Power systems adaptability evaluation using neural network

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Abstract

This paper proposes a new strategy at the system level to evaluate and mitigate power system cascading outages adaptability considering protection system hidden failure. An explicit probability model of protection system hidden failures is established to demonstrate its effects on power system adaptability. The event tree is used to analyse the cascading outages sequences. Some adaptability indices are used to evaluate cascading outages adaptability. The neural network is used to obtain the adaptability indices and to propose a solution that can decrease the system cascading outage adaptability under limited budget. The IEEE system is used to illustrate the methodology and present the results.

Keywords: power system, adaptability, evaluation, fuzzy, neural network

1 Introduction

Cascading Outages become a major concern in the power industry again recently as a result of some large-scale blackouts all over the world [1]. A cascading outage refers to a series of trips initiated by one component failure in the system. The probability of a cascading outage is very small, while its impact is enormous. Adaptability evaluation is an ideal method for cascading outages due to it quantitatively captures the factors that determine security level: likelihood and severity of events [2].

Many studies have been conducted on adaptability evaluation. Reference [3] uses simulation approach to evaluate the power system reliability. Reference [4] uses small-world model to probe the mechanism of cascading outages happened in bulk power system. Power systems are complex very much, so using these approaches has some inherent limitation in speed and efficiency. Energy function methods are used in reference [5]. It is difficult to construct an appropriate Lyapunov function and to achieve the level of accuracy desired. Reference [6] presents expert system, which relies on decision trees to evaluate the system stability and tend to be less robust to changes in power system state. Consequently, a more dependable and efficient approach is needed for adaptability evaluation under a variety of time-varying network configurations and events. Using neural networks is an ideal choice for adaptability evaluation. Neural network methods rely on reducing the computational at the expense of intensive studies. By performing training of a neural network using results obtained from history data or extended equal criterion simulator, accuracy can be achieved within the computational and time constraints [7].

This paper proposes a new strategy at the system level to evaluate and mitigate the cascading outages that involve protection system hidden failures. The strategy includes three parts: a) Improving evaluation method. Adaptability evaluation approach is used in this paper to overcome weakness in using deterministic methods. b) Valuing the adaptability index. Fuzzy neural network is used to improve accuracy and efficiency. c) Mitigating the adaptability of cascading outages. Some high-adaptability relays are replaced according to proposed upgrading solution based on relay sensitivities.

2 Hidden fault model and cascading outages

2.1 LINE PROTECTION HIDDEN FAILURE MODEL

Studies have shown that hidden failures in the protective devices have a great impact on cascading outages [8]. Hidden failures denote the incorrect operations that usually remain undetected until abnormal operating conditions are reached. The stochastic model [9] for hidden failures is used to evaluate each hidden failure's impact on the global system. The model shows the hidden failure probability of line protective relay tripping as a function of impedance seen by the relay as in Figure 1.

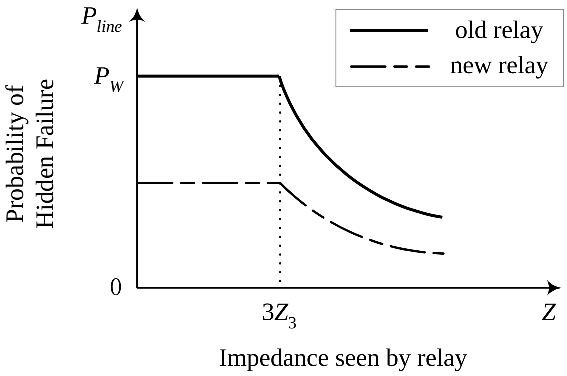


FIGURE1 Hidden failure probability in a line-protective relay

For the line protective relay, the probability of hidden failure P_{line} remains to be a small constant PW as long as the impedance Z seen by the relay is less than three times the zone three setting Z3. Beyond that boundary, it decreases exponentially. The function is

$$P_{line} = \begin{cases} P_W & Z \le 3Z_3 \\ P_W \times \exp(-\frac{Z}{Z_3}) & Z > 3Z_3 \end{cases} . \quad (1)$$

2.2 CASCADING OUTAGES SEQUENCES

Due to the complicated stochastic features of cascading outages, a simple network is used to describe the basic cascading outages sequences. The event tree in Figure 3 just illustrates certain possible cascading outages sequences, in which there are only seven events listed. In real system, other cascading outages sequences might happen also.

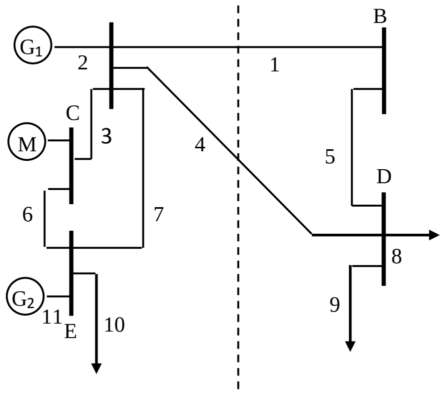


FIGURE 2 Simple power system

For simplify, the numbers of relays are the same with the numbers of lines.

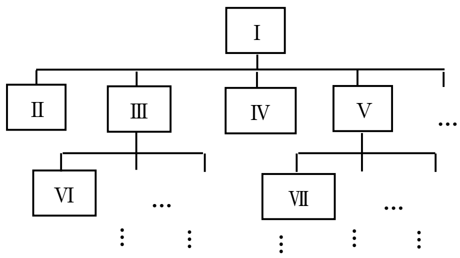


FIGURE 3 Possible event-tree for cascading outages

These seven possible events in Figure 3 are explained as follows.

Event I: Faults occurs on transmission line 1, and relay 1 trip. All lines connected to the faulted line are exposed lines. Event II: Relay 2 trips, and generator G1 is isolated. Event III: Relay 3 trips, and lines 2, 4, 6, and 7 are exposed lines. Event IV: Relay 4 trips, and the network splits into two parts. Event V: Relay 5 trips, and lines 4, 8, and 9 are exposed lines. Event VI: Relay 6 trips, and load M is dropped from the network.Event VII: Relay 8 trips, and lines 4 and 9 are exposed lines. The relays of exposed lines may trip continually.

Event tree in Figure 3 does not exhaust all possible event paths. It just gives an example to describe the sequence of cascading outages due to protection system hidden failure. In Figure 3, there are three types of cascading outages resulting from protection system hidden failures.

These three types of cascading outages in Figure 3 are explained as follows. Type 1: It consists of event I, III, and VI. Relay 1, 3 and 6 trips sequently. The result is that the load is dropped from the network. Type 2: It consists of event I and II. Relay 1 and 2 trips sequently. The result is that the generator is isolated. Type 3: It consists of event I and IV. Relay 1 and 4 trips sequently. The result is that the network is split into two parts.

3 Adaptability theory and its application

3.1 ADAPTABILITY THEORY

Adaptability is a condition under which there is a possibility of an adverse deviation from a desired outcome that is expected or hoped for. Adaptability theory researches the impact of credible contingency on system. There are two primitives included within this definition: future uncertainties and impact of outcomes. The adaptability index is a measure of systems' exposure to failure. It is also a leading indicator for security level, in that evaluation is done for the conditions under which the action is taken [10]. The basic equation to calculate adaptability index is

$$R_{Event} = P_{Event} \times I_{Event} , \quad (2)$$

where R_{Event} is the adaptability of event, P_{Event} is the probability of event, I_{Event} is the impact of event.

3.2 INDICES FOR ADAPTABILITY EVALUATION

The adaptability of cascading outages is evaluateed by adaptability indices, Load Dropped Adaptability (R_{LD}), Generator Isolated Adaptability (R_{GI}), and Network Split Adaptability (R_{NS}). In addition, an integrated index, Integrated System Adaptability (R_{IS}) is used to give a more comprehensive description of the system cascading outages adaptability.

1) Load Dropped Adaptability (R_{LD})

$$R_{LD} = P_{LD} \times I_{LD} . \quad (3)$$

Load Dropped Probability (P_{LD})

$$P_{LD} = \frac{1}{N}\sum_{i=1}^{N} L(i) , \quad (4)$$

where $L(i)$ is 1 if there is load dropped in events i, otherwise it is 0, N is total number of event.

Load Dropped Impact (I_{LD})

$$I_{LD} = \frac{1}{P_S \times N}\sum_{i=1}^{N} P_L(i) . \quad (5)$$

where $P_L(i)$ is load loss in events i, P_S is the system capacity, which is used to normalize load loss to account for the difference among various power system.

2) Generator Isolated Adaptability (R_{GI})

$$R_{GI} = P_{GI} \times I_{GI} . \quad (6)$$

Generator Isolated Probability (PGI)

$$P_{GI} = \frac{1}{N}\sum_{i=1}^{N} G(i) , \quad (7)$$

where $G(i)$ is 1 if there is generator isolated in events i, otherwise it is 0.

Generator Isolated Impact (I_{GI})

$$I_{GI} = \frac{1}{P_S \times N} \sum_{i=1}^{N} P_G(i), \tag{8}$$

where $P_G(i)$ is load loss in events i.

3) Network Split Adaptability (R_{NS})

$$R_{NS} = P_{NS} \times I_{NS}. \tag{9}$$

Network Split Probability (P_{NS})

$$P_{NS} = \frac{1}{N} \sum_{i=1}^{N} S(i), \tag{10}$$

where $S(i)$ is 1 if there is network split in events i, otherwise it is 0.

Network Split Impact (I_{NS})

$$I_{NS} = \frac{1}{P_S \times N} \sum_{i=1}^{N} P_N(i), \tag{11}$$

where $P_N(i)$ is load loss in events i.

4) Integrated System Adaptability (R_{IS})

$$R_{IS} = w_{LD} \times R_{LD} + w_{GI} \times R_{GI} + w_{NS} \times R_{NS}, \tag{12}$$

where $w_{LD} + w_{GI} + w_{NS} = 1$, w_{LD}, w_{GI}, w_{NS} are weighting factors.

After obtaining R_{LD}, R_{GI}, and R_{NS}, R_{IS} can be calculated by choosing proper weighting factors.

4 Adaptability evaluation using FNN

4.1 FRAME FOR ADAPTABILITY EVALUATION

A functional block diagram of an adaptability evaluation of cascading outages, based on combined fuzzy neural network approach, is given in Figure 4.

Relays information is measured and recorded in database, where the corresponding system faults are recorded also. These are used for either fuzzy neural network training and testing or implementation. The training of fuzzy neural network can be performed by accessing historical record. Since interesting cases do not happen frequently, sufficient data are provided using Monte Carlo simulation [11] of relevant power system scenarios. The main function of fuzzy neural network is to evaluate cascading outages adaptability. Supplemental function is to calculate relay parameter sensitivity to cascading outages adaptability, which can pinpoint the adaptability relays in a power system, and find the protection system upgrading solution. The cascading outages adaptability can decrease by installation of more reliable relays. However, changing all relays in the system is economically prohibitive. Under limit budget, only a small portion of relays can be upgraded. The high-adaptability relays are located by listing the relays having higher sensitivities. Then the cascading outages adaptability can be reduced if such reliable relays with lower hidden failure probabilities are put into service.

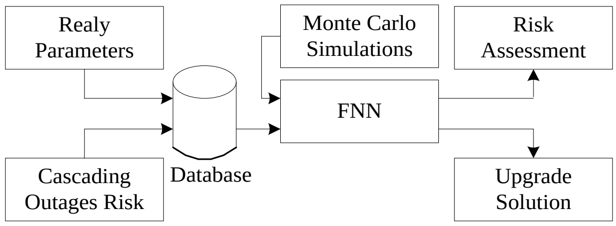


FIGURE 4 Adaptability evaluation using FNN

Fuzzy neural network is an enhanced combination of fuzzy logic and artificial neural network [12]. It is ideally suited for identifying large, high dimensional and time varying set of input data. This type of fuzzy neural network algorithm in this paper is firstly used for cascading outages adaptability evaluation.

4.2 THE FNN STRUCTURE

Figure 5 is a schematic diagram of the fuzzy neural network used for adaptability evaluation of cascading outages in power systems. Two subsections are separated from the dashed line. One is the data preprocessing subsection, the other is the network subsection.

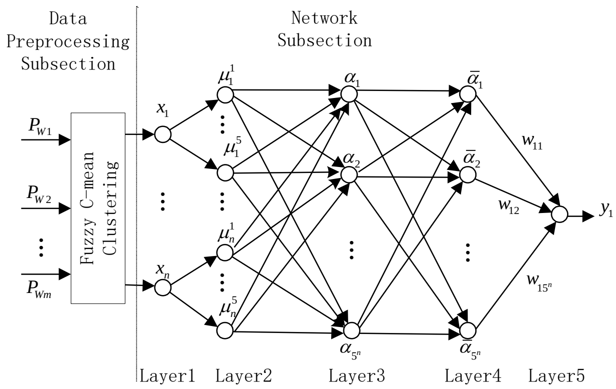


FIGURE 5 Structure of fuzzy neural network

The parameter vector $\boldsymbol{P_W}$, $\boldsymbol{P_W} = [P_{W1}, P_{W2}, \ldots, P_{Wm}]$, where m is the number of relays, has a close relationship with cascading outages adaptability, so it is used as input. In application to real systems, the dimension of input is always high. To avoid "dimension exploding", fuzzy C-mean clustering approach is used to pre-process the input data. Fuzzy C-mean clustering approach can identify natural groupings of patterns from large data set through clustering [13]. The result of pre-processing is cluster vector $\boldsymbol{x}=[x_1, x_2, \ldots, x_n]$, where the value of n ranges from 1 to 5 according to scale of the system.

The input of the network section layer 1 is $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$. The nodes of this layer is connected directly with x_i, and transmit $\boldsymbol{x}$ to the next layer. The number of nodes in this layer is $N_1=n$.

Every node in the network section layer 2 represents a language variable. There are generally five values of the language variable according to the parameters of relays. They are Negative Big (NB), Negative Small (NS), Zero (ZE), Positive Small (PS), and Positive Big (PB). The nodes in this layer is used to calculate the membership function

μ_i^j of input, where i=1, 2,…, n, j=1, 2,…, 5. In this paper, Gauss function is used as the membership function. The number of nodes in this layer is $N_2 = 5n$.

Every node in the network section layer 3 represents a fuzzy rule. The using degree of every rule is

$$a_j = FUN(\mu_1^{i_1}, \mu_2^{i_2}, \cdots \mu_n^{i_n}), \tag{13}$$

where $i_1, i_2, \cdots i_n \in [1, 2, \cdots, 5]$, $j = 1, 2, \cdots, 5^n$; FUN stands for multiplication. The number of nodes in this layer is $N_3 = 5^n$.

The network section layer 4 is used to normalizing by

$$\bar{\alpha}_j = \alpha_j / \sum_{i=1}^{5^n} \alpha_i, \tag{14}$$

where $j = 1, 2, \cdots, 5^n$. The number of nodes in this layer is $N_4 = 5^n$.

The network section layer 5 is output layer. The output of traditional security analysis using yes-no logic is coarse. The output of this approach is adaptability index, and it is a more accurate result after de-fuzzy fiction as Equation (15). The number of nodes in this layer is N_5=1.

$$y_1 = \sum_{j=1}^{5^n} w_{1j} \bar{\alpha}_j, \tag{15}$$

where w_{1j} is weighting factor.

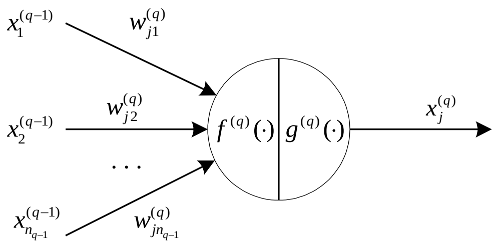


FIGURE 6 Structure of single node

In the network section, back-propagation algorithm is used to modify the weighting factor w_{1j} in layer 5, where j = [1, 2,…, 5^n], and fuzzy membership parameters, mean value c_{ij} and width value σ_{ij} in layer 2, where $i = 1, 2, \cdots, n,\ j = 1, 2, \cdots, 5$. It is assumed that the input of node j in layer q is $f^{(q)}(x_1^{(q-1)}, x_2^{(q-1)}, \cdots, x_{n_{q-1}}^{(q-1)}, w_{j1}^{(q)}, w_{j2}^{(q)}, \cdots, w_{jn_{q-1}}^{(q)})$, and the corresponding output is $x_j^{(q)} = g^{(q)}(f^{(q)})$ as Figure 6.

5 Case study

In order to demonstrate the proposed strategy, a case study is given based on the IEEE 118-bus system [14].

5.1 THE FNN STRUCTURE

There are 186 lines in the IEEE 118-bus system. It is assumed that there is one set of relay for one line for simple. So the dimension of fuzzy neural network input is 186. According to the scale of the system, 3 clusters are obtained using fuzzy C-mean clustering approach. The 3 clusters are the input of the network subsection. So there are 3 nodes in the network subsection layer 1.

The number of nodes in the network subsection layer 2 is 15 (3×5). The initial membership functions of relay parameters are shown as Figure 7.

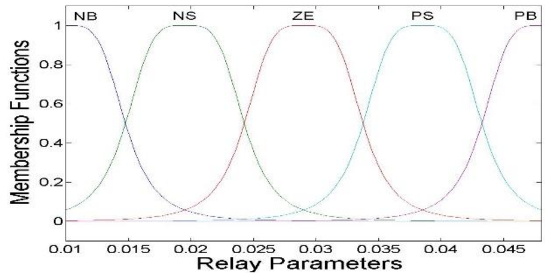


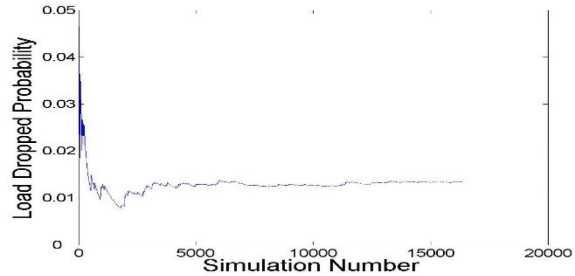
FIGURE 7 Membership function before training

There are 125 (5^3) nodes in the network subsection layer 3 and layer 4 respectively. There is one node in the network subsection layer5.

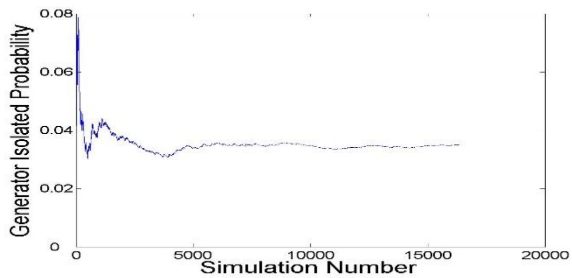
5.2 TRAINING AND TEST DATA

Matlab is used for detailed modelling of power network and simulation of cascading outages. Monte Carlo method is used for simulation. Setting procedure for the network simulation scenarios and relaying algorithm parameters is implemented in the Matlab software package, which calculates the cascading outages adaptability. Relay parameters and corresponding cascading outages adaptabilities are used as training and test data for fuzzy neural network.

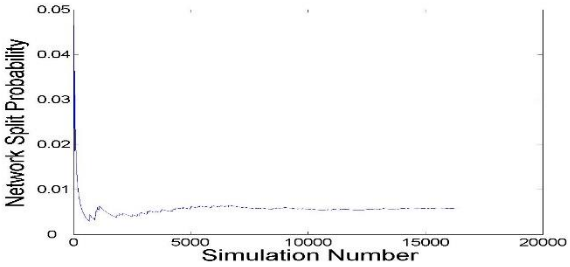
One simulation course is shown as Figure 8. After the simulation converges, there have been 16348 events, result in 221 load dropped, 564 generator isolated, and 93 network split.



(a) Load dropped probability by simulation



(b) Generator isolation probability by simulation



(c) Network split probability by simulation

FIGURE 8 System cascading outages by Monte Carlo simulation

According to adaptability equation, the cascading outages adaptability on this system state is

$$R_{IS} = \frac{1}{3} \times 0.0135 \times 0.0108 + \frac{1}{3} \times 0.0345 \times 0.0189 + \frac{1}{3} \times 0.0057 \times 0.1250 = 5.04 \times 10^{-4}$$

Based on the relay parameters on this system state, 40% relay are selected random. The parameters P_W of the selected relays increased or decreased 20% randomly. Based on the new relay parameters, 20 simulations are done again to obtain the training data as Table 1.

TABLE 1 Training data

No.	R_{IS} (10^{-4})	No.	R_{IS} (10^{-4})
1	5.04	11	4.99
2	5.94	12	6.35
3	4.02	13	4.16
4	3.66	14	4.87
5	4.34	15	2.54
6	4.75	16	5.83
7	6.44	17	3.11
8	4.34	18	4.58
9	4.12	19	6.88
10	3.02	20	3.54

Test scenarios are selected to be statistically independent from the training scenarios. Based on the relay parameters on this system state, 30% relay are selected random. The parameters of the selected relays increased or decreased 30% randomly. Based on the new relay parameters, 10 simulations are done again to obtain the test data as 'o' in Figure 11.

5.3 FNN TRAINING AND TEST

The training course of Fuzzy neural network is described as Figure 9. It is obviously that high precision (10^{-5}) has been achieved after limited iterative times.

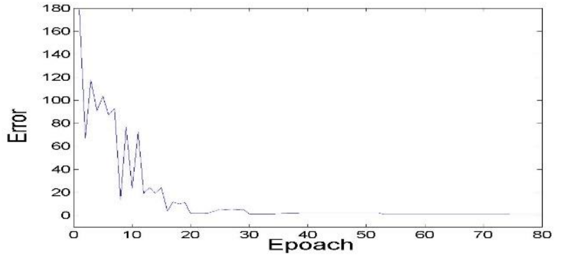


FIGURE 9 Training error

The membership function after training is shown as Figure 10.

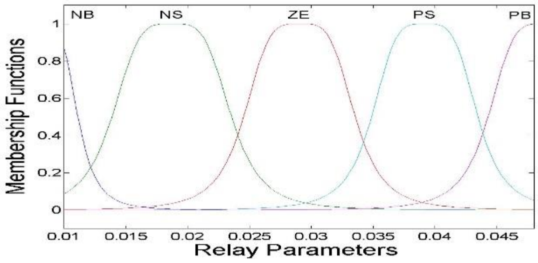


FIGURE 10 Membership function after training

Comparing Figure 7 and Figure 10, it is obviously that the membership functions of relay parameters vary after training, especially the NB membership function. The reason is that there are more relay parameters distributing in this zone. The variation reflects that adjustment to membership function by fuzzy neural network is effective. The distribution of membership function satisfied the real system after adjustment.

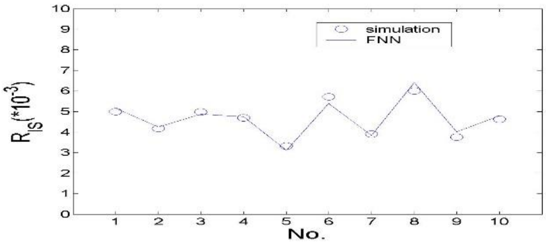


FIGURE 11 Testing results

The test data are used to verify the fuzzy neural network. The results are shown as Figure 11, where "simulation" refers to values obtained by simulating and "FNN" refers to values obtained by fuzzy neural network. The results clearly show that the training of the fuzzy neural network has been successful for a variety of system state and disturbances for the IEEE 118-bus system. When the training times are sufficient, even for previously unseen data, correct evaluation of cascading outages adaptability has been achieved by the fuzzy neural network.

5.4 THE APPLICATION OF FNN

The supplemental function of fuzzy neural network is to calculate the relay parameter sensitivity to system cascading outage adaptability. The top 10 sensitivities are listed in Table 2. They should gain more attentions than other relays when planning a protection system upgrade.

TABLE 2 Top 10 relays of sensitivity

No.	Relay#	Sensitivity (10^{-3})
1	115	8.29
2	11	8.17
3	178	8.11
4	95	8.06
5	161	7.68
6	45	7.63
7	59	7.43
8	151	6.76
9	108	6.57
10	131	6.19

If the number of relays can be upgraded is 4, relay 115, 11, 178 and 95 are selected to upgrade, whose replacement can decrease cascading outages adaptability effectively. Their improvements over the original system and replacement of another 4 relays random are compared in Figure 12. The relative cascading outages adaptability is used, and the adaptability of the original system is defined as base value one.

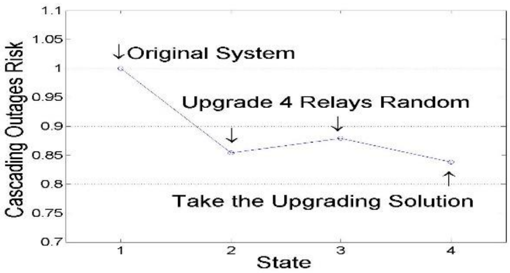


FIGURE 12 Result of upgrading

6 Conclusions

This paper proposes a new strategy to evaluate and mitigate power system cascading outages adaptability considering protection system hidden failure based on fuzzy neural network. An explicit probability model of protection system hidden failures is established to demonstrate its effects on power system adaptability. The mechanism and scheme of protection systems have been analyzed for their contribution to cascading failures after a fault occurs. The event tree is used to provide an understanding of the cascading outages sequences. Adaptability theory is used in the cascading outages security analysis and some adaptability indices are used to evaluate cascading outages adaptability. The fuzzy neural network is used to obtain the adaptability indices and to give a solution that can decrease the system cascading outage adaptability. Extensive sets of training and test data have been utilized by Monte Carlo simulation. The result of a case study on the IEEE 118-bus system illustrates the methodology.

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