Reliability analysis in distribution system by deep belief neural network

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Article Info

Article history:

Received Mar 26, 2023
Revised Sep 4, 2023
Accepted Oct 11, 2023

Keywords:

Artificial neural network
Computation complexity
Deep belief neural network
Feed forward neural network
Particle swarm optimization
Power quality

ABSTRACT

Rapid increase in the usage of intermittent renewable energy, ongoing changes in electrical power system structure and operational needs posing growing problems while ensuring adequate service reliability and retaining the quality of power. Power system reliability is a pertinent factor to consider while planning, designing, and operating distribution systems. utilities are obligated to offer their customers uninterrupted electrical service at the least cost while maintaining a satisfactory level of service quality. The important metrics for gauging the effect of distributed renewable energy on distribution networks is reliability analysis. Reliability analysis in distribution systems involves evaluating the performance and robustness of electrical distribution networks. An artificial intelligence approach is implemented in this paper to improve reliability analysis with dispersed generations in distribution network. Deep belief neural networks (DBNNs) are a type of artificial neural network that can be used for various tasks, including analyzing complex data such as those found in power distribution systems. This paper integrated a DBNN using a particle swarm optimization (PSO) technique. The proposed model performance is assessed using mean square error, mean absolute error, root mean square error, and R squared error. The findings reveal that reliability analysis with this novel technique is more accurate.

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1. INTRODUCTION

The main objective of the power system is to provide its consumers with consistent electricity as affordably as feasible. Power distribution systems (PDS) have gained less attention in the past than in comparison with transmission and distribution [1]. Since both generation and transmission networks need significant investment, their insufficiency might have negative effect on social and environmental aspects. However, a distribution system is substantially less costly. According to customer failure statistics from major utilities, the maximum unavailability of electrical power to consumers is due to distribution system outages. Currently, deregulation is driving electric utilities to modify their former prospects. Therefore, the focus has turned to distribution networks in the new age of deregulation to deliver a reliable and cost-effective service to clients in the system. To make decisions, particularly those involving planning, operation, and maintenance, it is critical to investigate and assess the reliability of power system networks

[2]. Power utilities are obligated to offer their customers uninterrupted electrical service at the least cost while maintaining a satisfactory level of power quality and reliability. Quantifying, predicting, and comparing reliability indices for various reliability improvement programs and network topologies is the primary goal of reliability analysis. The reliability assessment may be used to determine which distribution system components are malfunctioning and need to be replaced right once, as well as to suggest how many new components should be added to increase network reliability [3]. Because of these technical and economical attributes, the reliability approach is acknowledged as a standard for design and operation of the power system in all the phases [4]. The ability of a system to meet consumer requests is encompassed by the broad idea of reliability. Reliability analysis approaches for power distribution networks are often divided into four categories: analytical methods, simulation methods, hybrid methods, and artificial intelligence algorithms.

Analytical procedures assess the reliability indices using straight forward mathematical solutions and portray the system as a set of simplified mathematical models obtained from mathematical equations [5], [6]. Some of the commonly employed techniques are “block diagram, event tree, cut set, fault tree, state enumeration, Markov modelling, and failure effect analysis”. Although using reliability sets in the calculation has appeared in recent years, the fact of making assumptions and using approximation are still major problems of these approaches [7], [8]. The analytical approach takes less time than simulation, it encounters a problem accurately portraying repair time. This method is predicated on statistical hypotheses about the distribution of failure rates and repair times. Simulation method is the most versatile among all, but it has a high processing cost and a high degree of accuracy uncertainty. This approach simulates the system's stochastic behavior and real process to determine the reliability indices. As a result, the technique approaches the issue as a collection of genuine experiments carried out in a time-simulated environment. By counting the instances of an event, it evaluates the frequency of the events and other indices [9]–[14]. The combination of both will be of hybrid method has been considered [15], [16]. Several academics have used artificial intelligence in research in recent years [17]–[21]. Deep learning algorithms, genetic algorithms, particle swarm optimization (PSO) algorithms, and other intelligence techniques are used for distribution network reliability assessments [22]–[26].

In this paper a novel technique based on PSO deep belief neural network (DBNN) has been developed for evaluating and analyzing the distribution network reliability. This is accomplished by the effective use of optimized deep belief network (DBN) model with powerful automatic features extraction function and characteristic features were absorbed from original data, resulting in satisfactory outcomes. Within a brief time frame, the trained PSO-DBN model can assess the reliability of distribution system with 50% less number iteration and 24% reduced mean squared error than in comparison with DBN technique.

2. METHOD

The most widely used artificial intelligence approach is the deep learning algorithm. The study of distribution systems (DS) reliability is a multi-dimensional, complex regression problem. Layer-by-layer learning allows a DBN to absorb feature specifics from huge amount of data. Figure 1 depicts the layered restricted boltzmann machines (RBMs)-based DBN model. An RBM is a model based on undirected energy with visible (v) and hidden (h) layers. The contrastive divergence technique is used to train each RBM module unsupervised and one at a time. The output from each step is sent into the following RBM stage as an input. Subsequently, the whole network is trained using supervised learning to improve classification performance.

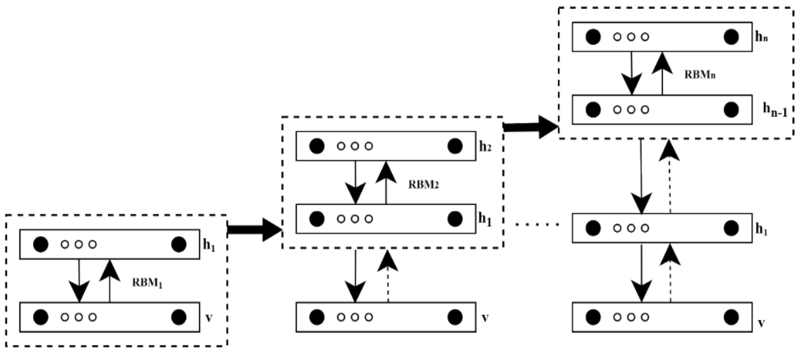

Figure 1. Deep belief architecture

The DBN approach uses layer-by-layer learning in discovering a specific correlation to accomplish the objective of analysis. The same combination of PSO-DBN has been implemented in enhancing power quality of the distribution [27], [28]. The scientific contribution of this approach is tried to implement for reliability analysis in DS which provides more accurate results. This finding may be used in lowering the distribution network's failure rate in reduced time required for troubleshooting, enhancing the distribution network's reliability.

DBNNs can learn complex patterns, their interpretability helps in understanding how the model arrives at specific predictions. It is crucial, especially in critical applications like power system reliability. DBNNs for modelling the relationships and patterns within a power distribution network, especially considering the impact of dispersed generation sources on power system reliability. The approach includes data collection, data processing, feature engineering, model training, integration of dispersed generation impact, validation and testing, and performance evaluation.

3. PSO-DBN IMPLEMENTATION FOR RELIABILITY ANALYSIS

An improved DBN model is created for analyzing the reliability of a network in DS. The total procedure is divided into three stages. Throughout these stages, best practices in machine learning, such as data preprocessing, cross-validation, and model evaluation has been followed and periodically retraining and updating of DBN model has been done as the distribution system evolves.

3.1. Training

The DBN training technique consists of pre-training and reverse fine-tuning. In first stage the input and hidden layers will have n and m nodes, respectively. The visible layers with node state are vi, while the hidden layers jth node state is hj. In (1) expresses the energy function formulation for a particular RBM state:

$$E\,(v, h; \theta)=-\sum_{i=1}^{n}\sum_{j=1}^{m} Wij\ Vi\ hj - \sum_{j=1}^{m} bj\ hj - \sum_{i=1}^{n} ai\ vi \quad (1)$$

Where W_{ij} is weight of the link between nodes, v_i and h_j, a_i, b_j are the biases, $\theta=\{\omega, a, b\}$ is RBM parameter. Contrastive divergence (CD) technique is used for pre-training. Reverse fine tuning is carried out by back propagation method is used to reverse fine tuning. To fulfil the criteria of convergence speed in various iteration times, the magnitude of parameter modification must be large enough to increase training and learning efficiency.

3.2. Optimization

DBN optimization has been carried out by the PSO technique. According to PSO, the population is updated for each iteration and verified for convergence with the objective function. In (2) and (3) yield the velocity and location of each particle:

$$V_{ij}\,(t+1)=\omega V_{ij}\,(t)+C_1\,r_1\,(P_j\,(t)-X_{ij}\,(t))+C_2\,r_2\,(g_j(t)–X_{ij}\,(t)) \quad (2)$$

$$X_{ij}\,(t+1)=X_{ij}\,(t)+V_{ij}\,(t+1) \quad (3)$$

Where r_1 and r_2 are random numbers, C_1 and C_2 are acceleration coefficients, V_{ij} (t) is velocity, ω is inertia weight, r_1c_1 (P_{ij} (t)-X_{ij} (t)) are cognitive component, and r_2c_2 (g_j(t)–X_{ij} (t)) are social component.

3.3. Designing

The following approaches are used to optimize DBN using PSO for reliability analysis:

Step 1: the reliability analysis index of deep neural (DN) is provided.

Step 2: the DBN's network parameters are initialized by feeding it training data.

Step 3: DBN models are optimized using PSO once they have been trained

a. To represent each particle in a population, encode the weights and thresholds between neurons into a real number vector.
b. Compute the fitness value of each particle, with best location, and initiate iteration.
c. Updating particle position and velocity.
d. Change inertia weights of the particle based on its fitness value.
e. If the maximum number of iterations has been reached, the iteration concludes; otherwise, the search for the best particle location continues.
f. To optimize DBN, the PSO technique is used.

Step 4: analyses of reliability samples utilizing an optimized DBN.

Step 5: power distribution network reliability be calculated and analyzed.

PSO can be employed to optimize the parameters of a DBN: the goal is to minimize the objective function (error between the predicted outputs of the DBN and the actual targets). Each particle in the PSO population represents a candidate solution, which corresponds to a set of parameters for the DBN (weights and biases). Where, population of particles with random positions and velocities were initialized. The fitness of each particle based on the DBN's performance with the corresponding parameters were evaluated. Each particle maintains its personal best position. Based on the best-performing particle in the entire population, the global best position is updated. The position of each particle based on its current position and velocity is updated and steps must be repeated until a convergence criterion is met.

4. PERFORMANCE CHARACTERISTICS OF THE MODEL

The performance of regression model can be evaluated by the following error matrices, each of these error metrics provides different insights into the performance of your regression model. Mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) gives information about the accuracy and precision of your predictions, while R^2 provides information about the goodness of fit. It's common to use a combination of these metrics to thoroughly evaluate a regression model's performance and understand its strengths and weaknesses.

a. MAE is the average absolute difference between observed and predicted values can be measured from MAE.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i| \tag{4}$$

b. MSE is the squared difference between actual and predicted value.

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{5}$$

c. RMSE is the square root of MSE. Taking square root to MSE returns it to the same level of prediction error.

$$\text{RMSE}=\sqrt{(\frac{1}{n}\sum_{j=1}^{n}(Y_i - \hat{Y}_i)^2)} \tag{6}$$

d. R square is the square of the correlation coefficient is R square (R). R square is calculated by dividing the total of squared prediction error by the full sum of the square, which replaces the computed forecast with mean.

$$R^2=-\frac{ss_{Regression}}{ss_{Total}}=1-\frac{\sum_i(Y_i-\hat{Y}_i)^2}{\sum_i(Y_i-\bar{Y}_i)^2} \tag{7}$$

5. RESULTS AND DISCUSSION

A 16-bus system is taken for reliability analysis, the input data is given in Table 1. T is the matrix of dimension 17x17 which provides the topology of the line with line sectionalized and the switch in the connection. Failure rate matrix is 17x17. Total inputs that are taken for the prediction algorithm include 37 inputs. After data pre-processing the input data is reduced to the size of 24 inputs. Reliability indexes that define the degree of reliability in the 16-bus system are taken for different combinations of disconnection of the line. Around three lines are removed to get the reliability indexes for disconnection.

5.1. Steps followed for evaluation of reliability indices

From the reliability analysis code input and output data are prevailed. The steps involved in the code for a 16-bus system are:

a. Get the topology that has been updated
b. Select three lines to be broken
c. Breaking the line from FL1 (choose from 4, 5, 8, 9, 11, 17)
d. Breaking the line from FL2 (choose from 8, 10, 14, 18)
e. Breaking the line from FL3 (choose from 4, 6, 7, 15, 16, 19)
f. Troubleshooting for two additional tie switches (line 5)

g. If l4 is down, the route should be allowed to transit from node 5 to node 6, but not vice versa.8. Select first available point into path 1 and store as the beginning of branch
h. Select second available points to path3, and store as the beginning of branch
i. Repeat 7, 8, and 9, for all three paths
j. Create a matrix of unavailability
k. Locate the sectionalizer
l. Check = 1 - the nearest sectionalizer if found
m. Check = 0 - not yet
n. Analyse Unavailable Time for other lines
o. Find modified failure rate matrix
p. Find unavailability matrix
q. Find SAIFI, SAIDI, CAIDI, ENS
r. Taking failure matrix and unavailability matrix as the input and SAIFI SAIDI CAIDI ENS as the output the DBN is trained

Co-linearity is applied to the pre-processed data, resulting in the density plot shown in Figure 2. The usage of density graphs is another method for quickly grasping the distribution of each attribute.

Table 1. Input data

Line number	Start bus	End bus	Failure rate
1	1	2	0
2	1	3	0
3	1	4	0
4	2	5	3.5
5	5	6	3
6	5	7	1.5
7	7	8	3.5
8	3	9	1.1
9	9	10	2.8
10	9	11	1.1
11	10	12	0.8
12	10	13	2
13	4	14	0.5
14	14	15	1
15	14	16	1.5
16	16	17	4.4
17	6	12	4
18	11	15	5
19	8	17	1

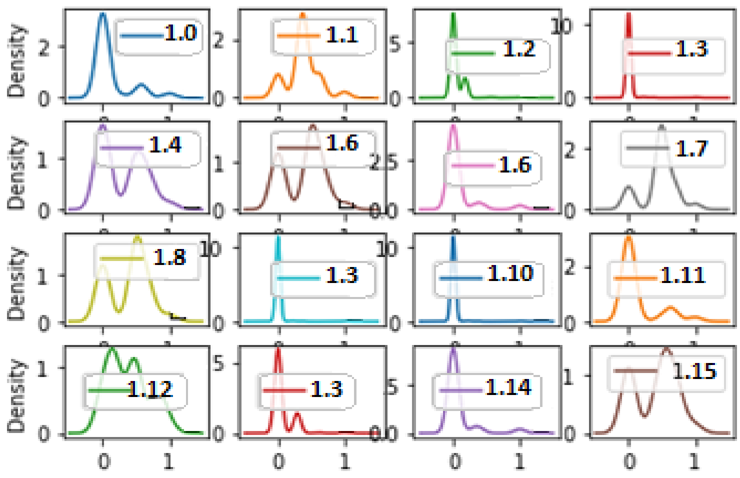

Figure 2. Density graphs

Total number of data pair datanum is 145, number of output nodes outputnum is 4, total number of hidden layers hidden num is 3, nodes structure: nodes is [16 16 16 4], and random generation of the DBN structure using the function rand DBN.

5.2. Restricted version of the boltzmann machine

Boxplots represent the distribution of each characteristic by drawing a box around the 25th and 75th percentiles and a line around the median. The dots outside of the whiskers indicate possible outlier values, while the whiskers themselves provide a notion of the data spread. Figure 3 shows RBM, the restrictions in the RBM architecture simplify training and make RBMs computationally more tractable than general Boltzmann machines. These characteristics make RBMs a useful tool in unsupervised and deep learning tasks, especially in cases where capturing complex dependencies in data is essential.

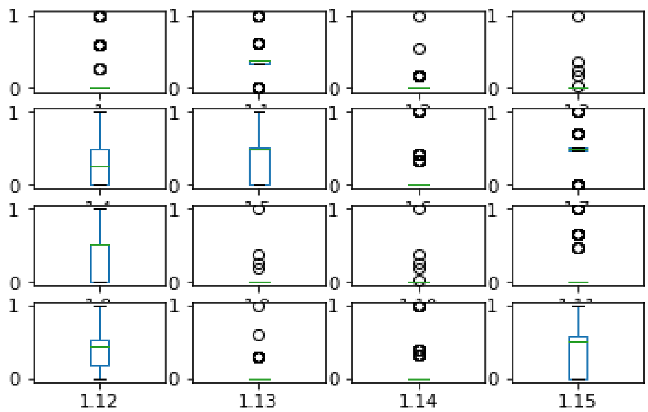

Figure 3. RBM

Using one axis for each characteristic, a scatterplot displays the relationship between two variables as dots in two dimensions. For identifying organized correlations between data, scatter plots are beneficial. Structured connection attributes may also be associated and make suitable candidates to be dropped from dataset.

5.3. Representation of performance parameters

Machine learning model requires an evaluation to check the model correctness. "MSE, MAE, RMSE, and R-squared" are used in regression analysis to assess the effectiveness of the model. Test set data samples are utilized to test the DBN and PSO-DBN models correspondingly. Figures 4 and 5 illustrate MSE plots on DBN and PSO-DBN. Mean square error for every iteration is as given in the following graph for DBN implementation. Since MSE is the convergence standard for every iteration the mean square error function is reduced in run for 300 iterations to make it settled at 0.009 as MSE.

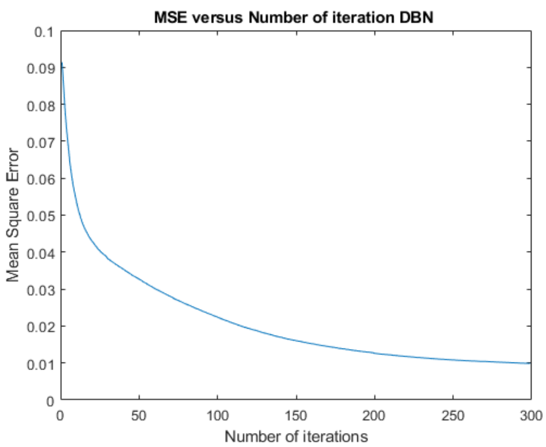

Figure 4. MSE plot for DBN with the number of iterations

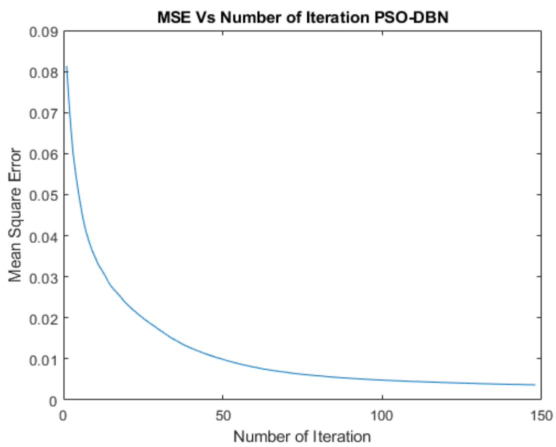

Figure 5. MSE plot for PSO-DBN with the number of iterations

For a DBN implementation the learning factors involving the shape of the RBM and the parameters are not decided manually. Considering the amount of effort involved in setting the RBM parameters, the PSO optimization for the parameter optimization. Learning rate is optimized to obtain better performance characteristics for the DBN learning process.

Figure 6 shows the convergence plot of PSO-DBN implementation. Learning factor is used as the stochastic variable that is used for optimizing the DBN implementation. It can be observed that within 150 iterations the PSO-DBN has converged that too to a very low value of .002457. Although the conventional DBN method converged at 300 iterations represented in Table 2.

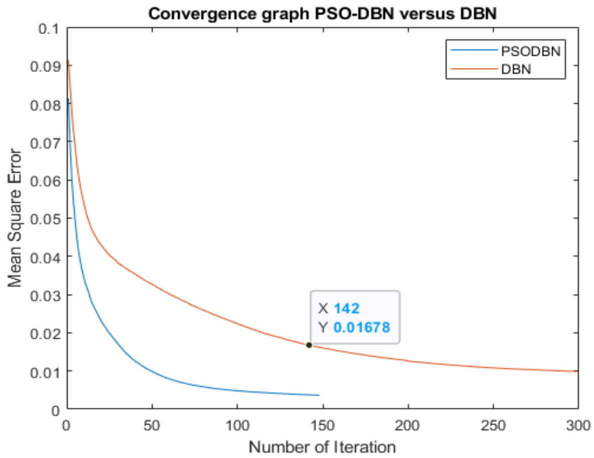

Figure 6. Comparative convergence graph DBN and PSO-DBN

Table 2. Comparative analysis

SL No.	Method	Number of iterations	MSE
1	DBN	300	0.09
2	PSO-DBN	142	0.002457

The performance parameters such as MSE, MAE, MSE, R^2 are used to assess the effectiveness of the model in regression analysis using DBN and improved DBN, as shown in Table 3. A regression model with lower MAE, MSE, and RMSE values is more accurate. In contrast, a greater R square value is deemed advantageous.

Table 3. Comparative analysis of convergence criteria of various performance parameters

		Performance parameters			
		MSE	MAE	RMSE	R-squared
Convergence criteria	DBN	0.008188	0.047360	0.21762	0.913874
	PSO-DBN	0.002457	0.01398	0.04960	0.936669

6. CONCLUTION

A novel technique based on PSO-DBN has been developed for evaluating distribution network reliability. This is accomplished by the effective use of optimized DBN model with powerful automatic features extraction function and the characteristic features may be directly absorbed from original data, resulting in satisfactory outcomes. The reliability of power distribution networks may also be investigated using an optimized DBN model, which can then be used on a variety of grid configurations in distribution networks. Within a brief time, frame, the trained PSO-DBN model can assess the reliability of the power distribution network. This research introduces a unique AI approach for reliability analysis in distribution networks, that increases the precision of reliability analysis findings for power distribution networks.

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