**Based on Rough Set and RBF Neural Network Power Grid Fault Diagnosis**

Xiaoqin Liu*, Haijun Sun*, Mengchan Wu* and Jiayao Yang

School of Information and Control Engineering, Liaoning Shihua University, Fushun Liaoning 113001, China

*Corresponding author e-mail: qinbuluo@163.com, *sun_hai_jun@163.com, wu767366413@qq.com

**Abstract.** In order to improve the accuracy of troubleshooting results and save diagnostic time, rough set and RBF neural network are used to diagnosed fault of power grid. Rough sample reduction program is used to reduce the fault samples, and the reduction decision table is obtained as the input of the RBF neural network, get the training results. The fault samples without rough set reduction are input into RBF for training, and the two training results are compared. It is found that the samples using the rough set reduction have the same diagnostic ability as the initial decision table. Obviously, the rough decision set initial decision table can greatly reduce the size of the training sample and save diagnosis time.

1. **Introduction**

Modern production and life are increasingly dependent on the development of electricity, which will lead to a large-scale power outage, which will quickly spread to the entire power grid, resulting in considerable losses and impacts [1, 2, 3]. Ensuring continuous and stable power supply to power users has become a necessary prerequisite for modern production and even national security. However, the fault cannot be completely avoided, so when the fault occurs, it is possible to diagnose the fault component immediately and analyze the fault type to become the first task.

Rough set theory and RBFNN are merged and complement each other, forming a good cross complement. If only rough set is used for diagnosis, it is likely to cause errors due to its fault tolerance; if only neural network is used to process the initial decision table, if the initial decision table is inconsistent, it is very likely that the training result is inaccurate, or because the sample is too Large, greatly reducing the diagnostic efficiency. Therefore, only the combination of two methods can solve the problem of power grid fault diagnosis accurately and efficiently [4, 5].

2. **Rough set and RBF neural network power grid fault diagnosis method**

Due to the excessive amount of power grid monitoring data, neural network fault diagnosis method has a complicated structure and the training time is too long [6, 7]. In response to this problem, rough sets is introduced into grid fault diagnosis. The algorithm flow of fault diagnosis is shown in Figure 1.
2.1. Fault information collection and knowledge reduction of power grid
Rough set is used to deal with uncertain information, the initial decision table composed of grid fault samples is reduced to a reduction decision table, and is diagnosed as an input of RBFNN, so that the number of input neurons is greatly reduced, network structure simplified [8, 9].

1) The extraction of various fault samples from the grid is a very important step, it is necessary to select a sample that is valid for diagnosis in a large number of fault samples in a given power system. The information that needs to be collected includes information on the various protections and circuit breakers in the event of a fault and the area in which the fault has occurred. The action or no action is then converted to 0-1 logical value, finally the information is organized into an initial decision table.

2) According to the reduction principle of rough set theory, rough set reduction program is written in Matlab2010a, and the formed initial decision table is reduced by rough set. The fault sample is processed into a reduction decision table by a rough set reduction process. It is necessary to convert it to the input vector of RBFNN.

2.2. Establish RBF neural network model
1) Matlab is used to write program, extract the condition attribute value in the reduced decision table is as RBFNN input, and use the decision attribute value in the decision table as the target vector.
2) RBF is used to learn and train the reduced fault samples.

Action information of protection and circuit breaker from SCADA system may be wrong, or rejected or malfunction, some wrong information needs to be added to the test sample to be close to the actual fault information, the tolerance of the fault diagnosis method is verified [10, 11, 12, 13]. This forms a sufficiently realistic fault test sample. The test samples are analyzed using by trained neural network. Select the fault area with the largest fault probability value as fault diagnosis result.

3. Simulation and analysis

3.1. Simple grid fault
Figure 2 shows a simple power grid with three zones, section1, section2 and section3. Abbreviated as S1, S2 and S3. Over current protection IP1, IP2 and IP3 are configured separately. S1 area is equipped
with distance protection DP1, which is a backup protection for S2 and S3. QF1, QF2 and QF3 are the paths of the corresponding areas.

![Figure 2. A simple power grid structure](image)

The initial decision table is reduced to the reduction decision table in Table 1 using the written rough set reduction procedure.

| sample | IP1 | QF1 | IP2 | IP3 | Diagnosis area |
|--------|-----|-----|-----|-----|----------------|
| 1      | 1   | 1   | 0   | 0   | S1             |
| 2      | 0   | 0   | 1   | 0   | S2             |
| 3      | 0   | 0   | 0   | 1   | S3             |
| 4      | 0   | 1   | 1   | 0   | S2             |
| 5      | 0   | 1   | 0   | 1   | S3             |
| 6      | 0   | 0   | 1   | 0   | S2, S3         |
| 7      | 0   | 0   | 0   | 0   | None           |

The condition attribute values in the reduction decision table are converted into inputs to RBFNN. $P$ is the input vector. The specific value of the input is read by the program from the reduced decision table of the EXCEL format and displayed in the command window of software. The target vector is also extracted into the command window in the same way.

$$
p = 0 \quad \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \quad \text{IN} = 0 \quad \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}
$$

After the input vector and the target vector are transposed, it is input into RBFNN training function. After less than 5 iterations, the set precision is reached.
The results are shown in Table 2. The results of this operation are compared with neural network training results whose tables are not processed by the rough set in Table 3. Obviously, RBFNN training results through rough set reduction are more accurate than those without rough set, which improves the reliability and accuracy of fault diagnosis.

Table 2. Training results of RBFNN by reduction samples

| samples | S1     | S2     | S3     | S2/S3  | aims | results |
|---------|--------|--------|--------|--------|------|---------|
| 1       | 1.0000 | -0.0000| -0.0000| -0.0000| S1   | S1      |
| 2       | -0.0000| 0.9534 | 0.0466 | 0.0000 | S2   | S2      |
| 3       | -0.0000| 0.0466 | 0.9534 | 0.0000 | S3   | S3      |
| 4       | -0.0000| 1.0392 | -0.0392| 0.0000 | S2   | S2      |
| 5       | -0.0000| -0.0392| 1.0392 | 0.0000 | S3   | S3      |
| 6       | 0.0000 | 0.0000 | 0.0000 | 1.0000 | S2/S3| S2/S3   |
| 7       | -0.0000| 0.0000 | 0.0000 | 0.0000 | None | None    |

Table 3. Training results of RBFNN

| samples | S1     | S2     | S3     | S2/S3  | aims | results |
|---------|--------|--------|--------|--------|------|---------|
| 1       | 0.9805 | -0.0207| -0.0537| -0.0248| S1   | S1      |
| 2       | -0.0237| 0.9748 | -0.0653| -0.0302| S2   | S2      |
| 3       | -0.0614| -0.0653| 0.8309 | -0.0781| S3   | S3      |
| 4       | 0.0030 | 1.0031 | 0.0082 | 0.0038 | S2   | S2      |
| 5       | 0.0077 | 0.0082 | 1.0211 | 0.0098 | S3   | S3      |
| 6       | -0.0248| -0.0264| -0.0684| 0.9684 | S2/S3| S2/S3   |
| 7       | 0.1188 | 0.1263 | 0.3272 | 0.1512 | None | None    |

It can be found from the comparison of error curve that RBFNN training example after rough set reduction has a shorter time convergence, saving for the preliminary work of fault diagnosis.

3.2. Complex power grid fault

A more complicated four-bus system is used as an example. The relay protection is shown in Figure 3. There are four buses (B1, B2, B3, and B4), a transformer T and four transmission lines L1-L4; CB1-CB10 are circuit breakers for their respective transmission lines; MB is main protection device for buses, ML is main protection device for transmission lines, BL is backup protection device for transmission lines, and MT is main protection device for transformers. There are a total of 22 protection devices, each named according to the line and type. For example, ML2 indicates that the transmission line is in the main protection corresponding to the circuit breaker 2 (CB2), and BL5 indicates the backup protection corresponding to the transmission line in the circuit breaker 5 (CB5).
The results of the complex grid fault diagnosis is gotten using the same diagnostic process for the simple grid fault example. The comparison found that, except for the two redundant samples in the original sample, the results of neural network training of the rough set reduction samples are exactly the same as those of the unprocessed original decision table. But it greatly reduces the number of conditional attributes required for diagnosis, saving time and improving diagnostic efficiency.

3.3. Fault tolerance research
In order to verify the accuracy and tolerance of the fault diagnosis method, several samples are taken from the fault sample to simulate data transmission errors, protection or circuit breaker refusal and malfunction that may occur the actual fault diagnosis process. Change the value of certain condition attributes and input neural network. Table 4 shows the test samples set. Except for samples 4 and 7 which are not subject to noise interference, other samples have signal transmission errors or fault. Error condition attribute values are underlined.

| samples | CB1 | CB2 | CB4 | CB5 | CB6 | CB7 | CB10 | MB1 | MT | ML2 | ML7 | ML8 | ML9 | BL4 | BL7 | BT | fault area |
|---------|-----|-----|-----|-----|-----|-----|------|-----|----|-----|-----|-----|-----|-----|-----|----|-----------|
| 1       | 1   | 0   | 0   | 0   | 0   | 0   | 0    | 0   | 0  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | B1         |
| 2       | 1   | 1   | 0   | 0   | 0   | 0   | 0    | 0   | 1  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | T          |
| 3       | 0   | 0   | 0   | 0   | 0   | 0   | 0    | 1   | 0  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | B3         |
| 4       | 0   | 0   | 0   | 0   | 0   | 0   | 0    | 0   | 0  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | B4         |
| 5       | 0   | 0   | 0   | 0   | 0   | 0   | 0    | 0   | 0  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | L2         |
| 6       | 0   | 0   | 0   | 1   | 0   | 0   | 0    | 0   | 0  | 0    | 0   | 1   | 1   | 0   | 0   | 0   | L2         |
| 7       | 0   | 0   | 0   | 0   | 0   | 0   | 0    | 0   | 0  | 1    | 0   | 1   | 0   | 0   | 0   | 0   | L4         |
| 8       | 1   | 0   | 0   | 0   | 0   | 0   | 0    | 1   | 1  | 0    | 0   | 1   | 0   | 0   | 0   | 0   | B1,T       |
| 9       | 0   | 1   | 1   | 0   | 0   | 0   | 0    | 0   | 0  | 0    | 0   | 0   | 0   | 0   | 0   | 0   | B2,L1      |
| 10      | 0   | 0   | 0   | 0   | 1   | 1   | 0    | 0   | 0  | 0    | 1   | 1   | 0   | 0   | 0   | 0   | B3,L4      |

This test sample is input into RBF. The diagnosis results are shown in Table 5, in which the fault probability value of the fault component is marked with a horizontal line. The threshold for diagnostic result is 0.5. If the probability value is greater than 0.5, it is the fault component, otherwise it is ignored.
Table 5. Diagnosis result (1)

| Component failure probability | B1   | T   | B2   | B3   | B4   | L1   | L2   | L3   | L4   | B1,T |
|-------------------------------|------|-----|------|------|------|------|------|------|------|------|
| 1                             | 0.8388 | 0.4694 | 0.0061 | -0.0009 | 0.1692 | -0.1501 | 0.0840 | -0.1286 | 0.0189 | -0.3855 |
| 2                             | -0.0036 | 0.6483 | -0.1568 | -0.0062 | 0.5486 | -0.0735 | -0.0386 | 0.0880 | -0.0044 | 0.0043 |
| 3                             | 0.1000 | -0.1556 | 0.1364 | 0.9721 | -0.4052 | 0.0163 | -0.2015 | 0.2205 | -0.1422 | 0.1358 |
| 4                             | -0.0025 | -0.0007 | 0.0414 | 0.0080 | 0.9044 | -0.0514 | -0.0311 | -0.0497 | -0.0076 | 0.0021 |
| 5                             | -0.0079 | 0.0098 | 0.0045 | 0.2023 | -0.2284 | -0.0623 | 0.4313 | -0.0206 | 0.0774 | -0.0077 |
| 6                             | -0.3418 | 0.3005 | -0.1494 | 0.0131 | -0.2286 | 0.0610 | 0.7997 | 0.1444 | -0.0291 | 0.1314 |
| 7                             | 0.0009 | -0.0008 | -0.0040 | 0.0029 | 0.0085 | 0.0001 | 0.0002 | 0.0041 | 1.0000 | 0.0005 |
| 8                             | -0.0657 | 0.0908 | 0.1055 | 0.1009 | -0.2647 | -0.1219 | 0.0579 | 0.1129 | -0.1350 | 0.7653 |
| 9                             | -0.1541 | 0.1597 | -0.1281 | 0.0171 | 0.2083 | 0.4583 | -0.1744 | 0.0617 | -0.0577 | 0.0438 |
| 10                            | -0.0842 | 0.0915 | 0.4591 | 0.1013 | -0.3543 | -0.1333 | -0.3116 | 0.0321 | -0.2080 | -0.0673 |

Table 5. Diagnosis result (2)

| Component failure probability | B2,T  | B2,L1 | B2,L2 | B2,L3 | L1,L2 | L2,L3 | L3,L4 | L2,L4 | L4 | B4,L4 | B3,L1 |
|-------------------------------|------|-------|-------|-------|-------|-------|-------|-------|-----|-------|-------|
| 1                             | 0.0259 | -0.0259 | -0.0435 | 0.0271 | -0.0203 | -0.0163 | -0.0035 | -0.0323 | 0.0142 | 0.0063 |
| 2                             | 0.3274 | -0.0218 | 0.0056 | -0.0299 | -0.0057 | 0.0038 | 0.0020 | 0.0037 | -0.0030 | 0.0114 |
| 3                             | 0.0140 | -0.1365 | 0.1223 | -0.1763 | 0.2369 | 0.1589 | 0.0248 | 0.2486 | -0.1074 | -0.0434 |
| 4                             | 0.0042 | -0.0166 | 0.0076 | -0.0209 | 0.0077 | 0.0077 | 0.0019 | 0.0114 | -0.0056 | 0.0002 |
| 5                             | 0.0014 | -0.0328 | 0.0352 | -0.0277 | 0.0994 | 0.0474 | 0.0060 | 0.5919 | -0.0396 | -0.0545 |
| 6                             | -0.0075 | 0.1011 | 0.2822 | -0.0418 | -0.0608 | -0.0180 | 0.0059 | 0.0482 | -0.0218 | 0.0154 |
| 7                             | -0.0006 | 0.0012 | 0.0001 | 0.0019 | 0.0014 | -0.0000 | -0.0001 | 0.0003 | -0.0000 | -0.0023 |
| 8                             | 0.0020 | -0.1574 | 0.1813 | -0.1512 | 0.1567 | 0.1383 | 0.0225 | 0.2395 | -0.1023 | 0.0834 |
| 9                             | -0.0351 | 0.6602 | 0.0891 | -0.0559 | -0.1660 | 0.0234 | 0.0114 | 0.0963 | -0.0432 | 0.1587 |
| 10                            | 0.0272 | -0.2051 | 0.1657 | -0.2061 | 0.3665 | 0.2122 | 0.0341 | 0.3707 | 0.6831 | -0.0959 |

As shown in Table 5, only the sample 5 cannot determine the specific result of the diagnosis. The other samples accurately diagnose the faulty component, indicating that RBF neural network still has a strong diagnostic ability for the misaligned sample, and the fault tolerance is strong.

4. Conclusion
Fault diagnosis method based on rough set and RBF neural network is proposed. The simulation results show that the fault diagnosis method can quickly and accurately diagnose faulty components of complex power grids with high fault tolerance and high practical value.

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