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STATE ADEQUACY EVALUATION USING GENERALIZED REGRESSION NEURAL NETWORK FOR NON-SEQUENTIAL MONTE CARLO SIMULATION BASED COMPOSITE POWER SYSTEM RELIABILITY ANALYSIS

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Abstract
This paper presents a new approach for state adequacy evaluation of sampled system state in composite power system reliability analysis. Generalized regression neural network (GRNN) is used in conjunction with non-sequential Monte Carlo simulation (MCS) to evaluate the loss of probability and the power indices. GRNN approach predicts the test functions for all the sampled states after sufficient training patterns are obtained in the initial MCS sampling with dc load flow based load curtailment minimization model. This model predicts the test functions for both success and failure states. The sampled system states are used to evaluate annualized system and load point indices. The indices evaluated are loss of load probability, loss of load expectation, expected demand not served and expected energy not supplied. The results obtained in this approach are compared with the conventional non-sequential MCS which uses load curtailment minimization model for state adequacy evaluation. An error analysis for different reliability levels is also carried out to check applicability of GRNN approach for calculating the test functions in reliability optimization, where several reliability levels are analyzed. The application of the proposed GRNN approach is illustrated through case studies carried out using RBTS and IEEE-RTS test systems and annualized indices are presented. It is found that the proposed approach estimates indices nearer to the conventional non-sequential MCS.

Keywords:
Generalized Regression Neural Network, Composite Power System, State Adequacy Evaluation, Reliability Indices, DC Load Flow Based Load Curtailment Model

1. INTRODUCTION

Reliability is of critical importance in day to day operations of the power system. Inadequate reliability of electric power utility actually costs the customer much more than the cost of achieving good reliability. System plans that do not meet with the desired reliability criteria are assumed to be either modified or discarded. The determination of acceptable level in system reliability requires investigating of reliability indices for the different sets of system reliability parameters [1]-[3]. The approaches employed in composite system reliability analysis are broadly classified into Analytical and Monte Carlo methods [4]. Analytical techniques based on state enumeration are approximate which considered system states up to certain fixed contingency levels. These methods are more efficient when relatively small number of states accounts for most of the probability of the state space. Monte Carlo simulation (MCS) methods estimate the indices by simulating the actual random behaviour of the system. The sampling techniques used in MCS are sequential and non-sequential sampling. The sequential sampling simulates the chronological behaviour of the system operation which requires more computational effort than non-sequential and analytical methods. However, non-sequential sampling has high computational efficiency but can not simulate the chronological aspects of system operation. The major limitation of this method is the number of states sampled increases with the required indices accuracy [5].

The states enumerated in analytical methods and states sampled in MCS methods are needed to be examined for calculating the expected value of test functions. Some methods employed to examine the adequacy of the state are based on linear network flow, dc load flow based linearized power flow, AC load flow and fuzzy linear power flow [6], [7]. In reliability analysis computational burden is due to the evaluation of adequacy for large number of system states. MCS methods employ various variance reduction techniques to reduce the number of states sampled for achieving the required indices accuracy [8]-[11]. Heuristic algorithms such as genetic algorithm, particle swarm optimization are used as a search tool to explore the dominant system states which have large load curtailment and existing probability [12]-[14]. Leite da Silva et al. proposed an ANN based group method of data handling approach for classifies the sampled state as success or failure. In their approach, state evaluation optimization model for calculating the test functions has applied only to the failure state. This approach achieves significant reduction in computational cost by avoiding the optimization procedure for success states [15].

Cost-benefit analysis becomes an essential factor in the determination of optimal reliability parameters of the system. The cost invested is directly related with reliability which reflects the system performance for a prescribed operating condition. This analysis systematically attempts to balance both the investment cost and the system interruption cost for better planning. This analysis is an optimization procedure of minimizing the investment cost required for obtaining reliable components and system interruption cost. It requires the evaluation of reliability indices for different system reliability levels [16]-[18]. The states sampled in this optimization procedure are in the order of several millions and requires state adequacy evaluation for each state. The objective of this paper is to reduce the computational requirement for state adequacy evaluation by developing a method based on Generalized Regression Neural network (GRNN). The training data for GRNN is obtained in the initial sampled states of MCS for a particular system reliability level. The adequacy analysis for these initial states is performed using dc load flow based load curtailment minimization model. The trained GRNN is used for evaluate the adequacy of the remaining states sampled and computes the test functions in MCS for that reliability level and all states sampled for other reliability levels of the same system.

The applicability of the proposed approach is validated by case studies involving standard RBTS and IEEE-RTS systems with different reliability levels using non-sequential MCS.

The rest of the paper is organized as follows. Section 2 gives a brief explanation about the general approach for evaluating the reliability indices in non-sequential MCS and dc load flow based load curtailment model for state adequacy evaluation. Section 3 presents the proposed methodology for GRNN based state adequacy evaluation and its implementation on composite system reliability analysis. Section 4 presents the simulation results of proposed approach to the standard test systems. Finally the conclusions are presented in section 5.

2. COMPOSITE SYSTEM RELIABILITY EVALUATION

This section describes the conventional non-sequential MCS for composite reliability indices evaluation with dc load flow based load curtailment minimization model.

2.1 NON-SEQUENTIAL MONTE CARLO SIMULATION

The objective of calculating reliability indices in the non-sequential MCS approach is equivalent to calculating the expected value of a given test function,

$$E(F) = \sum_{x \in X} F(x) * P(x) \tag{1}$$

where, x is the vector representing the system state in which each component in x represents the state of system component, X is the set of all possible states x arising from combinations of component states, $P(x)$ is the probability of state x and $F(x)$ is the test function to verify whether the system state x is adequate.

The procedure involved in estimating the reliability index as the average of test function $E(F)$ in non-sequential MCS is as follows,

Step 1: Sample a vector or state $x \in X$ from their respective probability distribution.

Step 2: Repeat step 1 for NS times, where NS is a preestablished number which represent the set of sampled vectors as,

$$\{ x_j, j = 1, \ldots, NS\}.$$

Step 3: Calculate the test function $F(x)$ for each sampled vector or state using load curtailment model given in Section 2.2, i.e. calculate $\{ F(x_j), j = 1, \ldots, NS\}$.

Step 4: Estimate the expected value of the index $E(F)$ as the average of the test function values,

$$E(F) = \frac{1}{NS} \sum_{j=1}^{NS} F(x_j) \tag{2}$$

2.2 LOAD CURTAILMENT MINIMIZATION MODEL

In MCS approach, reliability indices evaluation is to calculate the expected value of a test function $F(x)$. Power indices such as expected demand not served (EDNS), the test function $F(x)$ represents the amount of load curtailment in MW required to alleviate the operating constraint violations and maintain power balance. The load curtailment is a non-zero value ($F(x) > 0$) for failure state and equal to zero for success state ($F(x) = 0$). For probability indices $F(x) = 0$ for success states and $F(x) = 1$ for failure states.

Each contingency state sampled in state sampling approach, the DC load flow based load curtailment model is used to examine` the adequacy of the system by rescheduling generation outputs in order to maintain the real power balance and alleviate the line overloads. Achieving the above requirements the model tries to avoid the load curtailment if possible otherwise it minimizes the load curtailment. If real power balance is achieved without load curtailment then the state belongs success state otherwise it belongs to failure state and load curtailment necessary to attain real power balance is calculated by solving the following model,

$$Min\ Cl = \sum_{i \in NC} (wf_i \sum_{j=1}^{l_i} \alpha_j Cl_{ij}) \tag{3}$$

Subject to,

$$Pline_o = \sum_{k=1}^{N} A_{ok} \left(Pg_k + \sum_{j=1}^{l_i} Cl_{kj} - Pd_k \right), \quad o = 1, \ldots, L \tag{4}$$

$$\sum_{i \in NG} Pg_i + \sum_{i \in NC} (\sum_{j=1}^{l_i} Cl_{ij}) = \sum_{i \in NC} Pd_i \tag{5}$$

$$Pg_{imin} \le Pg_i \le Pg_{imax}, i = 1, \ldots, NG \tag{6}$$

$$0 \le Cl_{ij} \le \gamma_j Pd_i \quad , i \in NC; j = 1, \ldots, m \tag{7}$$

$$Pline_o \ |\le Pline_o^{max}, o = 1, \ldots, L \tag{8}$$

where, C_{lij} is the j_{th} load curtailment sub variable at bus i; Pgi is the generation at bus i; Pdi is the load demand at bus i; $Pline_o$ is the line flow of line o; Pgi_{min} is the minimum generation at bus i ; Pgi_{max} is the maximum generation at bus i; $Pline_o^{max}$ is the maximum value of line flow of line o; A_{ok} is the element of the relation matrix between line flows and power injection; NC is the sets of all load buses; NG is the sets of all generator buses; L is the number of lines; N is the number of buses; l_i is the number of load curtailment subvariables at bus i; αj the weighting factor corresponding to subvariable j; γj is the load percentage associated with each subvariable j; wfi is the weighting factor corresponding to each load bus.

3. METHODOLOGY

This section describes the GRNN structure, data source and proposed implementation algorithm for GRNN based state adequacy evaluation approach for composite system reliability analysis.

3.1 GENERALIZED REGRESSION NEURAL NET

GRNN contrived by Specht is based on non-linear regression theory for function estimation [19],[20]. It has the ability of performing kernel regression and non-parametric approximation of any arbitrary function between input and output vectors. The network architecture is a single pass learning algorithm with massive parallel structure. The topological structure of GRNN consists of input layer, pattern layer, summation layer and output layer as shown in Fig.1. The number of input units in input layer depends on the total number of the variables in the input vector X. The input layer where no data processing performed is connected to the pattern layer. This pattern layer has a group of radial basis neurons and each neuron presents a training pattern in the data set. Its output is a measure of the distance of the input from the stored pattern. Bias *b* is used to adjust the sensitivity of radial basis neuron, when established in the network it can be automatically set to 0.8326/spread. Each neuron in the pattern layer is connected to two neurons in the summation layer. This layer has '*m*' number of S-summation neurons and one D-summation neuron, where '*m*' is the number of neurons in output layer. The S-summation neuron and D-summation neurons computes the sum of weighted outputs and unweighted outputs of the pattern layers respectively. The connection weights between pattern layer units and D-summation neuron is set to unity. The output layer neuron simply divides the output of each S-summation neuron by that of each D-summation neuron. The Gaussian function and linear function are used as activation functions in pattern layer and output layer respectively. The mathematical equations governing the network model is given in Eq.(9) –Eq. (11),

$$Y_i = \frac{\sum_{j=1}^{n} w_j \exp\left[-D\left(x, x_j\right)\right]}{\sum_{j=1}^{n} \exp\left[-D\left(x, x_j\right)\right]} \tag{9}$$

$$D\left(x, x_j\right) = \sum_{k=1}^{v} \left(\frac{x_j - x_{jk}}{\sigma}\right)^2 \tag{10}$$

$$b = \frac{0.8326}{\sigma} \tag{11}$$

where, Y_i is the predicted value of the i^{th} output to the unknown input vector *x*, *n* is the number of training patterns, w_j is the weight connection between the j^{th} neuron in the pattern layer and the S-summation neuron, *D* is the Gaussian function, *v* is the number of elements in the input vector, x_k and x_{jk} are the k^{th} element of *x* and x_j , σ is the spread factor and *b* is the biasing term of pattern layer neurons.

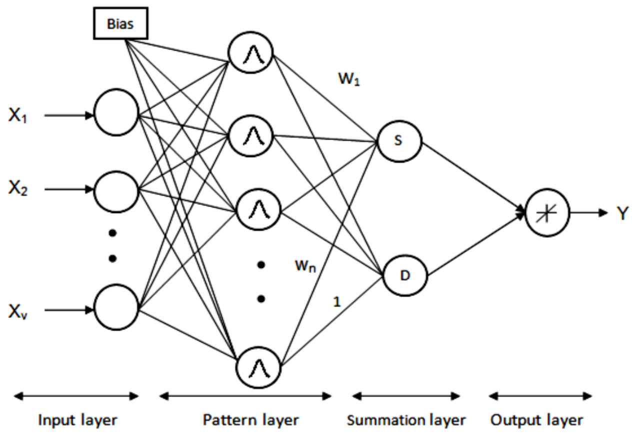

Fig.1. GRNN architecture

The GRNN for state adequacy evaluation of sampled states has input layer neurons equal to number of system components and the output layer neurons equal to number of buses with loads. The number of hidden layer neurons is equal to number of training patterns in the data set. All hidden units simultaneously receive the *m*-dimensional binary valued input vector, where *m* is number of components in the system (i.e. 1 for up state and 0 for down state).

3.2 DATA

In reliability optimization, non-sequential MCS is performed for several system reliability levels to choose the suitable level among them and in most of the cases the sampled states are repeated. So with one reliability level MCS is performed with states analyzed using dc load flow based load curtailment model and these analyzed states can be used as training data for GRNN. For other reliability levels of the same system, the sampled states are analyzed using the GRNN.

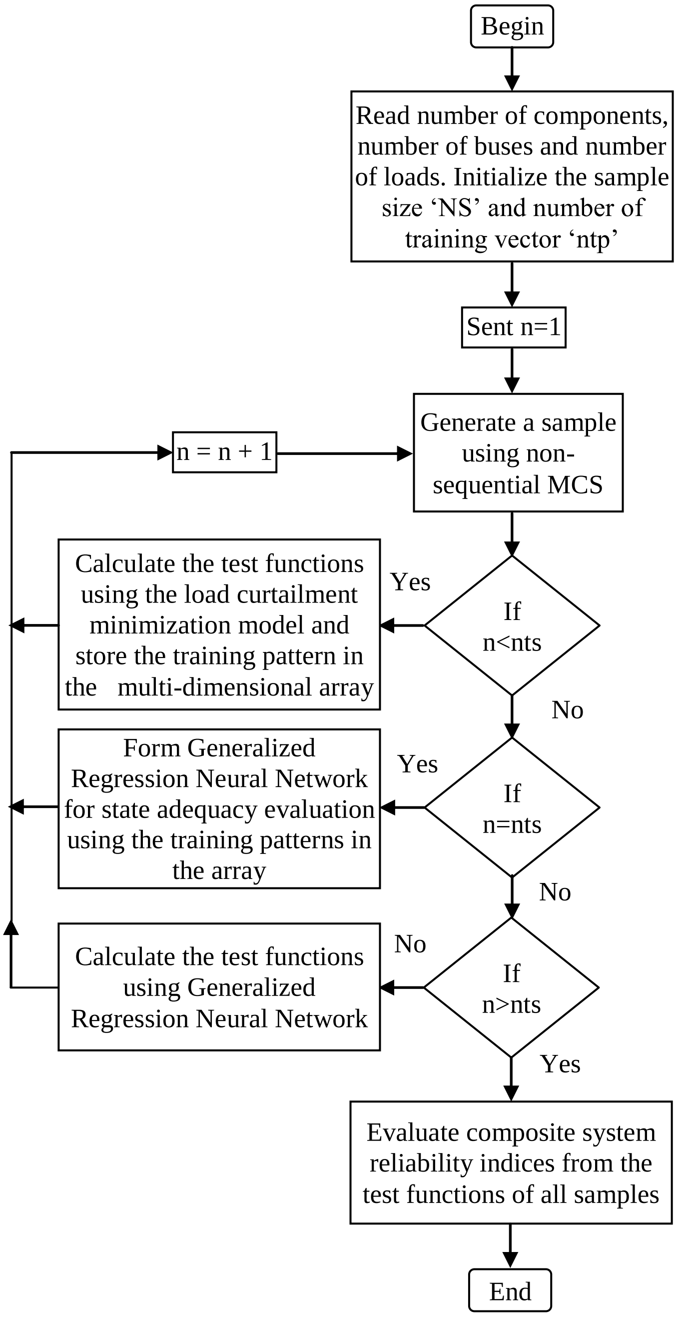

Fig.2. Flow of Reliability Evaluation methodology

In this paper the training data required for GRNN in single pass learning algorithm is obtained from the initial states sampled in non-sequential MCS. The number of states sampled in the simulation process is in the order of several thousands, out of which few thousands states are used as training data for GRNN. Load curtailment model given in section 2.2 which is used for calculating the test functions has linear objective and linear constraints, so this model can be solved using simplex algorithm. The training data is formed by creating a multi-dimensional array consists of components state and the load curtailment necessary to obtain power balance for buses having loads for that sample.

3.3 IMPLEMENTATION ALGORITHM

The basic principles of reliability analysis using GRNN based state adequacy evaluation is presented in Fig.2. The general non-sequential MCS algorithm for composite system reliability evaluation is modified to incorporate the GRNN approach for state adequacy evaluation is given below,

Step 1: Simulate a state sample $x \in X$ from their respective probability distribution and increment the sample counter. i.e. for j^{th} sample $x_j = (x_1, x_2, \ldots, x_{ng}, x_{ng+1}, \ldots, x_{ng+nl})$, where '*ng*' is number of generators and '*nl*' is number of lines.

Step 2: If the sample number $j \leq ntp$, evaluate whether load curtailment is necessary to achieve the real power balance using the model given in section 2.2 if it is a contingency state, else the load curtailment is zero and the state is a success state, where '*ntp*' is the number of training pattern specified. The state of all system components and load curtailment necessary for all buses having loads which is used as a test function is stored in the array and repeat step 1. If $j = ntp$, go to next step otherwise proceed to step 4.

Step 3: GRNN for state evaluation of composite system is formed with '*nts*' training patterns stored in the array. The GRNN has '*ng+nt*' neurons in the input layer, '*nts*' number of neurons in the hidden pattern layer and output layer has neurons equal to number buses having loads. Then go to step 1.

Step 4: If $j > nts$, apply GRNN to evaluate the state and predict the test function for that sampled state. (i.e. load curtailment necessary for buses having loads for failure state). If $j = NS$, evaluate the reliability indices by computing the expected value of a test function using the Eq.(2).

4. SIMULATION RESULTS

Non-sequential MCS with proposed GRNN approach for state adequacy evaluation is applied to composite reliability evaluation of RBTS and IEEE–RTS systems. The proposed approach is applied at base reliability level and five different reliability levels of the same system. The GRNN model is formed with training patterns obtained in initial MCS sampling for base reliability level. GRNN model is used to evaluate the test functions of sampled states for other reliability levels. The indices evaluated are loss of load probability (LOLP), loss of load exception (LOLE), expected demand not served (EDNS) and expected energy not supplied (EENS). Absolute error in indices evaluated using the proposed approach can be calculated using the relation given below,

$$\%Abs.Error = \left| \frac{Conventional\_MCS - Proposed}{Conventional\,MCS} \right| *100 \quad (12)$$

where, Conventional_MCS is the index evaluated in MCS using dc load flow based state adequacy evaluation and proposed is the index evaluated using MCS with state adequacy evaluation using GRNN for that reliability level.

4.1 CASE 1: RBTS TEST SYSTEM

The RBTS system [21] has 6 buses, 9 transmission lines and 11 generators. The minimum and maximum real power ratings of the generation units are 5 MW and 40 MW respectively. The total peak load for the system is 185 MW and the total generating capacity is 240 MW. The sample size is set to 50000 for non-sequential state sampling which is used by Jonnavithula [23] for estimating indices in non-sequential MCS. The total number of components in the system is 20 and number of buses having loads is equal to 5. The GRNN has 20 neurons in the input layer and 5 neurons in the output layer. Network is simulated for different values of spread and the most suitable value for GRNN structure for RBTS system is selected based on the performance. This best performance for this network is obtained for 0.15. The training data is formed from the initial 5000 samples simulated in state sampling non-sequential MCS.

Table.1. Annualized load point indices for base case with GRNN state adequacy evaluation (RBTS)

Bus No.	LOLP	LOLE hr/yr	EDNS MW	EENS MWhr/yr
2	0.00147	12.84192	0.00403	36.34176
3	0.00409	35.73024	0.06211	526.86820
4	0.00580	50.66880	0.03474	311.17630
5	0.00018	1.57248	0.00191	13.89024
6	0.00138	12.05568	0.02131	183.63070

The annualized load point indices evaluated in non-sequential MCS with GRNN based state evaluation for base reliability level is given in Table.1. These indices are helpful to the reliability engineers to identify the weak load points in the system and help them in planning the optimum response of equipment investment.

Table.2. Comparison of Annualized system indices (RBTS)

Approach	LOLP	LOLE hr/yr	EDNS MW	EENS MWhr/yr
MCS-GRNN	0.01019	89.0198	0.1241	1084.138
MCS-state sampling [23]	0.01014	88.5830	0.1239	1082.630

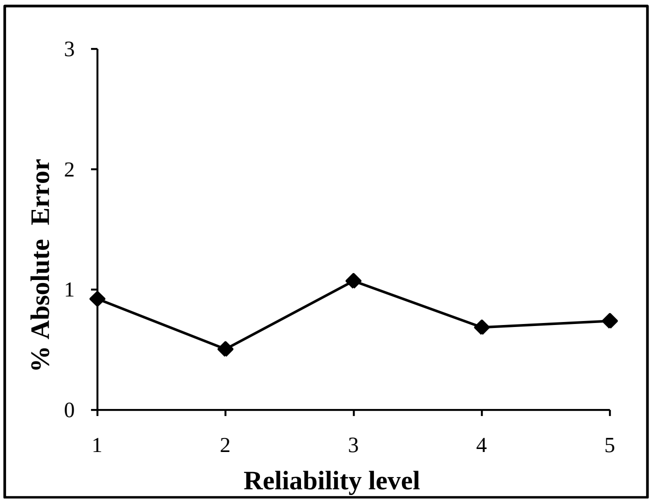

Fig.3. Error characteristics of EENS index for RBTS system

The annualized system indices evaluated by this approach are presented in Table.2. It also gives the comparison of the evaluated indices with the results of non-sequential state sampling MCS with dc flow based state evaluation [23]. It is from Table.2 that indices estimated in this proposed approach are in close agreement with the conventional non-sequential MCS approach.

The performance of the proposed approach has been tested by carrying an error analysis with conventional non-sequential state sampling MCS for five different reliability levels with sample size of 50000 and spread factor of 0.15 for GRNN. The percentage absolute error is calculated for EENS index which is graphically shown in Fig.3.

4.2 CASE 2: IEEE – RTS SYSTEM

For IEEE–RTS system [22] consists of 24 buses, 38 transmission lines and 32 generators with 10 of the buses connected to generators. The total peak load for the system is 2250 MW while the total generating capacity is 3405 MW. Only peak load levels were used for the purpose of this study. The sample size is set to 10000 for non-sequential state sampling which is used by Jonnavithula [23] for estimating indices in non-sequential MCS. The total number of components in the system is 70 and number of buses having loads is equal to 17. The neural network has 70 neurons in the input layer and 17 neurons in the output layer. Network is simulated for different values of spread and the most suitable value for IEEE-RTS system is selected based on the performance. This best performance for this network is achieved with spread factor of 0.18. The training data is formed from the initial 5000 samples simulated in state sampling non-sequential MCS.

Table.3. Annualized load point indices for base case with GRNN state adequacy evaluation (IEEE-RTS)

Bus No.	LOLP	LOLE hr/yr	EDNS MW	EENS MWhr/yr
1	0.0023	20.0928	0.087319	762.817
2	0.0079	69.0144	0.326996	2856.640
3	0.0492	429.8112	0.274542	2398.402
4	0.0083	72.5088	0.243024	2123.059
5	0.0054	47.1744	0.182078	1590.634
6	0.0079	69.0144	0.535145	4675.023
7	0.0083	72.5088	0.309355	2702.521
8	0.0093	81.2448	0.644181	5627.561
9	0.0001	0.8736	0.012444	108.714
10	0.0001	0.8736	0.021791	190.370
13	0.0307	268.1952	2.371307	20715.740
14	0.0003	2.6208	0.001683	14.706
15	0.0126	110.0736	0.968338	8459.402
16	0.0171	149.3856	0.647123	5653.264
18	0.0513	448.1568	7.082387	61871.729
19	0.0173	151.1328	0.815171	7121.337
20	0.0094	82.1184	0.413672	3613.841

The annualized load point indices evaluated for all 17 load points by this approach are presented in Table.3. It is inferred that load point 18 has highest probability of failure with 61871.729 MWhr of expected energy not supplied per year. The annualized system indices evaluated in this approach with sample size of 10,000 are shown in Table.4. The results are compared with the results of conventional non-sequential MCS approach [23]. It is from the results, the indices estimated in the proposed approach are nearer with the results of conventional non-sequential MCS.

Table.4. Comparison of Annualized system indices (IEEE-RTS)

Approach	LOLE	LOLE hr/yr	EDNS MW	EENS MWhr/yr
MCS-GRNN	0.08491	741.7737	14.9365	130485.76
MCS-state sampling [23]	0.08580	749.5488	14.9724	130799.00

The performance of the proposed approach has been tested by carrying an error analysis with conventional non-sequential state sampling MCS for different reliability levels with fixed sample size of 10000 and spread factor of 0.18 for GRNN model. The neural network formed with the training patterns obtained in initial samples for base reliability level is used in evaluating the test functions of sampled states.

The suitability of the proposed approach is tested by evaluating the reliability indices for five different sets of reliability parameters. The absolute error in estimating the EENS index results from the error analysis with conventional non-sequential state sampling MCS of 10000 samples and five different reliability levels is presented in Fig.4.

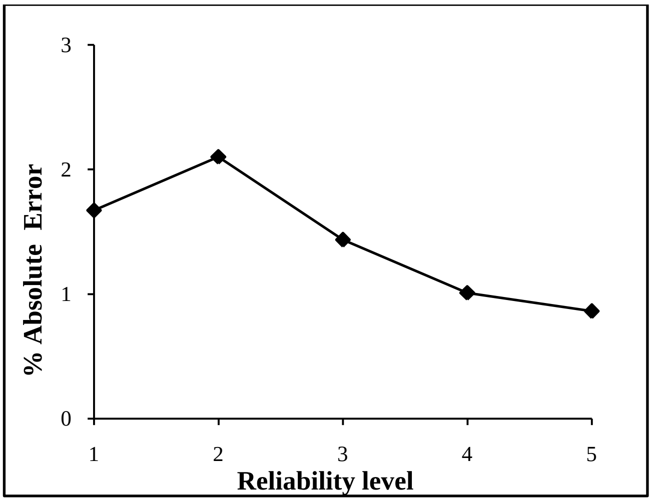

Fig.4. Error characteristics of EENS index for IEEE-RTS system

State adequacy evaluation to calculate the test functions is an essential step in composite system reliability analysis which requires huge computational requirement. In reliability optimization several alternate reliability levels are analyzed, requires the calculation of test functions for large number states of the same system which is in the order of several millions. It is inferred from Table.2 & Table.4 and Fig.2 & Fig.3, the GRNN approach has the ability to evaluate the test functions for sampled states similar to the dc load flow based load curtailment model. So the computational difficulty in solving the load curtailment optimization model for several million times can be effectively avoided for both success and failure states, especially for reliability optimization by using the proposed GRNN approach. The methodology given in reference [15] eliminates the optimization procedure only for success states.

5. CONCLUSION

This paper presented a GRNN approach for state adequacy evaluation of the sampled state in calculating the test functions for composite system reliability indices evaluation. In conventional MCS based reliability analysis, dc load flow based load curtailment minimization model has been solved for large number of sampled states and in reliability optimization the number of states sampled is in the order of several millions. The prediction of GRNN is used in calculating both the loss of probability and power not served test functions for both success and failure states.

The proposed GRNN approach has been tested on standard RBTS and IEEE-RTS systems. Simulation results show that the indices evaluated are similar to the conventional non-sequential MCS approach. This proves the suitability of GRNN approach for state adequacy evaluation where GRNN effectively predict the test functions similar to load curtailment minimization model. By utilizing the GRNN model several million numbers of optimization procedure required for state adequacy evaluation can be avoided. There by the proposed approach simplifies the composite system reliability evaluation by reducing the computational effort required for the state adequacy evaluation mainly in reliability optimization.

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