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PERCEPTRON LEARNING MODEL BASED RELIABILITY EVALUATION METHOD OF MEDIUM VOLTAGE ELECTRICAL DISTRIBUTION NETWORKS

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ABSTRACT

This paper deals with the feasibility of using perceptron learning model to build an empirical model for the reliability evaluation of medium voltage electrical distribution networks. The main idea is to develop a novel reliability evaluation algorithm, by training the perceptron on a restricted sample set, and replace the conventional system state evaluation methods by a simpler calculation, which can quantitatively analyze the reliability and component importance of distribution networks. The proposed approach is illustrated by case studies.

Keywords: electrical distribution networks, perceptron, reliability evaluation

NONMENCLATURE

Abbreviations

SCE	State consequence evaluation
SAIFI	System average interruption frequency index
SAIDI	System average interruption duration index
EENS	Expected energy not supplied
SGD	Stochastic gradient descent

Symbols

n	Number of system components
m	Number of load points
K	Number of samples used to train perceptron
x_i	State of component i
y_j	Interruption type of load point j
$\mathbf{s}_i$	System state vector i
$\mathbf{s}_i'$	Load point state vector i
λ	Component average failure rate (occ. /yr.)
r	Component average outage time (hr. /occ.)
d_{ij}	Interruption duration of load point j caused by the outage of component i
L_j	Average load at the load point j
Ω_j	The set of components that will lead to the interruption of load point j
N_l^j	Number of customers at the load point j
N_{total}	Total number of customers of the system
$\mathbf{x}_k$	Data vector of sample k
$\mathbf{y}_k$	Actual labels vector of sample k
$\hat{\mathbf{y}}_k$	Labels vector k predicted by perceptron
w_{ij}	Connection weight from neuron i to neuron j
θ_{ij}	Connection bias from neuron i to neuron j
E_k	The mean square error of the perceptron network at the sample k

1. INTRODUCTION

Reliability evaluation is of great importance for the planning and operation of the power system, by accurately reflecting the system reliability level. Generally speaking, the objects of reliability evaluation can be categorized into three parts: generation, transmission, and distribution systems [1]. Relevant researches on one part or several parts of them have attracted the attention of scholars. In the generation and transmission systems, we usually consider the multi-order outage of system, and calculate the corresponding reliability indexes. But for the medium voltage electrical distribution networks, due to the large number of system components, we usually just consider the first-order outage of system to reduce the computational burden.

Reliability evaluation methods generally can be divided into two types: analytical method and simulation method, and both include three main processes: system state generation, state consequence evaluation (SCE), and reliability indexes calculation. Among them, the SCE process is the most complex process. The aim of SCE is to quantify the impact of each outage on the system, e.g. the interruption duration and the energy not supplied at each load point resulted by a component outage. To achieve this goal, methods like the zone partitioning and minimal path search [2], the network-equivalent [3], and the fault incidence matrix [4] have been proposed.

In this work, an empirical reliability evaluation model built by training a perceptron learning model is proposed. Perceptron, as a neuron network model, is widely used in the two-category classification problem, which is similar with the reliability state of the load point (interrupted or not). Therefore, the perceptron model is modified and used in this paper, to evaluate the state consequences and replace conventional SCE methods. Moreover, relevant reliability evaluation algorithm is also proposed in this paper.

The organization of this paper is as follows: Section 2 introduces the basic definitions of reliability evaluation used in this paper. The perceptron based reliability evaluation model is established in Section 3, then followed by Section 4 that introduces the reliability evaluation algorithm. Section 5 presents relevant case studies and Section 6 concludes this paper.

2. DEFINITIONS

System states consist of the states of all components. Two states (operation or failure) component state model is adopted in this paper, which is formulated as below:

$$x_i = \begin{cases} 1 & \text{component in the failure state} \\ 0 & \text{component in the operation state} \end{cases} \tag{1}$$

Then, the system state can be formulated as:

$$\mathbf{s}_i = \{x_1, x_2, ..., x_n\} \tag{2}$$

In electrical distribution networks, system components (also load points) have two basic reliability parameters: average failure rate λ (occ. /yr.) and average outage time r (hr. /occ.).

The impact of a component outage on load point can be classified into three types [5]:

(a) The load resumes after the component is repaired. And the load point's interruption duration caused by this outage equal to the component outage time;

(b) The load resumes after the outage is isolated and is supplied by the main power supply. Then, the load point's interruption duration equal to the time needed to isolate the outage;

(c) The load resumes after the outage is isolate and is supplied by the alternative power supply. Then, the load point's interruption duration equal to the time needed to change the power supply path;

(d) The load point is not affected by the outage.

In this paper, interruption types (a), (b), (c), and (d) of load points are represented by digits '3', '2','1', and '0', respectively. Then, load point state, consisting of all load points' interruption types, can be formulated as:

$$\mathbf{s}_i' = \{y_1, y_2, ..., y_m\} \tag{3}$$

Three system reliability indexes are analyzed in this paper: SAIFI, SAIDI, and EENS. The calculation formulas of these indexes are as follows:

$$\begin{aligned} \text{SAIFI} &= \sum_{j=1}^{m} \sum_{i \in \Omega_j} \lambda_i \frac{N_l^j}{N_{total}} \\ \text{SAIDI} &= \sum_{j=1}^{m} \sum_{i \in \Omega_j} \lambda_i d_{ij} \frac{N_l^j}{N_{total}} \\ \text{EENS} &= \sum_{j=1}^{m} \sum_{i \in \Omega_j} \lambda_i d_{ij} L_j \end{aligned} \tag{4}$$

3. PERCEPTRON MODEL

Perceptron as a neural networks learning model, consists of two neuron layers. The perceptron network structure is shown in Fig 1.

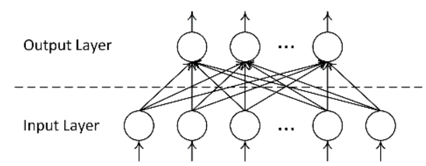

Fig 1 Diagram of perceptron network structure

It can be seen that perceptron consists of two neuron layers: input layer and output layer. And each neuron adopts the McCulloch-Pitts neuron model [6], as shown in Fig. 2. In this model, the neuron receive input signals delivered from other *n* neurons, and these input signals are transmitted through weighted connections. Then, the neuron compares the total input signals received with the threshold, and then processes it through the activation function to produce the output of the neuron.

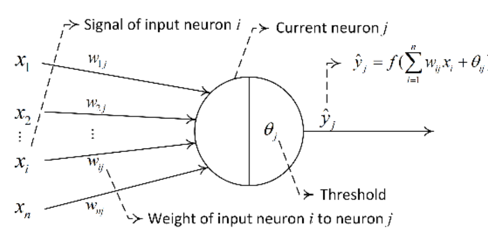

Fig 2 Diagram of McCulloch-Pitts neuron model

Therefore, for a training sample ($\mathbf{x}_k$, $\mathbf{y}_k$), the output of the perceptron network is $\hat{\mathbf{y}}_k = \{\hat{y}_1^k, \hat{y}_2^k, ..., \hat{y}_m^k\}$, and each y_j^k is formulated as follows:

$$\hat{y}_j^k = f(\sum_{i=1}^{n} w_{ij}^k x_i^k + \theta_{ij}^k) \tag{5}$$

The mean square error of the perceptron network in the ($\mathbf{x}_k$, $\mathbf{y}_k$) is formulated as follows:

$$E_k = \sum_{j=1}^{m} (\hat{y}_j^k - y_j^k)^2 \tag{6}$$

Perceptron learning model is adopted as the reliability evaluation model in this paper. To evaluate the reliability of an electrical distribution network with n components and m load points, we need to establish a perceptron learning model with n neurons at the input layer and m neurons at the output layer. Each system state $\mathbf{s}_i$ is considered as an input sample data of the perceptron network, and the relevant sample label consists of load point state $\mathbf{s}_i'$.

4. RELIABILITY EVALUATION ALGORITHM

4.1 System states generation

In the medium voltage electrical distribution network, due to the large number of components, we usually only consider the first-order outage state, which means that, for a system with n components, the number of system states needed to analyze is n. Therefore, system state $\mathbf{s}_i = \{0, 0, ..., x_i = 1, ..., x_n\}$ represents that the component i fails and the others works.

Moreover, the interruption type of each load point at state $\mathbf{s}_i$ can be obtained by conventional SCE methods. A set of system states with corresponding load points' interruption types is obtained which as the sample set to train the perceptron model.

4.2 State consequences evaluation

Based on the sample set obtained at the process of system states generation, stochastic gradient descent (SGD) optimization algorithm is adopted to train the perceptron parameters (w and θ). The optimization objection is to minimize the mean square error of the perceptron network, which can be formulated as follows:

$$\min \quad \frac{1}{K} \sum_{k=1}^{K} \sum_{j=1}^{m} (\hat{y}_j^k - y_j^k)^2 \tag{7}$$

Once the perceptron model has been trained successfully, the model parameters could be saved and invoked during the following reliability evaluation processes. Then, we input all possible system states into the trained perceptron model. And the interruption types of all load points at all system states can be obtained as the output of the perceptron model.

4.3 Reliability indexes calculation

Based on the interruption types obtained at the process of state consequences evaluation, the reliability indexes can be calculated by (4).

The reliability evaluation algorithm proposed in this paper is summarized and shown in Fig. 3.

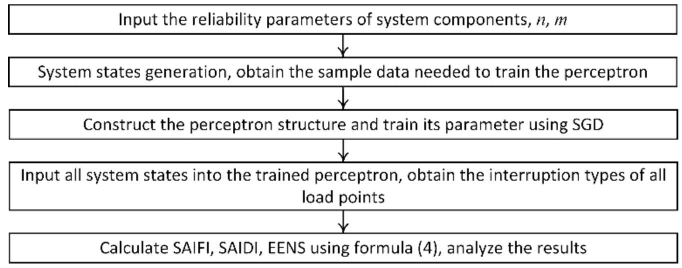

Fig 3 Reliability evaluation algorithm flowchart

5. CASE STUDY

The RBTS Bus2 system [7], as an 11kV electrical distribution network, is employed to verify the effectiveness of the method proposed in this paper. The structure of RBTS Bus2 system is shown in Fig. 4.

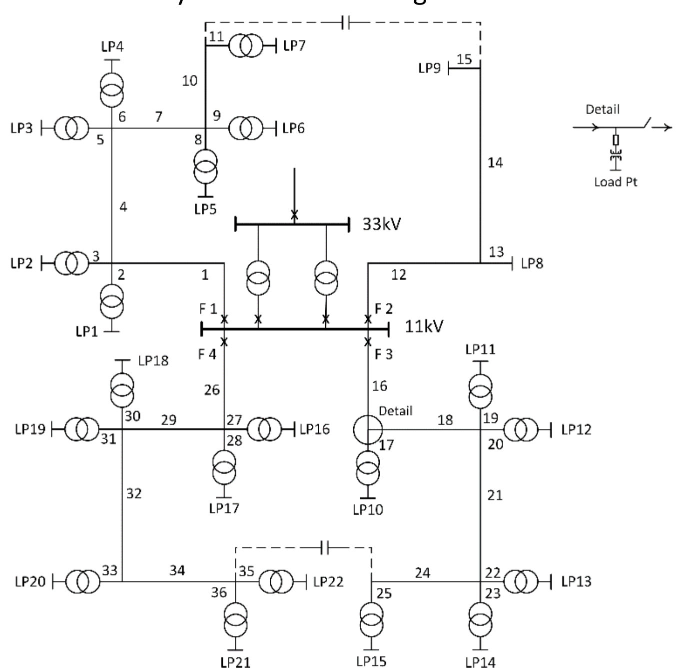

Fig 4 Diagram of RBTS Bus2 distribution network

The relevant assumptions and components' reliability parameters are consistent with [7]. The base case, assuming the system with disconnects, with fuses, with alternative supply and repairing transformers, is adopted.

5.1 Perceptron training

The components that may fails include 20 transformers and 36 lines, and there are 22 load points in the RBTS Bus2 network. Therefore, the input layer of perceptron consists of 56 neurons, and the output layer consists of

22 neurons. The number of basic samples that used to train the perceptron parameters is 56. To improve the prediction accuracy of perceptron, the sample set is expanded by multiplying the basic samples by a random number. The expanded sample set includes 56000 samples that used to train the perceptron parameters.

The parameters settings of the SGD algorithm: the learning rate is 0.001, the iteration is 25, and the batch size is 100. No active function is adopted in the perceptron, since the relationship between the component outage and the interruption type of load point is linear.

The mean square errors of the perceptron in the expanded sample set with different numbers of input samples are shown in Tab. 1.

Tab 1 The errors of prediction with different sample sizes

Number of samples	Error of prediction	Number of samples	Error of prediction
1000	45.95	30000	1.93e-1
5000	20.10	50000	7.02e-7
10000	8.96	56000	5.3e-8

5.2 System reliability indexes

The reliability indexes of RBTS Bus2 network is calculated based on the perceptron trained by 56000 samples. The comparison of the reliability calculation results using our method and reference [7] is shown in Tab. 2.

Tab 2 The comparison of reliability results

	SAIFI (fr./syst. cust.)	SAIDI (hr./syst. cust.)	EENS (MW/yr.)
Ref. [7]	0.248	3.61	37.746
This paper	0.24821	3.61259	37.74568

It can be seen that the results using the method proposed in this paper are consistent with the results in reference [7], which verifies the effectiveness of perceptron learning model based reliability evaluation method.

5.3 Component importance ranking

By evaluating the reliability indexes of each system state, the consequence resulted by each component's outage can be obtained. It is assumed that the more serious consequence that a component may cause, the more important it is. And the importance of component is ranked according to this principle. Since each transformer is equipped with a fuse, the outage of a transformer affects only the load point it directly connects to. Therefore, we only rank the important of lines. We list the 10 most important lines according to the reliability index EENS (MW/yr.), and the results are shown in Tab. 3.

It can be seen from Tab. 3 that most of top ranked lines are main lines, since an outage of the main line will result in multiple load points' interruptions, while an outage of the branch line will just lead to the interruption of the load point it directly connects to. And only one branch line – Line 15 appears in the top 10 because the load at load point 9 that it directly connects to is heavy.

Tab 3 Component importance ranking according to EENS

Rank	Comp.	EENS	Rank	Comp.	EENS
1	Line 4	0.39239	6	Line 29	0.34076
2	Line 1	0.38634	7	Line 12	0.29981
3	Line 7	0.37659	8	Line 15	0.29900
4	Line 18	0.36639	9	Line 21	0.29773
5	Line 26	0.36431	10	Line 34	0.29133

6. CONCLUSION

This paper proposed a novel reliability evaluation method based on perceptron learning model, which can be used to quantitatively analyze the reliability and component importance of medium voltage electrical distribution networks. The effectiveness of this method is verified by case studies. In the future research, the method proposed in this paper will be further improved and used in the system reliability enhancement.

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