Power System Reliability Evaluation using Monte Carlo Simulation and Multi Label Classifier

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***Abstract*—This paper presents a new method for evaluation of power systems reliability indices. In this study, a combination of Monte Carlo Simulation (MCS) and Multilabel Radial Basis Function (MLRBF) classifier is used for computing system reliability indices. Multilabel classification algorithms is different from single label approaches, in which each instance can be assigned into multiple classes. This study shows that MLRBF can be used to classify composite power system states (success or failure) without requiring optimal power flow (OPF) analysis, with exception of training phase. Therefore, this approach shows that the computational efficiency of the reliability evaluation analysis to evaluate reliability indices can be significantly increased. The proposed method is applied to the IEEE Reliability Test System (IEEE-RTS-79) for different load levels. The outcomes of case studies show that MLRBF algorithm provides good classification accuracy in reliability evaluation while reducing computation time substantially.**

***Index Terms*— Power System Reliability Evaluation, Multi Label RBF Learning Algorithm, Monte Carlo Simulation.**

I. Introduction

Power system reliability evaluation techniques generally use either simulation approach or analytical solution methods. Simulation based methods provide more flexibility in estimating complex system parameters in various conditions [1] and are therefore preferred for composite system analysis. The MCS based techniques, including, Importance Sampling and Latin Hypercube Sampling, are currently the preferred methods to estimate the reliability indices of composite power systems [2]. One drawback of the MCS is that these methods require excessive amount of computational time solving optimization equations for implementing OPF analysis for evaluating the states whether or not they satisfy the load.

Tremendous amount of research has been done on increasing computational efficiency of these simulations. The most prominent approaches are variance reduction techniques [3], state space pruning [4], fuzzy optimal power flow [5] or more efficient sampling techniques like LHS [1] or IS [6]. Some of these researches also use population-based intelligence search (PIS) methods as an alternative to search for meaningful states to increase the computational efficiency of these simulation methods [7,8,9,10].

Pattern classification techniques have also been widely explored to reduce the number of states to be evaluated in power system reliability assessment. Artificial Neural Network (ANN) based classifiers [11], Artificial Immune Recognition System (AIR) [12] or Least Squares Support Vector Machine based classifiers [13] are some of the successfully implemented examples of these techniques. These methods are generally directed towards identifying the system state (failure - success) by utilizing the chosen classification method and increase the computational efficiency of reliability analysis by reducing the amount of optimal power flow analysis (OPF) in computation. These approaches manage to classify successful system states with high accuracy and reduce the computational burden required for reliability analysis however, their contribution mainly stayed at system level classification rather than bus level.

Multi label classification is a type of learning where each sample is associated with multiple labels, providing a potential for calculation of bus level indices. The multilabel algorithms can be categorized into two main groups, problem transformation and algorithm adaptation methods [14]. The objective of transformation methods is to handle a multi label classification problem by converting it into a single label classification problem. Binary reverse method [14] or pair-wise method [15] are examples for this method. The algorithm adaptation methods, on the other hand are designed from some specific single label learning algorithms to solve multi label classification problems directly. MLKNN [16], neural networks based MLL [17] or decision trees [18] are some examples of this group.

This paper proposes a new approach by combining MCS and MLRBF classifier [19] for reliability evaluation of composite power systems. The main contribution of this paper is proposing a method that decreases computation time of classification of sampled states with MCS by reducing requirement for OPF for the reliability evaluation at system bus level. Efficiency of proposed approach is shown on 24 bus IEEE reliability test system (RTS).

The remaining of this paper is organized as follows. In section II, mathematical background of the MLRBF is provided briefly for composite system reliability analysis. Application steps of proposed method is described in section III. Results of case studies on RTS are discussed in this section IV. Finally, conclusion is given in Section V.

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II. MLRBF CLASSIFIER FOR POWER SYSTEM RELIABILITY EVALUATION

RBF is one of the most popular among neural network classification methods. RBF Neural Networks are generally comprising of two layers of neurons. In RBF, each hidden neuron (basis function) in the first layer is associated with a prototype vector while each output neuron corresponds to a possible class. Usually training an RBF neural network is handled in a two-stage procedure. In the first layer, the basis functions are learned by performing clustering analysis on training instances while weights are optimized by solving a linear problem in second layer. Comprehensive descriptions on RBF neural networks are available in [20].

In this section, first, a general formulation of composite system reliability evaluation parameters for MLRBF classification is explained, later, application of the proposed method is described in steps. Finally, a pseudo code is provided for clear understanding.

A. General Definition of MLRBF Parameters

In this study, total generation capacities and total demand for each bus of composite system are taken as input parameters for MLRBF classifier. So, generation and demand information for each bus in the system is considered as an element of input matrix I for every sample (instance) m as described in (1).

$$I_{input} = \begin{bmatrix} G_{11}-D_{11} & G_{12}-D_{12} & G_{1N}-D_{1N} \\ G_{21}-D_{21} & G_{22}-D_{22} & G_{2N}-D_{2N} \\ G_{M1}-D_{M1} & G_{M2}-D_{M2} & G_{MN}-D_{MN} \end{bmatrix} \quad (1)$$

where N is the number of the buses and M is the total number samples in the input matrix.

State information for each bus of the system for M different samples is stored in a target matrix T for purpose of training the MLRBF classifier which described in (2).

$$T = \begin{bmatrix} S_{11} & S_{12} & S_{1Q} \\ S_{21} & S_{22} & S_{2Q} \\ S_{M1} & S_{M2} & S_{MQ} \end{bmatrix} \quad (2)$$

where Q is the number of the load buses in the system and S is the status information of bus q. While defining status of buses '-1' is taken for corresponding 'success states' and '1' for 'failure states'.

P_{out}, contains failure probability for each bus of composite reliability system for each sample M as the output for this classifier which described in (3).

$$P_{out} = \begin{bmatrix} P_{11} & P_{12} & P_{1Q} \\ P_{21} & P_{22} & P_{2Q} \\ P_{M1} & P_{M2} & P_{MQ} \end{bmatrix} \quad (3)$$

After the definition for general parameters of MLRBF classifier is made, training and testing procedure is explained in steps in following subsection.

B. Explanation of MLRBF Classification Procedure

It is necessary to describe some related parameters before starting explanation;

m: defines index of current sample of total M samples.
i_m: defines the input vector for sample m.
q: defines the bus index of total Q buses of system.
Y_m defines the state of bus *q* in sample *m* so;

$$Y_m(q) = \begin{cases} 1\ (failure)\ where\ \ T_{iq} = 1 \\ 0\ (success)\ where\ \ T_{iq} = -1 \end{cases} .$$

Let I=R^d be the input space and Q= {1, 2,…, Q} be the finite set of Q possible classes. Given a multilabel training dataset DSet= {(i_m,Y_m)| ≤ m ≥ M}, where $i_m \in$ I is a single instance and $Y_m \subseteq$ Q is label set associated with i_m.

In this study, k-means clustering is applied for each class q ∈ Q on the set of instances U_q with label q which described in (4).

$$U_q = \{i_m \mid (i_m Y_m) \in DSet,\ q \in Y_m\} \quad (4)$$

In next step, k_q number of clustered groups are formed for class q and the jth centroid (1≤j≤k_q) is regarded as a prototype vector c^q_j of basis function $\alpha^l_j(.)$. It should be noted that, k_q is taken as a fraction of the total number of instances in U_q.

As each output neuron of the MLRBF neural network is related to a possible class, weights between hidden and output layer can be shown as (5).

$$W=[w_{jq}]_{(K+1)\ XQ} \quad (5)$$

Here, $K = \sum_{q=1}^{Q} k_q$ shows the total number of prototype vectors retained in the hidden layer. The weight matrix W can be learned by minimizing the following sum-of-squares error function as it described below (6).

$$E = \frac{1}{2}\sum_{m=1}^{M}\sum_{q=1}^{Q}\left(Y_q(i_m) - T_q^m\right)^2 \quad (6)$$

Where T_q^m is the represents the output of i_m on the q-th class, which takes the values of +1 if q ∈ Y_i and -1 otherwise. So, the output of i_m for the *q*-th class can be calculated as presented below (7).

$$y_q(i_m) = \sum_{j=0}^{Q} w_{jq}\phi_j(i_m) \quad (7)$$

In this study, the basis function a_j represented with the following widely-used Gaussian style activation (8).

$$\phi_j(i_m) = \exp\left(-\frac{dist(i_m,c_j)^2}{2\sigma_j^2}\right) \quad (8)$$

Here dist (i_m,c_j) calculates the distance between i_m and the j-th prototype vector c_j with the usual Euclidean distance algorithm.

The smoothing parameter σ is shown with the equation below (9).

$$\sigma = \left(\frac{\sum_{p=1}^{K-1} \sum_{r=p+1}^{K} dist(c_p, c_r)}{\frac{K(K-1)}{2}} \right) \tag{9}$$

Differentiating the error function (6) with respect to w_{jq} and setting the derivative to zero will be resulted with the equation given below (10).

$$(\phi^T \phi)W = \phi^T T \tag{10}$$

In equation 10, $\phi = [\phi_{mj}]_{m \times [K+1]}$ with elements, $\phi_{mj} = \phi_j(i_m)$, W= $[w_{jq}]_{Q \times [K+1]}$ and T=$[t_{mq}]_{m \times Q}$ with elements $t_{mq} = t_q^m$.

A Pseudo code is presented for a clear understanding below;

Inputs:
DSet: the multilabel training dataset {(i_1, Y_1),…, (i_m, Y_m)}
i_{test}: the test instance ($i_{test} \in G$)

Outputs:
P: predicted label set for i_{test} ($P \subseteq Q$)

Process:
1- for $q \in Q$ do
2- Set U_q = {i_m | (i_m,Y_m) ∈ DSet, q, ∈Y_m}
3- Cluster U_q into k_q groups by invoking the k-means algorithm. (described in eq. 4)
4- Set the centroids of all clustered groups as the prototype vectors for the q-th class;
5- Form matrix ϕ (using Eqs.(3) and (4)) and T;
6- Compute weights W by solving Eq. (10)
7- P = $\{q | y_q(i_{test}) = \sum_{j=0}^{K} w_{jq}\phi_j(i_{test}) > 0, q \in Q\}$

III. Application of Proposed Method

This paper proposes a hybrid MLRBF classifier with non-sequential MCS for evaluating reliability indices of composite systems. Nonsequential MCS is chosen in application because of simplicity of the model. A benchmark is also created by results obtained from Crude Monte Carlo Simulation (CMCS) for compression to measure the performance of proposed method.

The first step of implementing MLRBF classifier in proposed methodology is generating a training database. A proper dataset is created using a set of sampled states and the corresponding state classification labels for each bus (success or failure), which are obtained by OPF analysis in MCS process. In this phase, CMCS is run until previously specified stopping criteria is satisfied to obtain adequate number of samples. Once the appropriate training patterns are obtained, then the MLRBF classifier can be classified, which would then be used for the state space classification of the testing database to evaluate the reliability.

Later, CMCS is applied until it reaches previously specified stopping criteria for testing purpose. In this stage status of the system busses (success- failure) for sampled states characterized by MLRBF classifier instead of OPF. At the end, obtained results by classifier are compared with the results CMCS benchmark for measuring the performance of the proposed method.

Input vector of the proposed classifier is created according to equation (1) while output of the classifier is defined as state (success or failure) of each bus of the selected test sample by applying a threshold to the equation (3).

The overall procedure of the proposed method is explained in the following steps;

- Training dataset is obtained by running CMCS until it reaches stopping criteria. States of each sample are characterized through OPF analysis (1 if failure -1 if success) to create a target vector. Then training is done.

- Obtain the samples required for testing purpose by considering previously specified stopping criteria. Then classify the states of samples by using the MLRBF classifier.

- Calculate reliability indices and compare the obtained results with the ones gathered from CMCS benchmark to measure the performance of proposed method.

General steps of proposed method explained in flow chart given in figure 1.

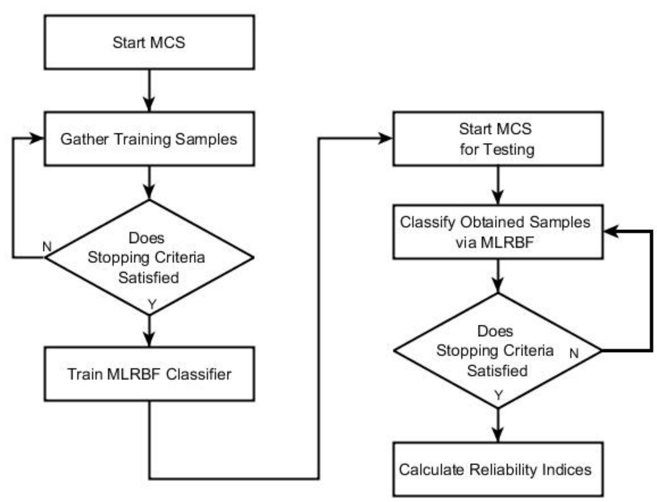

Figure 1: General Flow Chart for Proposed Methodology

Stopping criteria for this study can be either defined as coefficient of variation (COV) (for both training and testing stages) as it represents the estimated uncertainty or a specified number of samples. COV is given by equation (11).

$$\beta = \frac{\sqrt{V(E(F))}}{(E(F))} \quad (11)$$

In this equation $V(E(F))$ represents the variance of the estimated value E(F).

IV. CASE STUDIES

The proposed MLRBF classifier is applied to the IEEE RTS test system (RTS) which has 24 buses (10 of them are generation buses), 38 transmission lines and 32 generation units. In RTS, the total installed capacity is 3405 MW and the system has 2850 MW at annual peak [21].

Two case studies are used to illustrate the proposed method. In first case study, a constant load level is used which is equal to the annual peak level of RTS. In second case study 52 different load levels are implemented to represent weekly peak levels of RTS. In each case study, randomly selected samples are used for generating training dataset. Later, performance comparison of the classifier is made with CMCS benchmark after calculation of reliability indices for all 24 system buses. Generally, failure rates of transmission lines are much lower than generation units, for this reason, states of transmission lines are considered as available at all the time. The capacities of transmission lines are, on the other hand, considered.

All simulations of this study are performed using MATLAB (2012) planform on a PC with Intel Core i7-4510 CPU (~2.6GHz), 16 GB Memory. It should be noted that the results presented below are the average of the 10 simulations.

A. Constant Load Level

In this case study, load for the system is considered to be constant and at its peak value of 2,850W. To generate a training matrix CMCS is run until COV reaches the limit of ≤ 3%.

There are 14682 samples classified with 13381 successes and 1301 failure in this process. After classification, the training patterns are recombined to generate a balanced training dataset (some of the success states are discarded to prevent overtraining). A total of 3000 samples are selected with 1301 failure and 2699 success states for this dataset (some of the success states are discarded to prevent overtraining). After training of MLRBF classifier completed, MCS was simulated until COV reaches 1% as it specified for stopping criteria of testing phase.

In this process a total of 109,743 samples were obtained with 100470 successes and 9273 failures characterized. The obtained results compared with the ones obtained from CMCS.

Simulation results for overall system performance of MLRBF Classifier on RTS are presented in Table 1 and the simulation results for bus level classification performance stated in Table 2. In this study, performance comparison in this study is made based on Loss of Load Probability (LOLP). Finally, performance comparison of computational time of proposed method and CMCS benchmark is illustrated in Table 3.

Table 1 & Table 2 show that MLRBF classification method can compute LOLP with a small fraction of error and provides reasonably accurate classification on characterizing the failed bus states of RTS. Table 3 also shows that computational time required to evaluate the reliability indices can be significantly reduced by proposed MLRBF classification method the when compared to CMCS.

Method	Success States	Err (%)	Failure States	Err (%)	LOLP (%)	Err (%)
CMCS	100470	N/A	9273	N/A	8,45	N/A
MLRBF	100426	0.043	9317	0.47	8,49	0.47

Table 1: Performance Analysis for MLRBF Classifier

Location	CMCS (Number of Failure)	CMCS (LOLP) (%)	MLRBF (Number of Failure)	MLRBF (LOLP) (%)
Bus 1	2934	2.67	2965	2.7
Bus 2	2953	2.69	2946	2.68
Bus 3	0	N/A	0	0
Bus 4	0	N/A	0	0
Bus 5	952	0.87	924	0.84
Bus 6	29	0.03	37	0.03
Bus 7	5063	4.61	5081	4.62
Bus 8	642	0.59	667	0.60
Bus 9	1	~0.0	3	~0.0
Bus 10	21	0.02	19	0.01
Bus 11	0	N/A	0	0
Bus 12	0	N/A	0	0
Bus 13	471	0.43	453	0.41
Bus 14	224	0.20	211	0.19
Bus 15	0	N/A	0	0
Bus 16	51	0.05	61	0.05
Bus 17	0	N/A	0	0
Bus 18	1034	0.94	1072	0.97
Bus 19	51	0.05	45	0.04
Bus 20	3879	3.53	3798	3.46
Bus 21	0	N/A	0	0
Bus 22	0	N/A	0	0
Bus 23	0	N/A	0	0
Bus 24	0	N/A	0	0

Table 2: Classification Performance at Bus Level Based on LOLP

Process	CMCS (Sec)	MLRBF (Sec)
Training	N/A	41
Testing	4,370	273

Table 3: Timing Analysis of MLRFB Classifier with Comparison with CMCS

B. Varying Load Levels

In this case study load level of the system is chosen randomly from the 52 different load levels of weekly peak values of annual load chart of RTS. For this case study stopping criteria for MCS is specified as 75,000 samples for training case. Since failure rate of system for weekly peak load level is much lower than system peak load, unviability ratios of all generators multiplies by 3 to create an appropriate training dataset. At the end, a total of 150,000 samples with 38,721 failures and 36,279 successes were characterized by DC-OPF. After training dataset created, CMCS run until 1,000,000 samples obtained for testing purpose. In this process a total of 1,000,000 samples were obtained with 990,620 successes and 9,380 failures characterized. The obtained results compared with the ones obtained from CMCS.

Simulation results for overall performance of this case study are given in table 4, the results of classification performance at bus level are stated in table 5 and the results for timing analysis are given in Table 6.

It is observed in Table 4 & Table 5 that the proposed method can classify failure states in multi-level loads with a good accuracy. It should also be noted that rate of classification errors increasing in states with low frequency failures. The main reason of this situation is the difficulty of capturing those states in training dataset. Performance of the proposed method can be increased by adding more samples to the training dataset as a natural outcome.

It is also observed that the proposed method providing a huge boost in terms of calculation time as it can be shown in Table 6.

Method	Success States	Err (%)	Failure States	Err (%)	LOLP (%)	Err (%)
CMCS	990620	N/A	9380	N/A	0.938	N/A
MLRBF	990303	0.03	9073	3.2	0.90	~3.2

Table 4: Performance Analysis for MLRBF Classifier

Location	CMCS (Number of Failure)	CMCS (LOLP) (%)	MLRBF (Number of Failure)	MLRBF (LOLP) (%)
Bus 1	2496	0.25	2423	0.24
Bus 2	1615	0.16	1649	0.16
Bus 3	0	N/A	0	N/A
Bus 4	2	0.0002	4	0.00
Bus 5	703	0.07	792	0.08
Bus 6	45	0.0045	62	0.01
Bus 7	5274	0.53	5072	0.51
Bus 8	412	0.04	410	0.04
Bus 9	3	0.0003	5	0.00
Bus 10	14	0.0014	6	0.00
Bus 11	0	N/A	0	N/A
Bus 12	0	N/A	0	N/A
Bus 13	345	0.035	409	0.04
Bus 14	257	0.026	281	0.03
Bus 15	0	N/A	2	0.00
Bus 16	94	0.0094	106	0.01
Bus 17	0	N/A	0	N/A
Bus 18	1305	0.13	1098	0.11
Bus 19	167	0.017	176	0.02
Bus 20	3855	0.39	3694	0.38
Bus 21	0	N/A	0	N/A
Bus 22	0	N/A	0	N/A
Bus 23	0	N/A	0	N/A
Bus 24	0	N/A	0	N/A

Table 5: Classification Performance at Bus Level Based on LOLP

Process	CMCS (Sec)	MLRBF (Sec)
Training	N/A	489
Testing	48,640	5297

Table 6: Timing Analysis of MLRFB Classifier with Comparison with CMCS

V. CONCLUSION

In this study, a new method is presented to evaluate reliability indices for composite power systems. The proposed method uses a MLRBF classifier to identify status of buses that does not require OPF analysis in the calculation/testing stage. The effectiveness of proposed method is demonstrated on the IEEE RTS.

As can be observed from the results, MLRBF classifier can classify loss of load states with good accuracy most of the times. But it should be noted that at some points with low failure frequency, the classifier starts losing performance. The main reason of this performance loss for those buses is lack of adequate samples in the training dataset.

The main advantage of the proposed method is the ability of reducing the required time for reliability analysis considerably.

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