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Reliability Analysis of Power Distribution Network Based on PSO-DBN

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ABSTRACT The main problem dealt with in this paper is to find a method to improve the performance of the reliability analysis of power distribution networks. With the help of deep learning, which has the characteristics of large-scale parallel processing and self-learning, a deep belief network (DBN) simulation model for power distribution network reliability analysis is established. After training RBM layer by layer and extracting feature information from complex data, DBN model parameters are adaptively adjusted by particle swarm optimization (PSO) algorithm. The results of power distribution network reliability analysis based on PSO-DBN model is compared with those of Monte Carlo model. In order to evaluate the performance of the proposed model, the coefficient R^2, the mean absolute error and the root mean square error are used to evaluate the model. The results show that the reliability analysis model based on PSO-DBN is more accurate, and the reliability analysis efficiency of the trained PSO-DBN model is higher, which to some extent proves the superiority of applying deep neural network to the reliability analysis of distribution network.

INDEX TERMS DBN, Power distribution network, PSO-DBN, RBM

I. INTRODUCTION

The power distribution network is an essential part of the power system, and its wide range and complex structure have a significant impact on reliability. Therefore, it is of considerable significance to study fast and accurate power distribution network reliability analysis methods [1]. Power distribution networks reliability analysis methods usually include three categories: analytic reliability algorithm, simulation methods, and artificial intelligence methods [2].

The classical analytical methods of reliability of power distribution network include failure mode analysis method [3-4], minimum cut set method [5-7], network equivalent method [8-10], state-space method [11], Bayesian algorithm [12-13] and feeder analysis algorithm [14-15]. Among them, failure mode impacted analysis methods are more commonly used. However, with the complexity of the network structure increases, the difficulty of reliability analysis also increases, which leads to the problem of large amount of calculation and slow speed[16].

Monte Carlo simulation is a method with high accuracy in the traditional method, which has been studied by many scholars [17]. The Monte Carlo simulation method obtains the reliability index value by simulating the failure process of components and counting the number of network failures of the simulation times[18]. For example, Goal L. recommend a compromise parameter selection method, which not only considered the speed and accuracy of the analysis but also studied the impact on the compromise parameters on the reliability analysis accuracy [19-20]. To improve the simulation efficiency of the Monte Carlo method, Ding Ming adopted an improved control variable method to reduce the error [21].

In recent years, many scholars have introduced artificial intelligence into the study of power systems[22]. Artificial intelligence methods for distribution network reliability analysis includes deep learning algorithm, genetic algorithms, particle swarm optimization algorithms and so on[23]. Deep learning algorithm is the most commonly used method of artificial intelligence[24]. The DBN model in deep learning has been widely used in power distribution network fault diagnosis and other fields. The SVM algorithm in the artificial intelligence algorithm is a classification algorithm. In the existing research, the support vector machine (SVM) algorithm is often used to solve the classification problem [25]. PSO is a random search algorithm that finds the best global solution by simulating the foraging behavior of birds, which is very effective for finding the global optimal solution[26].

Deep neural network models have the structural characteristics of hidden layers stacked one by one, and each layer extracts different data features as the input of the next layer [27]. Through the non-linear relationship between input and output, low-level features can combine with high-level abstract representation. Currently, DBN has been successfully applied to solve many problems, such as dimension reduction [28], classification [29], and information retrieval [30-31].

Distribution system reliability analysis is a complex, high-dimensional regression problem. DBN can extract feature information from massive and complex data through layer-by-layer learning[32]. The DBN algorithm uses the advantages of layer-by-layer learning to seek a certain correspondence, and ultimately achieves the purpose of analysis[33]. The structural characteristics and training characteristics of the DBN have obvious advantages for solving the complex regression problem of the power distribution system[34-35]. Therefore, this paper proposes a method of applying PSO-DBN to the reliability analysis of distribution networks.

The main scientific contributions of this article are: Firstly, applying PSO-DBN to the reliability analysis of distribution network can obtain more accurate distribution network reliability analysis results. This result can guide troubleshooting of the distribution system, which can not only reduce the failure rate of the distribution network, but also reduce the time for troubleshooting, thereby increasing the reliability of the distribution network.

Secondly, compared with the Monte Carlo method, the trained PSO-DBN model takes less time to analyze the reliability of the power distribution network.

Thirdly, the PSO-DBN reliability analysis method proposed in this paper can analyze the reliability of different grid structure of power distribution network.

The main structure in this article is: The part Ⅱ mainly introduces the application of optimized DBN in reliability analysis of power distribution network; The part Ⅲ introduces the experimental simulation of applying PSO-DBN to power distribution network reliability analysis; The part Ⅳ describes the comparison process of the PSO-DBN method proposed in this paper with Monte Carlo model.

Ⅱ. PSO-DBN APPLICATION IN POWER DISTRIBUTION NETWORK

This paper uses a deep belief network model formed by layer-by-layer stacking of several restricted Boltzmann machines (RBM) for reliability analysis of power distribution networks. Each RBM consists of a visible layer and a hidden layer. RBM has the robust unsupervised learning ability and can automatically extract the complicated rules of the sample [36-37].

In this paper, an optimized DBN model is designed for the reliability analysis of power distribution networks. The overall process includes three parts: the DBN training process, optimization of DBN using particle swarm optimization, and the design of reliability analysis of power distribution network using optimized DBN.

A. THE DBN TRAINING PROCESS

The DBN training process can be divided into two parts: pre-training and reverse fine-tuning[38].

1) PRE-TRAINING

Let n and m be the number of nodes in the input layer v and the hidden layer h, respectively. v_i represents the ith node state of the visible layer; h_j represents the jth node state of the hidden layer. Then, the energy function expression of a given state (v, h) of RBM is:

$$E(v,h;\theta) = -\sum_{i=1}^{n}\sum_{j=1}^{m} W_{ij} v_i h_j - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n} a_i v_i \tag{1}$$

Where θ={ω, a, b} is the parameter of RBM, and W_{ij} is the link weight between nodes v_i and h_j, a_i ,*and* b_j are their biases[39]. According to the above energy function formula, the joint probability distribution $P(v,h;\theta)$ of the hidden layer and the visible layer can be defined as:

$$P(v,h;\theta) = \frac{1}{Z(\theta)}\exp(-E(v,h;\theta)) \tag{2}$$

In the formula (2), Z is the normalization factor, and its expression is:

$$Z(\theta) = \sum_{v,h} e^{-E(v,h;\theta)} \tag{3}$$

The status of the visible layer and the hidden layer is updated as follows:

$$P(h_j = 1|v) = \frac{1}{1+e^{(-\sum_i W_{ij}v_i - a_j)}} \tag{4}$$

$$P(v_i = 1|h) = \frac{1}{1+e^{(-\sum_j W_{ij}h_j - b_i)}} \tag{5}$$

During pre-training, the visible layer v_1 and the hidden layer h_1 are used to form RBM_1 to be trained. Then, h_1 is regarded as the visible layer v_2, and the hidden layers h_2 and v_2 form RBM_2. The hidden layer of RBM_2 is regarded as the visible layer of RBM_3, and so on until all RBM training ends.

During the DBN pre-training process, the contrastive divergence (CD) algorithm is used for layer by layer training. The process of the CD algorithm can be divided into four steps. The first step is to use the training data as the state variables of the visible neurons; The second step is to calculate the state variables of hidden layer neurons according to formula (4); The third step is to use formula (5) to get the binary probability of the visible layer neurons so that the reconstructed result of the visible layer can be calculated; In the fourth step, the gradient descent algorithm is used to optimize the objective function to obtain the updated formulas of the parameters w_{ij}, a_i, and b_j:

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$$\Delta\omega_{ij} = \varepsilon(\langle v_i h_j \rangle_{P(h|v)} - \langle v_i h_j \rangle_{recon}) \tag{6}$$

$$\Delta a_i = \varepsilon(\langle v_i \rangle_{P(h|v)} - \langle v_i \rangle_{recon}) \tag{7}$$

$$\Delta b_j = \varepsilon(\langle h_j \rangle_{P(h|v)} - \langle h_j \rangle_{recon}) \tag{8}$$

Where ε is the learning rate, $\langle\bullet\rangle_{P(h|v)}$ is the expected value of the partial derivative under the sample data distribution $P(h|v)$, $\langle\bullet\rangle_{recon}$ is the expectation of the partial derivative under the reconstructed model distribution.

2)FINE-TUNE

The DBN training is a supervised process and the BP algorithm is adopted to reverse fine-tune [40]. The magnitude of parameter adjustment must not only meet the requirements of convergence speed in different iteration times but also improve training and learning efficiency. This problem can be transformed into a model for optimal solutions to mathematics.

Set weight and biases as a parameter θ , and the parameter update formula is as follows:

$$\theta(\omega,a,b)^{(T+1)} = \theta^{(T)} - \lambda\frac{\partial(\theta^{(T)})}{\partial\theta} \tag{9}$$

Where, T is the number of iterations, $\theta=\{\omega,a,b\}$, λ is the learning rate, Parameter adjustment is performed along the negative gradient direction[41].

The combination of supervised and unsupervised algorithms not only improves the accuracy of power distribution network reliability analysis based on deep belief networks, but also helps to improve the learning speed and efficiency of deep models.

B. OPTIMIZATION OF THE DBN USING PSO

In the PSO optimization process, all particles search for targets for multidimensional space, and all particles use the fitness value to judge the current position. The error function is taken as the fitness function of PSO. The optimization process of PSO-DBN is shown in Fig.1. Each particle has a memory function to remember the search for the best location, and each particle also has the speed to determine the distance and direction of flight [42,43]. According to formulas (10) and (11), the speed and position of the particles are continuously updated until the best solution of the particles that meet the conditions is found.

$$V_{ij}(t+1)=\omega V_{ij}(t)+C_1\bullet R_1\bullet(P_j(t)-X_{ij}(t))+C_2\bullet R_2\bullet(G_j(t)-X_{ij}(t)) \tag{10}$$

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{11}$$

Where, $j=1,2,\ldots,d$, t is the number of iterations; $X_{ij}(t)$ is the current position of the tth generation of particles; $V_{ij}(t)$is the speed of the tth generation of particles; ω is the inertia weight, which keeps the particles moving inertia. C_1 and C_2 are acceleration factors, which are respectively used to adjust the maximum flight step length of the global optimal particles and individual optimal particles, R_1 and R_2 are random numbers in the interval [0,1].

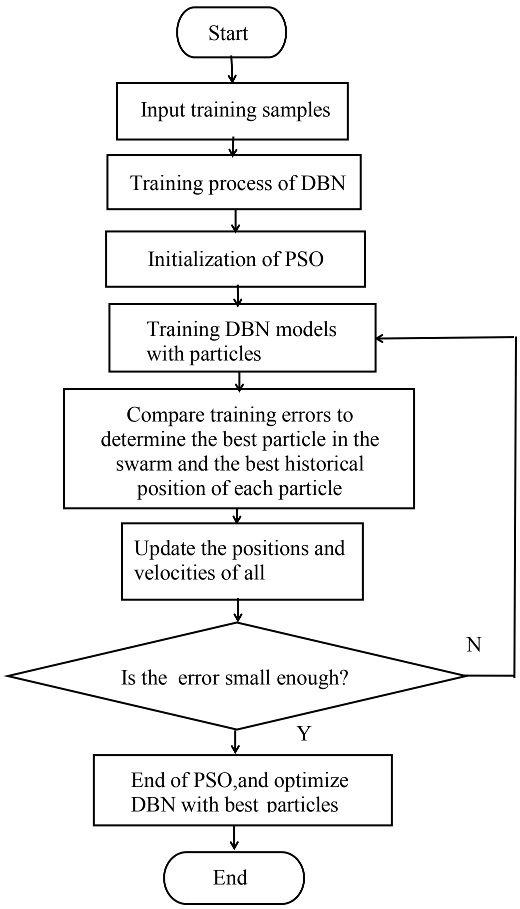

FIGURE 1. **The flow chart of the optimization DBN using PSO.**

C.GENERAL PROCEDURE FOR RELIABILITY ANALYSIS OF POWER DISTRIBUTION NETWORK USING THE PSO-DBN

The general steps for optimization DBN using PSO on power distribution network reliability analysis is as follows:

Step 1: The reliability analysis index of the power distribution network is given.

Step 2: The training data is input into the DBN network, and the network parameters of the DBN are initialized.

Step 3: After the DBN model is trained, PSO is used for DBN optimization:

(1) Encode the weights and thresholds between neurons into a real number vector to represent individual particles of the population, and initialize the speed and initial position of the particles.

(2) Calculate the fitness value of each particle, find the

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historical best position of each particle, and start iteration.

(3) Update the position and velocity of the particles.

(4) Change the particle's inertia weights according to the fitness value of the particle, and search for the best particle position.

(5) If the maximum number of iterations are reached, the iteration ends and the final weights and thresholds are output, otherwise the search continues for the best particle position.

(6) Use particle swarm optimization algorithm to optimize DBN.

Step 4: Analysis of reliability samples using optimized DBN.

Step 5: Calculate the reliability of the power distribution network and analyze the results.

Ⅲ. EXPERIMENTAL SIMULATION

Based on the reliability index of the power distribution network SAIFI, CAIDI, SAIDI, and ASAI, the accuracy and reliability of the PSO optimized DBN method will be verified.

A. EVALUATION INDEX OF DISTRIBBUTION NETWORK

The System average interruption frequency index (SAIFI) is the average number of power failures of each user power supplied by the system in each unit time. It can be calculated by the ratio of the number of user power outages in the year to the total number of power users:

$$\text{SAIFI}=\frac{\sum \lambda_i N_i}{\sum N_i} \tag{12}$$

where λ_i is the failure rate, and N_i is the number of users at the load point i. Customer average interruption duration index (CAIDI) is the average number of power outages per unit of time experienced by each affected customer. It can be calculated by the ratio of the duration of the user power outage to the total number of power outage users during the year:

$$\text{CAIDI}=\frac{\sum U_i N_i}{\sum \lambda_i N_i} \tag{13}$$

Where U_i is the annual outage time. The System average interruption duration index (SAIDI) is the average outage duration experienced by each user powered by the system during a year. It can be calculated according to the ratio of power outage time of users to the total number of annual electricity users:

$$\text{SAIDI}=\frac{\sum U_i N_i}{\sum N_i} \tag{14}$$

The average power supply availability index (ASAI) represents the ratio of the number of uninterrupted hours in a year to the total hours of power supply required:

$$\text{ASAI}=\frac{(\sum N_i \times 8760 - \sum U_i N_i)}{\sum N_i \times 8760} \tag{15}$$

B. THE EVALUATION INDEX OF THE MODEL

The Mean Absolute Percentage Error (MAPE), Root Mean Square Error(RMSE), and the coefficient of determination R^2 are selected as the evaluation models indicators. The R^2 factor is an important criterion when determining the fitness of a regression line. It can be obtained from formula (16) that the correlation coefficient is determined to be equal to the ratio of the sum of regression squares to the total amount of squares. R^2 is the square of the correlation coefficient R, which is also called the goodness of fit, and the closer R^2 is to 1, the better the goodness of fit is.

$$R^2=\frac{(\sum_{i=1}^{n}\hat{y}_i y_i-\sum_{i=1}^{n}\hat{y}_i\sum_{i=1}^{n}y_i)^2}{(\sum_{i=1}^{n}\hat{y}_i^{\,2}-(\sum_{i=1}^{n}\hat{y}_i)^2)(\sum_{i=1}^{n}y_i^2-(\sum_{i=1}^{n}\hat{y}_i)^2)} \tag{16}$$

Where (i = 1,2, ..., n) is the predicted value of the ith sample; y_i (i = 1,2, ..., n) is the true value of the ith sample; n is the number of test samples. The instructions are as follows:

(1) The smaller the relative error, the better the function of the model;

(2) 0 <R^2 <1, the closer the decision coefficient is to 1, the better the model function. Conversely, the closer to zero, the worse the function of the model.

MAPE represents the mean absolute percentage error, which can better reflect the actual situation of the error of the predicted value. RMSE represents the square root of the square to sample ratio of the predicted to true deviation. As shown in formulas (17) and (18):

$$MARE=\frac{1}{N}\sum_{t=1}^{N}\frac{|W_f-W_t|}{W_t}*100\% \tag{17}$$

$$RMSE=\sqrt{\frac{\sum_{t=1}^{N}(W_f-W_t)^2}{N}} \tag{18}$$

Where W_f is the predicted value of each sample point, and W_t is the true value of each sample point. N is the total number of data samples.

C. TRAINING PARAMETERS OF PSO-DBN MODEL

For the PSO-DBN model, the training parameters include the number of hidden layers, the number of neurons (nodes) in each hidden layer, and the number of training iterations. The setting of parameters will affect the training time, complexity, and convergence of the model and affect the accuracy of the model. Extensive experiments by Yoshua Bengio's research team show that multiple hidden layers perform better than a single hidden layer [44]. But in theory, there is no mature method to determine the optimal number of DBN hidden layers. In the simulation of this paper, a vertical comparison method (fixing other parameters when testing the effect of a parameter on the model) is used to achieve the optimal selection of parameters.

Three different test set samples were used to compare the accuracy of the DBN model with different hidden layers. Each test set contains 200 data samples. Table I shows the impact of different hidden layers on the DBN model. During the determination of the number of hidden layer layers, the number of hidden layer neurons is uniformly fixed at 512.

TABLE Ⅰ
THE EFFECT OF THE NUMBER OF HIDDEN LAYERS ON THE MODEL

Number of hidden layers	Average RMSE of test set 1	Average RMSE of test set 2	Average RMSE of test set 3
2	0.835	0.917	0.491
3	0.788	0.902	0.476
4	0.742	0.829	0.413
5	0.790	0.917	0.502

According to the table, as the number of hidden layers increases, the RMSE value of the test set decreases gradually, indicating that the accuracy of the DBN model is improved continuously. However, the DBN model effect of five hidden layers is worse than that of four hidden layers. Because although increasing the number of hidden layers will increase the fitting ability of the DBN model, too many layers will complicate the training process of the model and cause overfitting. Therefore, the number of DBN hidden layers is finally set to four.

TABLE Ⅱ. INFLUENCE OF THE NUMBER OF NODES IN THE HIDDEN LAYER ON THE MODEL

Number of nodes	Average RMSE of test set 1	Average RMSE of test set 2	Average RMSE of test set 3
64	0.973	0.957	0.632
128	0.906	0.931	0.583
256	0.824	0.897	0.511
512	0.742	0.829	0.413
640	0.793	0.904	0.537

The number of neurons in each hidden layer must be less than N-1 (N is the number of training samples), otherwise the network has no generalization ability and has no practical significance. From Table Ⅱ, as the number of nodes in the hidden layer increases, the average RMSE value of the test set gradually decreases. When the number of nodes reaches 512, the RMSE is the smallest and the result reaches the best. When the number of nodes is greater than 512, the error value increases, and the training time of the model increases. So first, the number of nodes in each hiddes layer is set to 512; The loss function is used to determine the number of RBM iterations. Then, PSO's automatic optimization function is used to adaptively adjust the DBN network parameters and automatically output the model parameters. The fitness curve of PSO is shown in Fig.2. When evolved to 23 generations, PSO starts to converge, and the best fitness individual can be found. The best DBN hidden layer network parameters are automatically output as [312, 524, 524,524]. Therefore, the number of neurons in the hidden layer is finally set to the type of rising firstly and then horizontal values, which is used for reliability analysis of power distribution network.

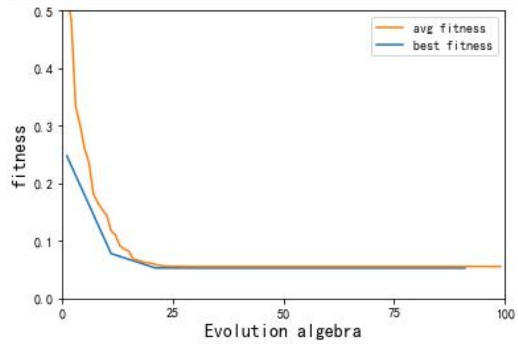

FIGURE 2. Fitness curve.

TABLE III
OPTIMIZATION PARAMETERS USED IN THE SIMULATIONS.

Description	Symbol	Value
The number of neurons in the input layer	–	209
The number of neurons in the output layer	–	4
The number of RBMs	–	4
Iteration number of each RBM	–	100
The number of neurons in the first hidden layer	h_1	312(given by PSO)
The number of neurons in the second hidden layer	h_2	524(given by PSO)
The number of neurons in the third hidden layer	h_3	524(given by PSO)
The number of neurons in the fourthly hidden layer	h_4	524(given by PSO)
Learning rate of the DBN	η	0.01(given by PSO)
Momentum of the DBN	α	0.5(given by PSO)
Acceleration factor of PSO	C_1,C_2	0.1，0.3
Population factor of PSO	N	100
Iteration number of PSO	M	110
Inertia weight of PSO	ω	0.95

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The data samples used in this research were collected using the Canadian power system's CYME software[38].The sample has 209 input features in total, so the number of neurons in the input layer is 209. The four indexes of the reliability analysis of the power distribution network are used as the output indexes of the network, so the number of neurons in the output layer is set to 4. During the training process, each layer of RBM is iterated 100 times. The momentum is 0.50. The RBM learning rate is 0.01, and the entire DBN learning rate is 0.01 given by PSO. The parameters are shown in Table Ⅲ.

D.EXPERIMENTAL SIMULATION OF PSO-DBN

The test set data samples are used to test DBN model and PSO-DBN model respectively. The calculation results are compared with the actual results. The RMSE curves based on DBN and PSO-DBN are shown in Fig.3.

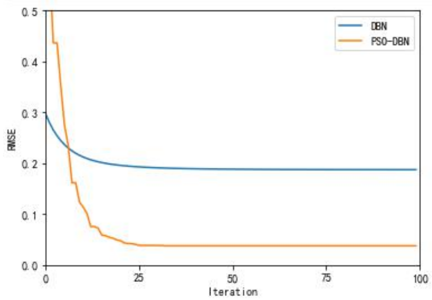
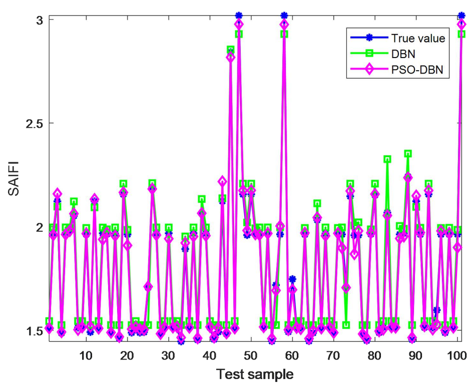
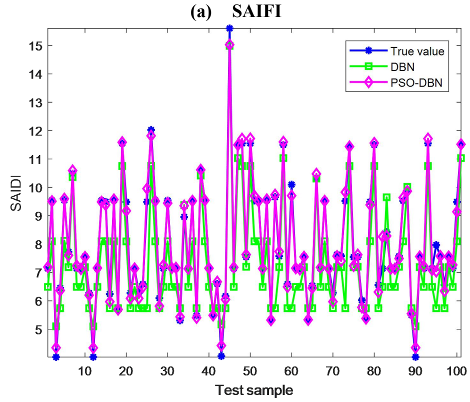


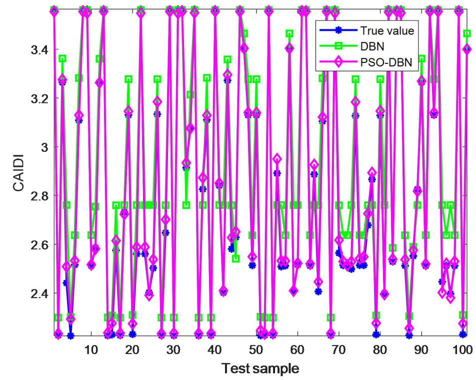
FIGURE 3. RMSE curve based on DBN and PSO-DBN.



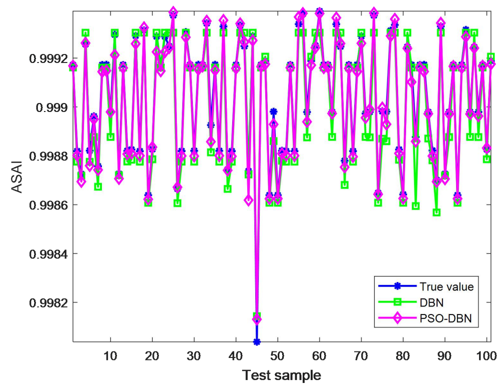
(a) SAIFI



(b)SAIDI



(c)CAIDI



(d)ASAI

FIGURE 4. PSO-DBN test set results.

It can be seen from the Fig.5 that the root-mean-square error of PSO-DBN gradually stabilizes below 0.1 and remains stable. It shows that the PSO-DBN model has a good result in the field of power distribution network reliability analysis. The output indexes SAIFI, SAIDI, CAIDI, and ASAI based on the DBN and PSO-DBN are shown in Fig.4. The abscissa is 100 tests set sample points. It can be seen from the figure that the PSO-DBN result (purple curve) is close to the actual value (blue curve), which is better than the DBN model. The overall error between the simulation result (green curve) of the DBN models and the actual value (blue curve) is slightly larger, but there is no particularly large error value. The results prove that the PSO-DBN model is more suitable for power distribution network reliability analysis.

E. THE SIMULATION COMPARISON BETWEEN PSO-DBN MODEL AND MONTE CARLO MODEL

1)MONTE CARLO MODEL

The Monte Carlo method can simulate various random load characteristics flexibly and is recognized as a more accurate algorithm in traditional methods. Based on this, for the same sample, the reliability analysis of power distribution network based on PSO-DBN model and Monte Carlo model is established. According to the R^2 relationship graph, the mean absolute percentage error (MAPE) and root mean square error (RMSE), the simulation results are compared and analyzed.

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Monte Carlo method is a typical simulation of the traditional method, also known as the statistical test method. The Monte Carlo method requires sampling the state of each component in the system. Monte Carlo simulation is often regarded as a state sampling method and has been widely used in reliability analysis projects. Each element in the system is simulated with a uniformly distributed random number in the interval [0,1]. Each component has three states of operation, maintenance, and failure, and the impact on component failure is independent of each other.

The main steps of Monte Carlo based electrical distribution network reliability analysis is as follows:

(1) Initialize the number of simulation years k to zero that is $k = 0$;

(2) k = k + 1; for the kth year, a random array $\{r_1, r_2, r_3 \ldots r_n\}$ is generated to simulate the running status of each node in the network;

(3) Find out the faulty components in the entire power distribution network;

(4) Count the number of power outages and power outage times at load points in the year and add up each year;

(5) If the simulation convergence condition is reached, the sampling simulation calculation is stopped; otherwise, it is transferred to (2).

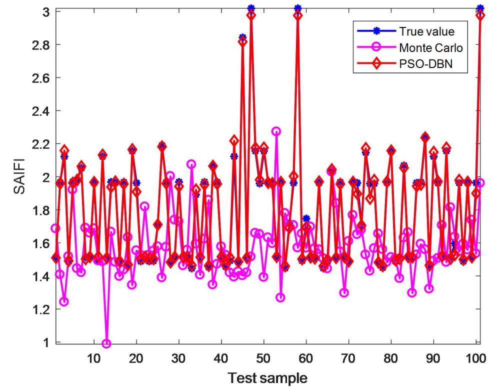
(6) Calculate the average failure rate, average power outage time, and annual average power outage time at each load point in the total simulated years and calculate the reliability index of the system.

The above Monte Carlo simulation method is used to simulate the system running for 10,000 years.

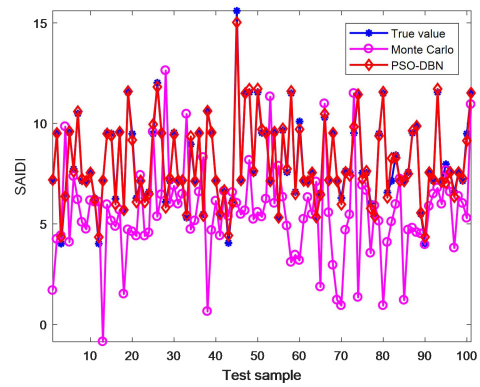
2) THE SIMULATION COMPARISION

The main influencing factors of the power distribution network are: the length of each line, the type of the line, the failure rate of the transformer, the average repair time of the transformer, the failure rate of the breaker, the average failure repair time of the breaker, the bus failure rate, the average bus repair time, segmented switch failure rate, segmented switch failure repair time, total number of load points users, and the topology of the power distribution network. The research object of this paper is a fourteen-node distribution network. The grid structure of the distribution network includes various types such as hand in hand, ring network, multi-segment single contact, 4 by 6 wiring, radial and so on. Tens of thousands of distribution grid samples are divided into training data set and test data set. The entire data sample is complete without missing values. During the model building process, the training data set is divided into two parts, one is the data set used for model training, and the other is the data set used for model testing. This can make the model have a good prediction effect and prevent over-fitting.

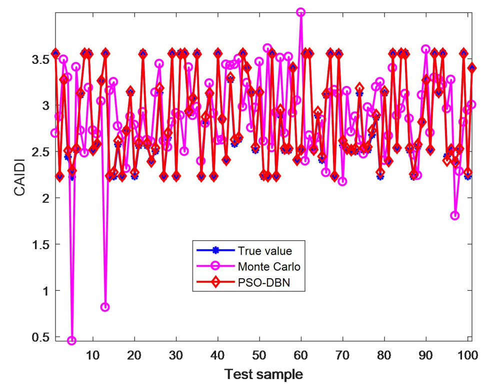
The four main reliability indexes of the power distribution network (SAIFI, SAIDI, CAIDI, and ASAI) are used as the output feature vectors of the analysis model. Fig.5 shows the test results of Monte Carlo and PSO-DBN test samples appli-



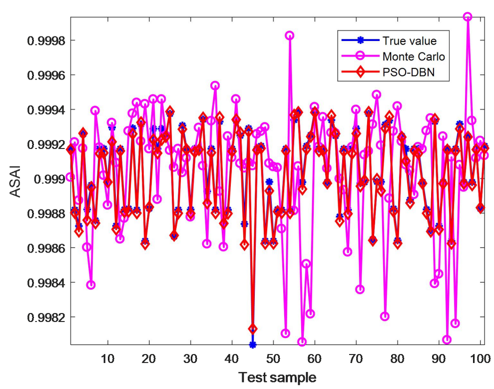
(a)SAIFI



(b) SAIDI



(c)CAIDI



(d)ASAI

FIGURE 5. Monte Carlo, PSO-BP, and PSO-DBN test sample results.

ed in the field of power distribution network reliability analysis. The PSO-DBN model is closest to the actual value (blue). The DBN model optimized by PSO can obtain perfect weights and thresholds, so that the DBN can be more accurately used in reliability analysis of distribution networks. In contrast, the Monte Carlo method is less efficient and has a large amount of calculation and a long calculation time, which is difficult to meet the needs of online analysis.

The determination coefficient R^2 is an important index for evaluating the quality of the model. For the Monte Carlo simulation method and PSO-DBN neural network method, the determination coefficients R^2 of the four indexes of SAIFI, SAIDI, CAIDI and ASAI are calculated, as shown in Figs. 6 and 7.

The R^2 is a measure of the fitting degree of the model through changes in the data. The closer R^2 is to 1, the stronger the explanatory power of the variables of the formula (16) to y, and the better of the model fitting degree.

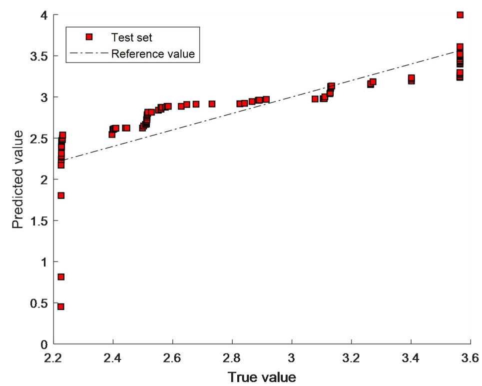
Fig.6 shows the R^2 diagram of the Monte Carlo model. Fig.(a), (b), (c), and (d) represent the R^2 relationships of the distribution network system indicators SAIFI, CAIDI, SAIDI, and ASAI, respectively. It can be seen from Fig.6 that points (predicted values) around the dotted line (true value) are relatively scattered, which shows that the Monte Carlo model has a poor fitting.

Fig.7 shows the R^2 diagram of the PSO-DBN model. It can be seen in Fig.7 that the red point sets (predicted values) are all concentrated on the dotted line (true value) or both sides, and there is no significant deviation. It indicates that the predicted value of the PSO-DBN model has a high degree of correlation between the true value, and the fitting degree of the model is also the best.

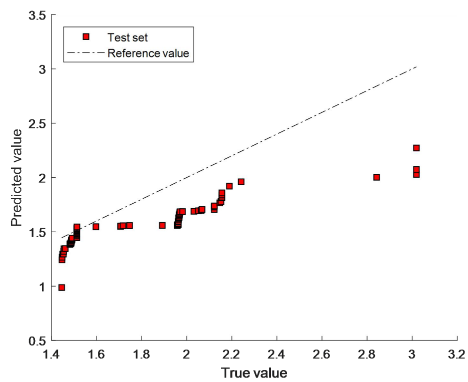
For the model analysis index MAPE in this experiment, based on the test set samples, the absolute error graphs of four indexes SAIFI, SAIDI, CAIDI, and ASAI based on two models are simulated. As shown in Fig. 8, the effects of the two models on the evaluation of the test set samples are shown. It is easy to see that the absolute error of the Monte Carlo simulation method is the largest, and the absolute error based on the PSO-DBN neural network model is the smallest. In other words, the PSO-DBN neural network models has the better result on the reliability analysis of power distribution networks.

Throughout the simulation experiment, the simulation calculation time of the Monte Carlo method is closely related to the number of samples. To obtain sufficiently accurate power distribution network reliability, it is usually necessary to increase the number of samples, which leads to a large amount of calculation and a long calculation time for the Monte Carlo model. In the case of ensuring the maximum accuracy, the calculation time of the Monte Carlo model is about 201s. Neural network training takes much longer than test time. The training process is more complicated than the test process because it requires iteration of the training data and inverse update of the parameters, and it also requires optimization of weights and thresholds by PSO. The training time of the PSO-DBN is about 108min, and the testing time is about 11.441s. The training strategy and model structure in the experiments are the same, and the selected training set and test set are also the same sizes, so the calculation amount of several experiments is also roughly the same.

Table V shows the calculated MAPE, RMSE, and correlation coefficient R based on the Monte Carlo and PSO-DBN models. By comparing the values of the evaluation index, it can be found that the average MAPE of distribution network reliability index based on the PSO-DBN model is the smallest. The closer the correlation coefficient R is to the value 1, the better the model is. The correlation coefficient of the PSO-DBN model is closest to 1. Therefore, the PSO-DBN model has better performance when applied to the reliability analysis of the power distribution network. On the whole, the PSO-DBN model has a better adaptability and best results in the two models when applied to power distribution network reliability analysis.



(a)SAIFI



(b) CAIDI

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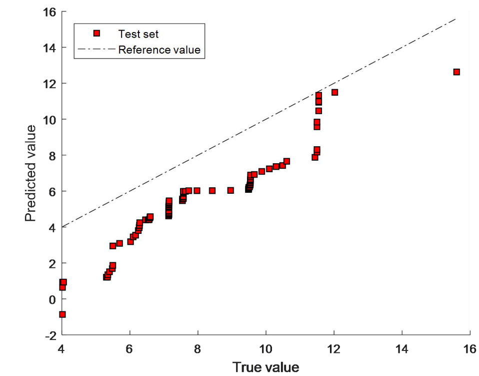
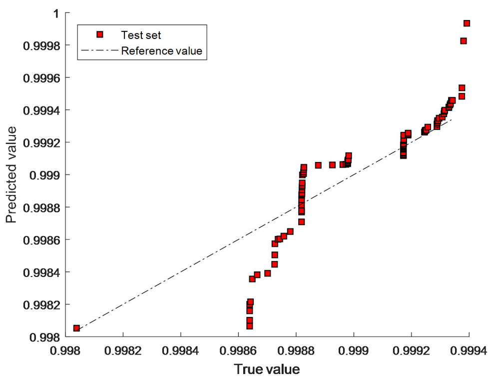


(c)SAIDI

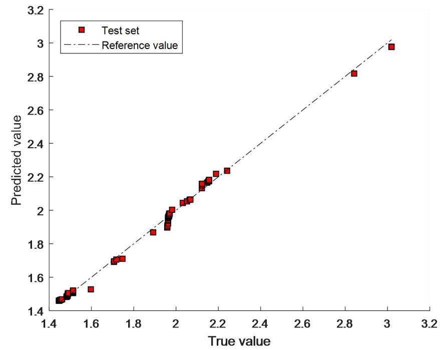


(d)ASAI

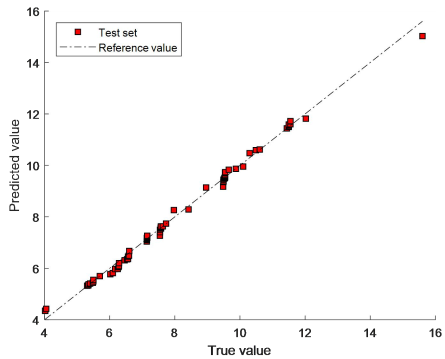
FIGURE 6. R^2 diagram of Monte Carlo model

TABLE V
MAPE, RMSE AND CORRELATION COEFFICIENT R VALUES

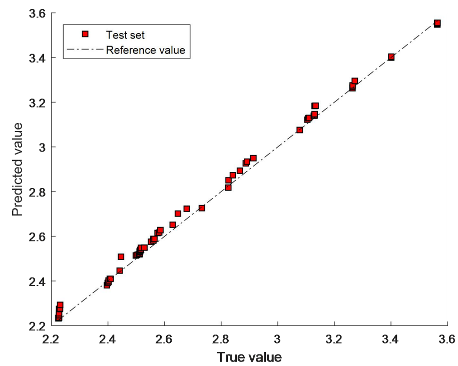
	Index	Monte Carlo	PSO-DBN
MAPE	SAIFI	0.93404	0.80398
	SAIDI	0.87542	0.68239
	CAIDI	0.95596	0.73848
	ASAI	0.033366	0.002085
RMSE	SAIFI	0.47273	0.023879
	SAIDI	3.9876	0.22009
	CAIDI	0.67538	0.025538
	ASAI	0.000445	0.000013
R	SAIFI	0.93404	0.99983
	SAIDI	0.76803	0.99929
	CAIDI	0.94519	0.99992
	ASAI	0.99718	0.99917



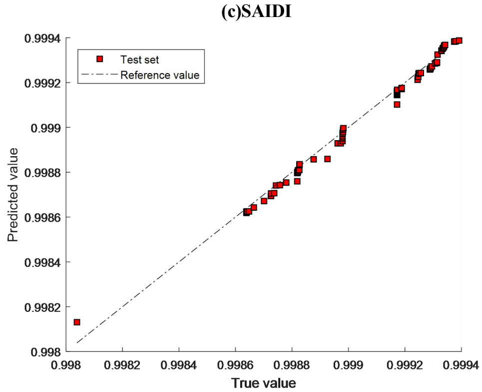
(a)SAIFI



(b)CAIDI

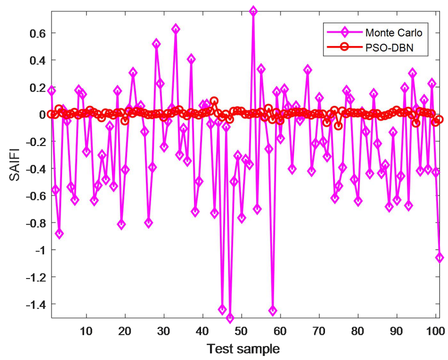


(c)SAIDI

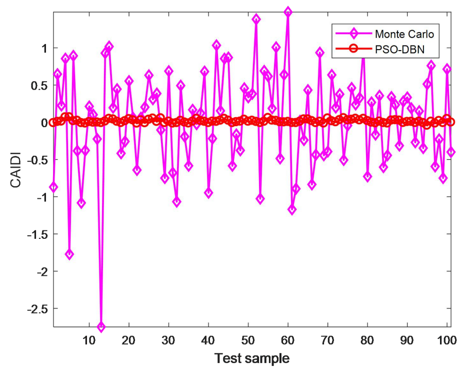


(d)ASAI

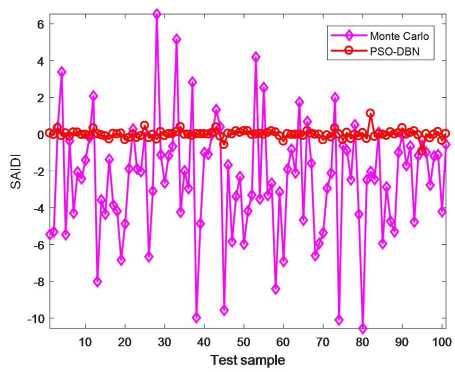
FIGURE 7. R^2 diagram of PSO-DBN model



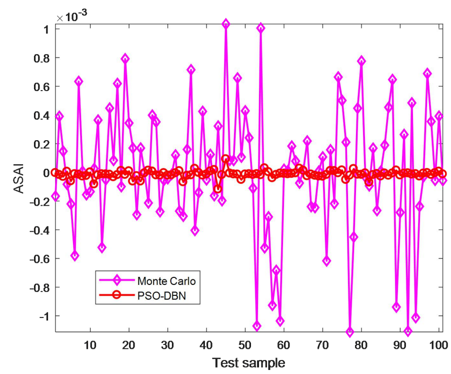
(a)SAIFI



(b)CAIDI



(c)SAIDI



(d)ASAI

FIGURE 8. Error graphs of the evaluation indicators (a)SAIFI, (b)CAIDI, (c)SAIDI, (d)ASAI

V. CONCLUSIONS

This paper proposes a new method of using PSO-DBN for reliability analysis of distribution network. The powerful automatic features extraction function of the optimized deep belief network model is efficiently used, and the inherent features can be directly extracted from the original data, and good results have been achieved.

This research has the following four conclusions: Firstly, the optimized DBN model is used to analyze the reliability of the power distribution network, which improves the accuracy of the reliability analysis results of the power distribution network; Secondly, after PSO optimization, network parameters of DBN were found; Thirdly, power distribution network reliability analysis based on optimized DBN model can be applied to different distribution network grid structures; Fourthly, the trained PSO-DBN model can quickly analyze the reliability of the power distribution network.

It is worth emphasizing that this research makes the results of power distribution network reliability analysis more accurate, and provides a new research idea for AI algorithm in the field of power distribution network reliability analysis.

REFERENCES

[1] Q. Song, B. Zhao, W. Liu, and R. Zeng, "An overview of research on smart DC distribution power network," *Proceedings of the CSEE,* vol. 33, pp. 9-19, 2013.

[2] S. Ge, H. Wang, Y. Wang, and X. Zhang, "Reliability evaluation of distribution system including distributed wind turbines, photovoltaic arrays and batteries," *Dianli Xitong Zidonghua(Automation of Electric Power Systems),* vol. 36, pp. 16-23, 2012.

[3] A. Pillay and J. Wang, "Modified failure mode and effects analysis using approximate reasoning," *Reliability Engineering & System Safety,* vol. 79, pp. 69-85, 2003.

[4] X. Sun, S. Wang, Y. Xia, and W. Zheng, "Predictive-Trend-Aware Composition of Web Services with Time-Varying Quality-of-Service," *IEEE Access,* 2019.

[5] S. Yannopoulos and M. Spiliotis, "Water distribution system reliability based on minimum cut-set approach and the hydraulic availability," *Water resources management,* vol. 27, pp. 1821-1836, 2013.

[6] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. Rao, "Optimal network reconfiguration of large-scale distribution system using harmony search algorithm," *IEEE Transactions on power systems,* vol. 26, pp. 1080-1088, 2010.

[7] G. T. Heydt and T. J. Graf, "Distribution system reliability evaluation using enhanced samples in a Monte Carlo approach," *IEEE transactions on power systems,* vol. 25, pp. 2006-2008, 2010.

[8] Q. Zhou, J. Wang, G. Zhang, K. Guo, X. Cai, L. Wang*, et al.*, "A Two-Phase Multiobjective Local Search for the Device Allocation in the Distributed Integrated Modular Avionics," *IEEE Access,* vol. 8, pp. 1-10, 2019.

[9] Z. Xu, Y. Ji, and D. Zhou, "Real-time reliability prediction for a dynamic system based on the hidden degradation process identification," *IEEE Transactions on Reliability,* vol. 57, pp. 230-242, 2008.

[10] G.-c. WAN, Z. Ren, and X. Tian, "Study on model of reliability-network-equivalent of distribution system reliability evalution [J]," *Proceedings of the Csee,* vol. 5, 2003.

[11] H. Bart, I. Gohberg, M. A. Kaashoek, and A. C. Ran, *Factorization of matrix and operator functions: the state space method* vol. 178: Springer Science & Business Media, 2007.

[12] G. Hamoud and I. El-Nahas, "Assessment of customer supply

reliability in performance-based contracts," *IEEE Transactions on power systems,* vol. 18, pp. 1587-1593, 2003.
[13] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of machine learning*: MIT press, 2018.
[14] K. Xie, J. Zhou, and R. Billinton, "Reliability evaluation algorithm for complex medium voltage electrical distribution networks based on the shortest path," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 150, pp. 686-690, 2003.
[15] H. Khan and M. A. Choudhry, "Implementation of Distributed Generation (IDG) algorithm for performance enhancement of distribution feeder under extreme load growth," *International Journal of Electrical Power & Energy Systems,* vol. 32, pp. 985-997, 2010.
[16] Y.-h. Xie and C.-s. Wang, "Reliability evaluation of medium voltage distribution system based on feeder partition method," *Proceedings of the CSEE,* vol. 5, 2004.
[17] G. Marmidis, S. Lazarou, and E. Pyrgioti, "Optimal placement of wind turbines in a wind park using Monte Carlo simulation," *Renewable energy,* vol. 33, pp. 1455-1460, 2008.
[18] I.-S. Bae and J.-O. Kim, "Reliability evaluation of customers in a microgrid," *IEEE Transactions on Power Systems,* vol. 23, pp. 1416-1422, 2008.
[19] L. Li, L. Qin, X. Qu, J. Zhang, Y. Wang, and B. Ran, "Day-ahead traffic flow forecasting based on a deep belief network optimized by the multi-objective particle swarm algorithm," *Knowledge-Based Systems,* vol. 172, pp. 1-14, 2019.
[20] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation,* vol. 18, pp. 1527-1554, 2006.
[21] G. Munoz-Delgado, J. Contreras, and J. M. Arroyo, "Distribution network expansion planning with an explicit formulation for reliability assessment," *IEEE Transactions on Power Systems,* vol. 33, pp. 2583-2596, 2017.
[22] Y. Bengio, "Learning deep architectures for AI," *Foundations and trends┬« in Machine Learning,* vol. 2, pp. 1-127, 2009.
[23] J. Olamaei, T. Niknam, and G. Gharehpetian, "Application of particle swarm optimization for distribution feeder reconfiguration considering distributed generators," *Applied Mathematics and computation,* vol. 201, pp. 575-586, 2008.
[24] J. K. Kim, Y. S. Han, and J. S. Lee, "Particle swarm optimization-deep belief network-based rare class prediction model for highly class imbalance problem," *Concurrency and Computation: Practice and Experience,* vol. 29, p. e4128, 2017.
[25] S. Basu, M. Karki, S. Ganguly, R. DiBiano, S. Mukhopadhyay, S. Gayaka*, et al.*, "Learning sparse feature representations using probabilistic quadtrees and deep belief nets," *Neural Processing Letters,* vol. 45, pp. 855-867, 2017.
[26] S.-Y. Kim and J.-O. Kim, "Reliability evaluation of distribution network with DG considering the reliability of protective devices affected by SFCL," *IEEE Transactions on Applied superconductivity,* vol. 21, pp. 3561-3569, 2011.
[27] A. Heidari, V. G. Agelidis, J. Pou, J. Aghaei, and A. M. Ghias, "Reliability worth analysis of distribution systems using cascade correlation neural networks," *IEEE transactions on power systems,* vol. 33, pp. 412-420, 2017.
[28] J. r. Schmidhuber, "Deep learning in neural networks: An overview," *Neural networks,* vol. 61, pp. 85-117, 2015.
[29] V. Ferreira, R. Zanghi, M. Fortes, G. Sotelo, R. Silva, J. Souza*, et al.*, "A survey on intelligent system application to fault diagnosis in electric power system transmission lines," *Electric Power Systems Research,* vol. 136, pp. 135-153, 2016.
[30] M. A. Nielsen, *Neural networks and deep learning* vol. 2018: Determination press San Francisco, CA, USA:, 2015.
[31] K. Wang, X. Qi, H. Liu, and J. Song, "Deep belief network based k-means cluster approach for short-term wind power forecasting," *Energy,* vol. 165, pp. 840-852, 2018.
[32] G. Hinton, L. Deng, D. Yu, G. E. Dahl, A.-r. Mohamed, N. Jaitly*, et al.*, "Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups," *IEEE Signal processing magazine,* vol. 29, pp. 82-97, 2012.
[33] Y. Zhang, G.-Q. Lu, Y. Zhang, G.-Q. Yu, and D.-K. Zhu, "Influence of grid connection of photovoltaic power station on power grid reliability," *East China Electric Power,* vol. 38, pp. 700-706, 2010.
[34] N. Le Roux and Y. Bengio, "Representational power of restricted Boltzmann machines and deep belief networks," *Neural computation,* vol. 20, pp. 1631-1649, 2008.
[35] S. Wan-Qing, X. Cheng, C. Cattani, and E. Zio, "Multi-Fractional Brownian Motion and Quantum-Behaved Partial Swarm Optimization for Bearing Degradation Forecasting," *Complexity*, vol. 2020, 12/20 2019.
[36] L.-h. DENG and X.-y. CHEN, "Review of distribution system reliability evaluation ," *Electric Power Automation Equipment,* vol. 24, pp. 74-77, 2004.
[37] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, "Robust optimization-based resilient distribution network planning against natural disasters," *IEEE Transactions on Smart Grid,* vol. 7, pp. 2817-2826, 2016.
[38] C. Iglesias, J. Martnez, and J. Taboada, "Automated vision system for quality inspection of slate slabs," *Computers in Industry,* vol. 99, pp. 119-129, 2018.
[39] M. H. Amini, M. P. Moghaddam, and O. Karabasoglu, "Simultaneous allocation of electric vehicles´ parking lots and distributed renewable resources in smart power distribution networks," *Sustainable Cities and Society,* vol. 28, pp. 332-342, 2017.
[40] W. Song, C. Cattani, and C. Chi, "Multifractional Brownian motion and quantum-behaved particle swarm optimization for short term power load forecasting: An integrated approach," *Energy*, vol. 194, p. 116847, 2020.
[41] Y. Gao, F. Villecco, M. Li, and W. Song, "Multi-Scale Permutation Entropy Based on Improved LMD and HMM for Rolling Bearing Diagnosis," *Entropy*, vol. 19, p. 176, 2017.
[42] H. Liu, S. Wanqing, M. Li, A. Kudreyko, and E. Zio, "Fractional Lévy stable motion: Finite difference iterative forecasting model," *Chaos Solitons & Fractals*, vol. 133, 01/31 2020.
[43] H.Y. Wang, W.Q Song, E. Zio, Y.J. Zhang,"Remaining Useful Life Prediction for Lithium-ion Batteries Using Fractional Brownian Motion and Fruit-fly Optimization Algorithm,"*measurement, https://doi.org/10.1016/j.measurement.*2020.107904
[44] F.-t Yan, J.-h Jia, Y.-h Hu, Q.-h Guo and H.-h Zhu,"Smart fire evacuation service based on Internet of Things computing for Web3D," *Journal of Internet Technology*, vol. 20, pp. 521-532,2019.

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