

Conventional methods are based on a single learning model, which usually suffer from unsatisfactory accuracy. As an emergent learning technique, ensemble learning have been shown with a higher DSA performance [4]. In ensemble learning, a collection of learning units are aggregated to solve the same problem. Owing to the compensation between different learning units, the overall DSA accuracy is improved. In the literature, decision tree (DT) [5]–[7], artificial neural network (ANN) [8], extreme learning machine (ELM) [2], and random vector functional link (RVFL) [9] are employed as the learning algorithms in ensemble learning. Among them, randomized learning algorithms, including ELM and RVFL, have shown their advantages owing to their stochastic modelling and fast learning capability. The stochastic modelling can improve the learning diversity in ensemble learning, while the fast learning capability helps alleviate the increased ensemble training burden [10].

Due to the statistical learning nature, the DSA error may always exist which leads to miss or fault DSA result [8], [11]–[13]. As discussed in [4], if DSA errors are still unavoidable, it is more reasonable to detect potential errors and avoid using incredible DSA results. Therefore, reference [4] proposes an ELM ensemble learning model that defines credible boundaries to distinguish credible and incredible results. However, such boundaries involve several manually-tuned key parameters. In [10], those key parameters are further optimized under a multi-objective programming framework to pursue the optimal balance between DSA accuracy and efficiency. Nevertheless, the ensemble learning models proposed in [4] and [10] only use ELM as a single learning algorithm. Considering the unique advantages of different learning algorithms, a single learning algorithm may not fully map the relationships embedded in the training data. Therefore, it is sensible to combine multiple diverse learning algorithms to further improve the DSA performance including the accuracy and the credibility of the assessment results.

Inspired by above logic, this paper applies ELM & RVFL randomized learning algorithms and develops a new ensemble model. With multiple learning algorithms, the learning diversity can be further improved, and more generalized

machine learning outcome can be obtained. Moreover, the credible and incredible classification results are discriminated using the credible boundaries in [2], [4], [10], and the involved parameters together with the participation factor of each learning algorithm are optimized using an evolutionary algorithm to pursue the highest DSA efficiency while achieving the industrial DSA accuracy target.

## II. RANDOMIZED LEARNING ALGORITHMS

For ensemble learning, one key is the diversity of the single learning units. Randomized learning algorithms are naturally diverse, so they are a perfect candidate for ensemble learning.

### A. Extreme Learning Machine (ELM)

ELM is proposed by Huang [14] and receives substantial attention from academic research and practical application. ELM belongs to single-hidden layer feedforward networks (SLFN) [15], and its structure is shown in Fig. 1, it is comprised of three layers: input layer, hidden layer, and output layer.

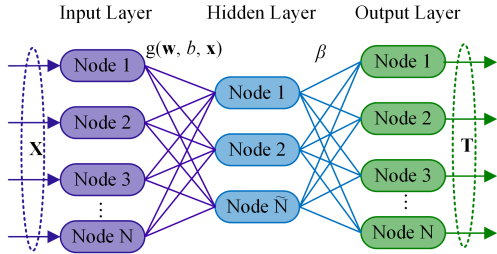


Figure 1. The Structure of ELM.

For a standard ELM with  $N$  hidden layer nodes, the output formula can be mathematically modelled as follows:

$$f_N(x_j) = \sum_{i=1}^N \beta_i \cdot g(\mathbf{w}_i \cdot \mathbf{x}_j + b_i) = t_j, j = 1, 2, \dots, N \quad (1)$$

where  $g$  represents the efficient activation function,  $\mathbf{w}_i \in \mathbf{R}^N$  is the input weight connecting all input layer nodes with the  $i$ th hidden layer node,  $\beta_i \in \mathbf{R}^N$  is the output weight connecting the  $i$ th hidden layer node with the output layer nodes, and  $b_i$  represents the bias at  $i$ th hidden layer node.

If the number of hidden nodes is less than the number of training instances in the dataset, it becomes a linear system for fixed  $\mathbf{w}_i$  and  $b_i$ , and output weight vector  $\beta^*$  can be estimated by using the minimal norm least square method as follows:

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

where  $\mathbf{H}$  is called the hidden layer output matrix, and  $\mathbf{H}^\dagger$  represents the *Moor-Penrose generalized inverse* of  $\mathbf{H}^\dagger = \mathbf{H}^T (\mathbf{H} \mathbf{H}^T)^{-1}$ . At training stage, the input weights and biases of the ELM are randomly selected, so the common iterative training procedure, such as back propagation, can be skipped. Compared to other methods, ELM shows much faster learning speed, whether categorical classification or numeric prediction. Other merits of ELM are excellent generalization ability and less parameter adjustment.

### B. Random Vector Functional Link Neural Network (RVFL)

RVFL belongs to random function version of the neural networks [16], [17]. Its structure is shown in Fig. 2. Compared to other neural networks, the distinctive feature of RVFL is its direct input-output connection.

Based on such unique structure, the output is mapped as follows:

$$\mathbf{t}_i = \mathbf{d}_i^T \beta, \quad i = 1, 2, \dots, P \quad (3)$$

where  $P$  is the number of instances,  $\mathbf{d}_i$  is a vector concatenating the hidden layer outputs and the input features,  $\beta$  is the output weight vector, and  $\mathbf{t}_i$  is the target output vector. The weights from the input layer to the hidden nodes are randomly selected within appropriate domain such that the activation function is not saturated all the time. Assuming that each instance has  $K$  input features and  $J$  hidden nodes, there are  $(K+J)$  nodes connected to output layer, thus  $\beta$  consists of  $(K+J)$  output weights. Learning process can be described as the minimization of the quadratic error  $E$  as follows:

$$E = \frac{1}{2P} \sum_{i=1}^P (\mathbf{t}_i - \beta^T \mathbf{d}_i)^2 \quad (4)$$

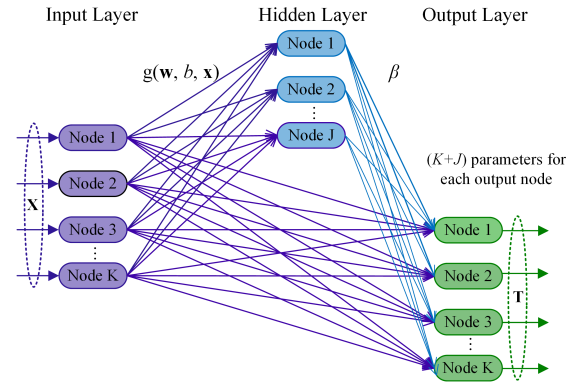


Figure 2. The Structure of RVFL.

The input weights and bias are randomly generated in a suitable domain, which is the same as ELM. However, RVFL has direct input-output link on top of the input-hidden-output structure of ELM, which is the main difference between the two randomized learning algorithms. Such unique structure of RVFL makes it capable of mapping both linear and nonlinear relationships between input and output nodes, which helps regularize the error incurred by the randomness in the input weights and biases, and thereby achieves better and more stable classification results [14], [18].

## III. MULTIPLE LEARNING BASED DSA MODEL

The existing ensemble models used for the DSA only employ a single learning algorithm [4]-[9], such as ANN ensembles, DT ensembles, SVM ensembles, etc. This paper integrates two different randomized machine learning algorithms to establish a new ensemble model which maps the input-output relationship in different ways. The error from the aggregated output tends to be decreased because of the compensation between different randomized learning algorithms. This section details the proposed ensemble model.

### A. Model Design

The proposed multiple learning based ensemble model is illustrated in Fig. 3. The whole model can be divided into two processes, including offline stage and online stage. At offline stage, it starts with feature selection and then training of the single learning models. After that, by randomly selecting single classifiers and using evolutionary algorithm to optimize

the classification boundaries and the number of different classifiers, the ELM & RVFL ensemble model can be obtained. At online stage, based on the real-time WAMS data, the ensemble model can provide credibility estimation to its computation output via credible decision-making. In doing so, only the credible outputs are used as the ultimate DSA decision, and the cases with incredible outputs are pending to T-D simulation for re-assessment.

This multiple ensemble learning model can not only increase the accuracy, but also provide a potential classification and prediction error to allow for more flexible and reliable mechanism before failure. Since ELM and RVFL both adopt random input weights and biases, the training speed is significantly improved, so the increased training burden of ensemble training can be greatly alleviated. Moreover, in ensemble training, each of the randomized learning algorithms also involve randomness including training samples, training features, hidden nodes, and activation function, which can improve the generalization ability and robustness of the ensemble learning model.

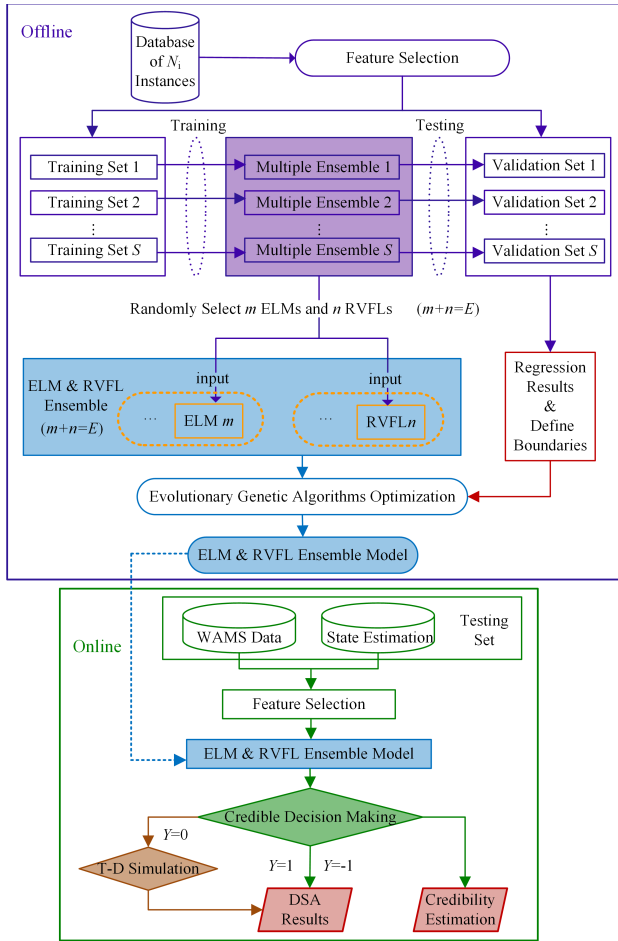


Figure 3. The Structure of Proposed ELM & RVFL Ensemble Model.

### B. Credible Decision Making

Due to the statistical learning nature, the output of a machine learning model may always contain errors. In order to avoid using the potential inaccurate DSA result, we have proposed to identify the incredible output of the model [4].

When using a learning method for DSA classification, the class labels are represented by binary numeric values, 1 (secure) and -1 (insecure). Owing to the prediction error, it is necessary to define the specific threshold as the decision boundary of classification. Obviously, the deviation between the actual outputs and the pre-defined class labels can be derived from the prediction error. On the other hand, it is also a direct indication of the approximate index of the actual distribution of the data. Thus, the deviation can be used to estimate the credibility of the output [10].

In reality, some instances may be very close to the boundary with the decision of the regression output. It can be indicated that most of output values of the misclassified instances are extremely close to the threshold value 0, under which the final stability status is determined. Therefore, if these marginal instances can be determined strategically, and then use a more reliable method (e.g. T-D simulation) for a reasonable classification, it will improve the overall classification accuracy.

Supposing the proposed model includes totally  $E$  single ELMs and RVFLs, we define that the multiple predicted outputs are divided into three different clusters so as to improve classification reliability. The classification rule and credibility estimation of every ELM and RVFL is as follows:

$$\text{If } \begin{cases} y_i \in [lb_s, ub_s] \Rightarrow y_i = +1 & (\text{Credible-stable}) \\ y_i \in [lb_u, ub_u] \Rightarrow y_i = -1 & (\text{Credible-unstable}) \\ y_i \in (-\infty, lb_u) \text{ or } (ub_u, lb_s) \text{ or } (ub_s, +\infty) \Rightarrow y_i = 0 & (\text{Incredible}) \end{cases} \quad (5)$$

where  $y_i$  represents the predicted output of each randomized learner,  $0 < lb_s < 1$ ,  $ub_s > 1$ ,  $lb_u < -1$ ,  $-1 < ub_u < 0$  are the boundaries that define the stable, unstable, and incredible  $y_i$ , respectively.

### Rule for Classification

Given totally  $E$  ELMs and RVFLs, which can totally get  $s$  "0" sub-learning outputs,  $u$  "+1" sub-learning outputs and  $v$  "-1" sub-learning outputs ( $s+u+v=E$ ).

$$\text{If } s > R \Rightarrow Y = 0 \quad (\text{Incredible ensemble}) \quad (6)$$

$$\text{Else If } \begin{cases} u > v \Rightarrow Y = +1 & (\text{Secure}) \\ u < v \Rightarrow Y = -1 & (\text{Insecure}) \end{cases}$$

End

The estimated credibility of the classification results is based on the quantity of sub-learning outputs that meet the classification criteria. It is clear that the larger the count, the less credible. In this multiple randomized ensemble model,  $Y$  is the ultimate classification result;  $R$  is the threshold that determines whether  $Y$  is a credible. In credible decision making, the boundaries  $[lb_u, ub_u, lb_s, ub_s]$ , the quantity of ELM  $m$ , the quantity of RVFL  $n$ , and threshold  $R$  are the credible decision parameters that should be optimized to adjust the credible status.

### C. Single Learning Unit Training

For each single learning unit in the proposed ensemble model, the training process is as follow:

### Single Learning Unit Training

Given a database of  $S \times F$  size to train  $E$  classifiers, including  $m$  ELMs and  $n$  RVFLs ( $m + n = E$ ), where  $S$  is the number of instances and  $F$  is the number of input features.

**For**  $i = 1$  to  $E$ :

- 1) Randomly sample  $s \in [1, S]$  instances in the database.
- 2) Randomly select  $f \in [1, F]$  features.
- 3) Choose the an effective activation function and ELM hidden layer nodes  $h_E$  which is within the optimal range  $[h_{MIN}, h_{MAX}]$  (Depend on the pre-tuning value).
- 4) Choose an effective activation function and RVFL hidden layer nodes  $h_R$  which is within the optimal range  $[h_{MIN}, h_{MAX}]$  (Depend on the pre-tuning value).
- 5) Train the ELM and the RVFL by using the selected instances, features, activation function, and number of hidden layer nodes.

**End**

### D. Classification Performance Indices and Ensemble Training Algorithm

For the DSA developed in this paper, since the purpose is to accurately classify all decision instances, we need to define the following indicators:

$$C = \frac{\text{Number of credible classifications}}{\text{Total number of testing instances}} \times 100\% \quad (7)$$

$$A = \frac{\text{Number of correctly classified instances}}{\text{Total number of credible classifications}} \times 100\% \quad (8)$$

In DSA with credible decision-making, accuracy ( $A$ ) controls the overall DSA accuracy, and credibility ( $C$ ) controls the overall DSA efficiency. Depending of different values for the credible decision parameters, there shows a tradeoff between accuracy  $A$  and credibility  $C$  in the proposed multiple ensemble model. By dominating the accuracy greater than industrial requirement in a suitable domain, we can get the corresponding robust credibility range. We can make the whole DSA more efficient and smarter since the credibility determines the efficiency. Thus, the optimization of the credible decision parameters can be formulated in a single-objective optimization problem as follow:

$$\begin{aligned} & \underset{x}{\text{Minimize}} \quad q = -p(x) \\ & \text{s.t.} \quad \begin{cases} x = [lb_u, ub_u, lb_s, ub_s, R, m, n] \\ p(x) = [\text{Credibility}] = [p_n(x)] \\ lb_u < -1, -1 < ub_u < 0, 0 < lb_s < 1, ub_s > 1 \\ 0 < R < m + n \\ m + n = E \\ \text{Accuracy} \geq \text{Industrial Requirement} \end{cases} \quad (9) \end{aligned}$$

By solving this single-objective optimization problem, decision makers can obtain the corresponding solutions according to their actual needs.

## IV. CASE STUDY

The proposed model is tested on New England 39-bus system which represents a standard benchmark power system for stability analysis [19].

### A. Database Generation

The operating instances in the knowledge base are decided based on Monte-Carlo technology, which randomly samples wind and load within its predetermined range. Then, other candidate features are obtained by running the optimal power flow in order to minimize the generation cost. The contingencies considered in the study are the three-phase faults on bus 3 with inter-area corridor trip (i.e. trip line 3-4) and cleared 0.25 s after their occurrences. The reason for choosing this contingency is that interruption between areas can lead to large disturbances to normal grid operation, which in turn leads to a high risk of insecurity. The security conditions subject to the selected contingency are obtained by running a time domain simulation using the Transient Stability Analysis Tool package. Finally, 7127 operating instances with security conditions were obtained, and the number of secure instances and insecure instances are 4350 and 2710, respectively. In the study, 70% of the instances were randomly selected as for model training, and the remaining 30% instances construct the test dataset.

### B. Feature Selection

The power system has a high dimension in nature, which means that the features can characterize its operating status. However, the core goal of the power system is stability, so only the important features are useful inputs. The *RELIEFF* algorithm is a feature weight algorithm that assigns features with different weights according to the relevance of each feature and category, and the features with weight values less than a certain threshold will be removed. The higher the weight of the feature, the stronger the classification ability of the feature, and vice versa, the weaker the feature classification ability. Thus, a feature with a high positive weight is chosen as a key feature.

### C. Ensemble Learning Parameter Selection

1) *Total Number of ELMs and RVFLs in an Ensemble E*: In the existing ensemble learning, with the number of neural networks increasingly, the predictable error has gradually decreased but converges to a limit [20], [21]. In this case study,  $E$  is defined as 200.

2) *Activation Function and Optimal Hidden Node Range*: The number of hidden layer nodes and the choice of activation functions are also needed to adjust constantly in ELM and RVFL training process. If operating the activation function, the ELM and RVFL classification accuracy can only be maximized within a specific hidden node range. This is because that the classification performance of the different activation functions would deviate in different ways, only the Sigmoid function and Sine function are chosen as valid activation hidden optimal range of ELM and RVFL classifiers.

3) *Number of Training Instances S*: The quantity of instances which are selected to train ELMs and RVFLs determines the whole performance of the robustness. In this case study,  $s$  is chosen to be 5000.

4) *Number of Important Training Feature F in an Ensemble E*: Among the 320 candidate features, we can select the top ranked 190 features whose weights are positive in order to make the final results more reliable.

#### D. Testing Results

To demonstrate the upgraded DSA performance of the proposed multiple ensemble model, we separately test the ELM ensemble and RVFL ensemble for comparison. In the test, the credible decision-making mechanism is applied on all the tested ensemble models, so the test can purely compare the DSA performances between combining multiple randomized learning algorithms and using a single one. Four different industrial accuracy requirement levels are set, which are 99.50%, 99.70%, 99.90% and 100.00%, respectively. The testing results are shown in Table I. As long the accuracy requirement has been satisfied by the different models, the DSA credibility can be used as the index to compare their DSA performance. For each accuracy requirement, the highest DSA credibility is underscored.

TABLE I  
THE DSA PERFORMANCE OF DIFFERENT ENSEMBLE MODELS

DSA Accuracy Requirement	DSA Credibility		
	Single ELM Ensemble	Single RVFL Ensemble	ELM & RVFL Ensemble
99.50%	97.68%	96.05%	97.79%
99.70%	96.28%	95.06%	96.57%
99.90%	94.78%	93.04%	95.49%
100.00%	92.99%	91.77%	94.08%

In Table I, the DSA credibility corresponding to four DSA accuracy requirements varies greatly over different ensemble models. It can be observed that, while satisfying all different DSA accuracy requirements, the proposed ELM & RVFL ensemble achieves higher DSA credibility than single ELM ensemble or single RVFL ensemble. More specifically, compared to single ELM ensemble and single RVFL ensemble, 0.11% and 1.74% higher credibility for accuracy requirement at 99.50%, 0.29% and 1.51% higher credibility for accuracy requirement at 99.70%, 0.71% and 2.45% higher for accuracy requirement at 99.90%, and 1.09% and 2.31% higher for accuracy requirement at 100.00%, respectively.

In the proposed model, since the cases with incredible outputs are sent to T-D simulation for re-assessment which is a slow DSA process, the value of DSA credibility determines the overall DSA efficiency. Having high DSA efficiency is especially important when a large power system is to be assessed or a large number of credible contingencies need to be screened. As indicated in Table I, in regard to DSA efficiency, the proposed model outperforms other ensemble models with single learning algorithm, which pushes the proposed model more applicable to DSA on real-world power systems. Moreover, it is also observed that the proposed model is even better when a higher accuracy is required.

#### V. CONCLUSION

A novel multiple randomized learning based ensemble model is proposed in this paper for online DSA. The proposed model combines multiple randomized learning algorithms, including ELM and RVFL, in an ensemble form to provide more diversified machine learning results. Moreover, besides achieving the industrial DSA accuracy requirement, the proposed model also optimizes its DSA efficiency through credible decision-making. This model is tested on the New

England 39-bus system, and the testing results demonstrate its improved DSA performance, in regard to DSA accuracy and efficiency, over existing methods.

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