Research on Active Emergency Repair Technology of Distribution Network Based on Large Power Data

Yiping Mao, Jingfei Mao, Jiabo Situ, Bo Dong and Longjin Lv

1State Grid Ningbo Fenghua Power Supply Company, Ningbo, China
2School of Finance and Information, Ningbo University of Finance & Economics, Ningbo, China

*Corresponding author e-mail: magic316@163.com, 279817305@qq.com, 61342903@qq.com, 137882601@qq.com, 1601567427@qq.com

Abstract. Distribution network emergency repair is the most important work in power supply service and production management. Active emergency repair is an important way to improve the efficiency of emergency repair command. In this paper, we investigate the outage data of private and public transformer in the electric power information collection system. By using data mining technology, we build the relationship between outage data and actual line faults. A real fault identification model based on the detailed outage data of private and public transformer is established, which can quickly and accurately identify real faults and facilitate maintenance personnel to take timely measures, and achieve active emergency repair.

1. Introduction

Distribution network emergency repair command is the most important work in power supply service and production management. Distribution network is a key link between high-voltage transmission lines and low-voltage users. It is an indispensable energy supply system in modern cities [1]. It is located in the load center of power system, which characteristics the large power consumption, high load density, high requirements for safety, reliability and quality of power supply. With the progress of the times, people's requirements for the quality of power supply are constantly improving, which forces power supply enterprises to improve their lean management ability, improve work efficiency, and continuously improve the ability of safe and reliable power supply of power grid equipment. Among them, the demand for emergency repair of distribution network faults is particularly prominent, and the working ability of emergency repair of distribution network is also put forward higher requirements. The accurate location of fault points plays a very important role in the whole process of emergency repair. Distribution network emergency repair plays an important role in ensuring continuous power supply to minimize the economic and property losses caused by power accidents [2]. However, there are still some problems in the distribution network emergency repair in recent years.

Active rush repair is an important way to improve the efficiency of rush repair command. Because the distribution automation system does not cover the rural areas and the application of graded protection devices in distribution network, the current county-level power supply enterprise control department lacks timely and reliable perception of power outage due to local distribution line faults. In the face of sudden local distribution line faults, it is often necessary to follow the procedure "receive work orders-
rush repair dispatch single-user consultation". It takes a long time to determine the location and scope of the fault through the steps of "site investigation - fault confirmation". Moreover, there are many duplicate work orders formed at the same fault point, which requires a lot of manpower and material resources for work order circulation and customer response. So, the work is relatively passive. Therefore, active rush repair has become an urgent need. Before users apply for repair, the process of rush repair service should be started, so that the working mode can be changed from passive to active, which improves work efficiency, reduces the sound of stop movies and improves customer satisfaction[3].

Fault reliable recognition is the prerequisite for rapid and active repair [4]. Active rush repair aims to repair faulty lines quickly and accurately, usually before customer feedback. Therefore, how to identify faults quickly and accurately is an important prerequisite for the implementation of active rush repair. Power companies have accumulated a large amount of historical fault information, but at present, they can only carry out simple statistics, but cannot dig out the rich knowledge contained therein, cannot deeply understand and effectively use these data, which causes "data disaster" and "resource waste". However, the information collected from substations to dispatching centers in power grid system is huge, and manual identification is unrealistic [5]. This requires an intelligent fault identification model with high accuracy, which makes full use of the advantages of mass information, improves the accuracy of fault identification through information fusion, and implements the master of power grid fault identification. Emergency repair is of great significance [6]. The purpose of this paper is to explore and study a technology of "active emergency repair of distribution network based on large power data". By using data analysis technology, the correlation between the details of power outage and real faults is established, and the fault identification model is built by using neural network method, which helps facilitate maintenance personnel to find faults as soon as possible, and take action, then reduce the customers' complaints.

2. Data Acquisition and Processing

2.1. Data Acquisition
Log in to the power information acquisition system, and export the effective outage data of private and public distribution transformers from January 2017 to June 2018 respectively. The extracted fields include: line, account number, account name, outage time, and restore power supply time. And the effective outage signal is derived in total 465376, of which 83571 were blackouts in public transformers, 381805 were blackouts in private transformers.

Log in to PMS system and export the information of distribution network maintenance plan during this period. The fields extracted include: Line, start time, end time, performance description, etc. Log in to marketing system and export the details of 95598 work orders from January 2017 to June 2018. The fields extracted include: Job number, work order acceptance time. Finally, there are manual troubleshooting records, which include: start time, end time, line name.

2.2. Data Processing

2.2.1. Statistics of outage signals of public and private transformers. From January 2017 to June 2018, FH Power Supply Company has deduced 465376 effective outage signals in its power information acquisition system. Among them, 83571 transformer outages are public transformer outages, 381805 transformer outages are private transformer outages. In fact, the number of transformers is basically equal, but the number of private transformer outages is obviously more than that of public transformer outages. According to the time dimension from 1 minute to 5 minute aggregation, taking 5 minutes as an example, aggregation by 5 minutes means that the time interval between two successive outage signals on the same line is less than 5 minutes, then they belong to the same power outage event. With the help of Python software, the number of blackout signals of private and public transformer is sorted in 1 to 5 minutes respectively. From this, we can get a detailed list of the number of blackout signals of transformer and transformer on the same line for different time, as shown Table 1.
Table 1. Detailed List of Outage Signals for Five-minute of Transformer

| Line No. | Time     | Signals of Private | Signals of Public |
|---------|----------|--------------------|-------------------|
| Line A779 | 2017/1/9 | 7                  | 0                 |
| Line A719 | 2017/2/16 | 7                  | 0                 |
| Line A339 | 2017/4/16 | 6                  | 1                 |
| Line A739 | 2017/4/19 | 8                  | 1                 |
| Line A757 | 2017/4/20 | 7                  | 0                 |

The average number of blackouts in public and private transformer power outages is calculated according to different time dimensions. The number of blackouts does not change much, see Table 2. So we use 5-minute data as the research object.

Table 2. Aggregates in a time dimension from 1 to 5 minutes

| Time interval       | Outage event No. | Average No. of Private Signals | Average No. of Public Signals |
|---------------------|------------------|--------------------------------|-------------------------------|
| 1-minute aggregation| 56944            | 7.00                           | 1.40                          |
| 2-minute aggregation| 53221            | 7.13                           | 1.43                          |
| 3-minute aggregation| 51421            | 7.18                           | 1.54                          |
| 4-minute aggregation| 49947            | 7.22                           | 1.55                          |
| 5-minute aggregation| 48977            | 7.24                           | 1.56                          |

2.2.2. Statistics of the number of real faults. The real faults of the line mainly consist of two parts: one is the detailed information of 95598 work orders; the other is the manual fault records, which does not produce work orders, but actually carries out maintenance events. For the 95598 Work Order, after data processing, 1445 valid fault data are obtained. Fields include time and line names.

During the studied time, there are 1892 the manual fault records. But it is defined as invalid data, which should be removed, if there are the following circumstances, Firstly, the fuse of drop-type fuse is broken or the fuse pipe is burned out, and only replacing the fuse or fuse pipe will not cause the power failure of distribution transformer; Secondly, the slight skew of pole tower; Thirdly, the breakage of tie wire and the damage of grounding rod; Fourthly, the power failure of private line. The fifth is the internal line fault caused by the internal reasons of the users; the sixth is the fault of finding the grounding point and dealing with it without the power outage; the seventh is that the description of the recording content is vague, and it is impossible to judge whether the power outage occurs from the record. The fault records involved in the above seven types of fault data were cleaned. After that, we get 927 effective fault data.

Summarizing the two kinds of real faults, 2372 fault records are obtained. However, the fault records generated by planned maintenance cannot be seen as real faults. It is necessary to delete this part of data from the fault records, then the remaining effective fault records are 1826.

3. Relevance analysis

3.1. Analysis of the Relation between Outage Signal and Maintenance Plan

From January 2017 to June 2018, FH Power Supply Company had 2 263 effective outage maintenance plans. 34 517 outage signals were successfully matched with the maintenance plan. The matching success rate of the transformer was significantly higher than that of the transformer, as shown in the Table 3.
Table 3. Successful Matching of Outage Signal with Maintenance Plan

| Transformer | Total outage signals | Planned outage signals | Matching rate |
|-------------|----------------------|------------------------|--------------|
| Private     | 381805               | 22760                  | 0.0596       |
| Public      | 83571                | 11757                  | 0.1407       |

Comparing the planned outage signals with the unplanned, we find the average outage signals of private transformer is basically the same, but that for the public one is quite different, see Table 4.

Table 4. Average outage signals for planned and unplanned outage

| Type     | Total average outage signals | planned average outage signals |
|----------|------------------------------|-------------------------------|
| Private  | 7.235                        | 7.947                         |
| Public   | 1.445                        | 4.105                         |

Under the condition that the number of distribution transformers is basically equal, the average fault signals of private transformer is far more than that of public transformer, which indicates that the actual probability of power failure of private transformer er is far greater than that of the public one, that lies in it is common for users to pull and shut down electrical equipment by themselves.

3.2. Correlation between outage signal and fault outage

Further analysis is made to find the difference between private and public transformers when faults occur or not, see Table 5.

Table 5. Average Outage Signal Number under Fault and Non-Fault

| Transformation | Fault  | Non-fault |
|----------------|--------|-----------|
| Private        | 9.5949 | 7.1467    |
| Public         | 6.2039 | 1.3514    |

From the table, we find the average number of blackouts of private and public transformer under fault is higher than that under non-fault, especially the number of public transformer, which reaches about 5 times of that under non-fault, so there is a greater positive correlation between the increase of blackouts of public transformers and distribution line faults.

3.3. Analysis of unrelated outage signals

Among all 465376 outage signals, there are 31511 private transformer signals and 48695 public ones which are not related to maintenance plans or faults. For the outage events arranged in 5 minutes, the difference of the average number of private transformer outage signals is small, but the difference of the average number of public transformer outage signals is large, as shown in the Table 6.

Table 6. Average Outage Signal Number under related and unrelated

| Type       | Average No. of Private Signals | Average No. of Public Signals |
|------------|--------------------------------|------------------------------|
| related    | 8.5856                         | 4.856                        |
| Unrelated  | 7.097                          | 1.0967                       |

Generally speaking, the number of outage signals in power outage events is positively correlated with planned maintenance, fault work orders and fault records. The more the number of signals is, the greater the related probability is, but the number of outage signals of public transformer has greater impact on the fault.
4. Data Mining

In this section, by using the neural network model to analyze the sorted data, we try to establish the fault identification model. We take the number of blackouts as independent variable and the fault as dependent variable. We use the data of 2017 as sample data and the data of 2018 as test data. After the above data processing, we get a total of 24769 data in 2017. Among them, 1125 are related to faults, while 23644 are not related to faults. The distribution of sample data is seriously unbalanced. Direct training will lead to model failure. Using up-sampling method, the samples of rare classes are copied. After sorting the data, we get 45060 training data, including 19318 fault records and 25742 non-fault records. Using data mining based on Python, we obtained the training results, as shown in Table 7.

| real | Predict to 0 | Predict to 1 |
|------|--------------|--------------|
| 0    | 23,422       | 2,320        |
| 1    | 9,845        | 9,473        |

The recognition accuracy of the model is 73%. Because of the high cost of identifying non-fault as fault in active repair, the hit rate of fault is also an important index. It refers to the proportion of real fault in the event of identifying fault. The hit rate of the model is 80.32%. The fault recognition rate refers to the proportion of the accurate fault identification in the total number of real faults. The fault recognition rate of our model is \( \frac{9473}{(9473+9845)} = 49.04\% \).

Using the data from January to June 2018 as the prediction data, the test data are generated by the same up-sampling method, and then brought into the model for prediction. We obtain the following test results, as shown in the Table 8.

| real | Predict to 0 | Predict to 1 |
|------|--------------|--------------|
| 0    | 726          | 77           |
| 1    | 309          | 292          |

The test result shows that the accuracy of the predicted results is 72.51%, while the hit rate is 79.13% and the fault recognition rate is 48.58%, which indicates the model is stable.

5. Conclusion

Starting from the number of outage signals of the private and public distribution transformers of the line, this paper analyses the correlation between outage signals and faults. It is found that the outage signals of the private and public transformer will lead to the abnormal power loss of the distribution transformers. So there is a certain correlation between the outage signals of the distribution transformers and the faults of the distribution line. The private and public outage signals are taken as independent variable, the 95598 fault work order and manual fault records are taken as dependent variables, we establish the fault identification model based on the outage signal by using the neural network algorithm. By utilizing the existing data, the fault identification ability of distribution lines is greatly improved. Push real faults information to the relevant person in charge, so as to achieve the fault actively repaired.

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References

[1] H. Khurana, M. Hadley, N. Lu, D. Fraincke, Smart grid security issue. Security&privacy 8 (2010) 81 - 85.
[2] J. D. F. McDonald, B-C. Pal, P. D. Lang, Representation of distribution system reliability during
network restoration and repair, IEEE, 2007.

[3] S. M. Zali, J.V. Milanović, Generic model of active distribution network for large power system
stability studies, IEEE Transactions on Power Systems 28 (2013) 3126 - 3133.

[4] Y. You, D. Liu, W. Yu, et al. Technology and its trends of active distribution network, Dianli
Xitong Zidonghua(Automation of Electric Power Systems) 36 (2012) 10 - 16.

[5] C. Biyun, Q. Hong, D. Jin, A Reliability Forecasting Method for Distribution Network Based on
Data Mining [C]/2018 China International Conference on Electricity Distribution (CICED),
IEEE (2018) 2503 - 2506.

[6] P. Xue, Z. Zhou, X. Fang, et al. Fault detection and operation optimization in district heating
substations based on data mining techniques, Applied energy 205(2017) 926 - 940.