Fault Prediction Method for Distribution Network Outage based on Feature Selection and Ensemble Learning

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***Abstract*—In this paper, a fault level prediction method for distribution network based on feature selection and ensemble learning is proposed to solve the problem of high, redundant and low accuracy rate of level prediction in power distribution network. First, by preprocessing the fault data of the distribution network, the 23 kinds of initial fault features for distribution networks involving weather, load and equipment are summed up, and a new method of fault grade division for distribution network is proposed. Combined with grey relational analysis, a fault feature selection method which improves the characteristic that Relief-F algorithm can't eliminate redundancy is proposed. Finally, a strong classifier is used to predict the fault level for distribution network based on support vector machine improved by ensemble learning. Then, the proposed method is compared with the other feature selection and prediction methods. Through the actual example analysis, it is verified that the proposed method can effectively improve the prediction accuracy of distribution network fault, and has practical application value.**

Keywords-Distribution Network; Data Mining; Feature Selection; Ensemble Learning; Fault Level Prediction.

I. INTRODUCTION

In recent years, with the rapid development of power enterprise information construction and the comprehensive construction of smart grid, the scale of the information data carried by power system is becoming huger, and the power industry is fully entering the "big data" era [1]. With the continuous improvement of electrical information collection and distribution automation systems, the basic data, running data and management data of distribution network have exploded, and the large data characteristics such as mass, complex processing logic and complex data items are gradually presented. It is urgent to find an effective method for mining the knowledge related to power outage failures in mass data [2]. Due to the large number of influencing factors in distribution network failure, the fault characteristics are high dimension, redundancy and independence [3]. In order to improve the efficiency and accuracy of distribution network fault prediction, it is necessary to identify and extract fault features of distribution network from many characteristics. Therefore, it is vital to choose the best feature for distribution network fault level prediction.

Feature selection means that a representative feature subset is selected from a set of original feature sets to reduce the dimension of the feature space, on the premise of guaranteeing the classification performance of the feature set [4]. Feature selection algorithms can be divided into two types: filter (filter) and package (wrapper). Filter feature selection algorithm evaluates and selects the selected feature subset by using the intrinsic characteristics of the data, which usually runs efficiently, but the classification performance is poor. Wrapper feature selection algorithm relies on the classification accuracy of machine learning as the evaluation criterion for the selection of feature subset. The feature set selected by this kind of algorithm is superior in classification performance, but the efficiency is lower [5]. The research of feature selection is mainly focused on the field of information technology and statistics, which has made breakthrough applications in the fields of text recognition, face recognition and biology, but the research and application of feature selection method for the field of distribution system is less [6]. The Department of electrical machinery of Tsinghua University has studied the method of automatic discovery for the safe operation of power system, the key technology including method of the selection of the security feature [7]. In [8], a feature selection method based

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on weighted random forest and recursive feature elimination strategy was proposed. According to the high dimensionality of power system transient stability assessment, a double stage feature selection method based on support vector machine was proposed in [9]. In [10], two popular feature selection methods were reviewed: 1) hypothesis test, 2) stepwise regression, and another two: 3) stepwise selection by Akaike's Information Criterion, and 4) LASSO/ALASSO were introduced.

At present, a lot of research on short-term power network forecasting is carried out at home and abroad, and methods of neural network, Kalman filtering, time series, support vector machine and wavelet analysis are put forward [11-12], but the accuracy of prediction is still unable to meet the requirements. The neural network algorithm and time series method are relatively high prediction precision, but there are over fitting characteristic, weak generalization ability and easy to fall into the local optimal because of the weak learning algorithm [13].

Aiming at the above problems, this paper proposes a method of fault level prediction in distribution network based on improved Relief-F algorithm and Adaboost integrated support vector machine (Support Vector Machine, SVM) as a strong classifier. First, by preprocessing the related data of fault characteristics of distribution network, the characteristics of initial fault of distribution network are concluded, and the basis of fault risk classification of distribution network is determined. Then, the improved Relief F algorithm is applied for feature selection to get the optimal fault feature set. Finally, the SVM algorithm based on Adaboost (Ada-SVM) is used to predict the level, and the effectiveness of the proposed method is verified by comparing the results of before and after the feature selection, the other feature selection methods and classification methods.

II. DATA PREPROCESSING

A. Data base

Intelligent power distribution data has rich data sources, and most cities have multiple distribution information management systems, including distribution automation system, dispatching automation system, intelligent public distribution transformer online monitoring system, power grid meteorological information system, power quality management system, production management system, production management system, geographic information system, variable load monitoring system, load control system, marketing business management system, ERP system, 95598 customer service system and other data sources [14].

Through the investigation of the online monitoring system, distribution geographic information system (GIS), distribution automation system and power grid meteorological information system, the relevant data sources, data types are obtained, as shown in Table 1.

TABLE I. DATA OF FAULT LEVEL PREDICTION

Data source	Data type
Intelligent public distribution transformer monitoring system	Transformer capacity, Load node, Real-time load, Monthly maximum load data.
GIS	Location data, Operation time, Line length
Distribution automation system	Start / end time of failure, Power outage, Fault feeder name / type / times
Grid meteorological information system	Average high/low temperature, Extreme high/low temperature, Humidity, Strong wind days, Haze days, Snowfall days, Thunderstorm days, Wind speed

B. Fault classification basis

The fault level of distribution network is not only related to the number of power failures, but also related to the cumulative outage of failures, cumulative load and power shortage [15]. In this paper, a new method is proposed to divide the breakdown grade of the power outage loss load and the lack of power supply. The data and state of each feeder partition per month are taken as the statistical analysis object, and the rating index F_i of the power outage fault is obtained.

$$F_i = \frac{2 \bullet \sum_{j=1}^{n} \frac{S_{ij}}{S_{iN}} \bullet \sum_{j=1}^{n} \frac{E_{ij}}{E_{iN}}}{\sum_{j=1}^{n} \left(\frac{S_{ij}}{S_{iN}} + \frac{E_{ij}}{E_{iN}} \right)} \tag{1}$$

Where S_{iN} is the capacity of the feeder area i, S_{ij} is the total loss of load in the j power outage accident in this area, E_{ij} is the lack of electricity supply for the j power outage in this area, and N is the total number of power outages in the month.

According to the selected power failure times N and grade evaluation index Fi, the power failure degree of distribution network is divided into 3 levels: slight, important and serious. According to the actual situation, we set the discriminant limit of the fault grade, and select the highest failure level after calculation. The criteria for evaluation of fault classification are shown in Table 2.

TABLE II. LEVEL DIVIDED FOR FAULT OF DISTRIBUTION NETWORK

Fault level	Power failure state	Monthly fault number n	Fault grade evaluation index F_i
1	Slight.	<3	<40%
2	Important	4~7	40%~90%
3	Serious	>8	>90%

III. FEATURE SELECTION METHOD

Based on the Relief F algorithm, the feature weight is calculated [16], and gray correlation feature correlation analysis [17] is selected for feature selection. The concrete steps are as follows:

1) The distribution network fault data set D is divided into three fault grades, the sample number is m, the nearest neighbor sample number is K, and the number of runs is N.

2) Initialize all the feature weights to 0, and randomly select a sample R from D.

3) Find k nearest neighbor H_j (j=1, 2...) from the same sample set of R. K), find out k nearest neighbors M_j and L_j from every different sample set. The calculation formula of the close neighbor of the sample is as follows:

$$\mathrm{d}(A,B)=\sqrt{\sum_{i=1}^{n}\left(a_i-b_i\right)^2} \tag{2}$$

Where features *A* and *B* are represented by n-dimensional arrays *A= {a1, a2... an}, B= {b1, b2... bn}*, each sample is a point in the n-dimensional space.

4) Calculate the feature differences between K homogenous samples H_j and random samples R, and calculate the feature differences between K different types of nearest neighbor samples M_j and L_j and random samples. The sample feature difference calculation formula is as follows:

$$diff(A,R_1,R_2)=\begin{cases}\left|R_1[A]\text{-}R_2[A]\right|/(\max(A)\text{-}\min(A))\ A\ is\ cons\tan t\\ 0 \quad A\ is\ \text{discrete}, R_1[A]=R_2[A]\\ 1 \quad A\ is\ \text{discrete}, R_1[A]\neq R_2[A]\end{cases} \tag{3}$$

Where *diff (A, R1, R2)* represents the difference in feature A between sample $_R1$ and sample R_2.

5) Calculate the weight of all features. Calculated as follows:

$$W(A)=W(A)-\sum_{j=1}^{k}diff(A,R,H_j)/(mk)+\sum_{C\notin class(R)}\left[\frac{P(C)}{1-P(Class(R))}\cdot\sum_{j=1}^{k}diff(A,R,M_j(C))\right]/(mk) \tag{4}$$

Where H_j and M_j denote the samples of the same type and different types that are closest to each other in the training set and the sample *R*, *P(C)* is the ratio of the number of samples in the *C* type to the total number of samples.

6) Set the resolution coefficient P and associated thresholds, and analyze the fault features whose rejection degree is greater than the threshold. The degree of association is calculated as follows:

$$\begin{cases}\overline{\xi_{oi}(k)}=\dfrac{1}{n}\sum_{k=1}^{n}\dfrac{\Delta_{0i}(\min)+P*\Delta_{0i}(\max)}{\Delta_{0i}(k)+P*\Delta_{0i}(\max)}\\ \Delta_{0i}(\min)=\min_{(i)}\min_{(k)}\left|X_0(k)-X_i(k)\right|\\ \Delta_{0i}(\max)=\max_{(i)}\max_{(k)}\left|X_0(k)-X_i(k)\right|\\ \left(i=1,2,\cdots,m;\ k=1,2,\cdots,n;\ 0<\xi_{oi}(k)\le 1,\ P\in[0-1]\right)\end{cases} \tag{5}$$

Where X_0 is the reference sequence, X_i is the comparison sequence, and $\left|X_0(k)-X_i(k)\right|=\Delta_{0i}(k)$ is the absolute difference between the reference sequence and the comparison sequence at the k-th time.

7) In descending order of feature weights, SVM classifiers are used to evaluate feature subset. For the sorted feature subsets, the previous item selection strategy is used to traverse the feature space, and the accuracy of the classifier is calculated respectively to obtain the optimal fault feature set.

IV. ADA-SVM FAULT LEVEL PREDICTION

A. SVM algorithm

SVM is a machine learning method based on the theory of VC dimension and the minimum principle of structural risk in statistical theory. It is widely used in classification, function approximation and time series prediction. The main idea is to identify a classification hyper plane, separate the different class sample set and have the largest classification interval. In order to solve the problem of linear inseparable classification, the input space of the sample is converted to the high dimensional space by nonlinear transformation, and the optimal hyper plane is solved in the high dimensional space. We use the kernel function of input space to replace the inner product operation of high-dimensional feature space [18].

The objective function is:

$$\begin{aligned}\min_{\alpha}\quad & \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(x_i\bullet x_j)-\sum_{i=1}^{N}\alpha_i\\ s.t.\quad & \sum_{i=1}^{N}\alpha_i y_i=0\\ & 0\le\alpha_i\le C\end{aligned} \tag{6}$$

The decision function is:

$$f(x)=sign\left(\sum_{i=1}^{N}\alpha_i y_i K(x\bullet x_i)+b\right) \tag{7}$$

The commonly used kernel functions include linear kernel function, two kernel function, polynomial kernel function, radial basis kernel function (Radial Basis Function, RBF), and multilayer perceptron. RBF formula as follows:

$$K(x,z)=\exp\left(-\frac{\|x-z\|^2}{2\sigma^2}\right) \tag{8}$$

B. Ada-SVM algorithm

Adaboost algorithm is an important integrated learning algorithm in machine learning. By training different weak classifiers for the same training set, these weak classifiers are combined into strong classifiers. The core idea of the algorithm is to improve the weight of the sample and the weak classifier with strong learning ability, and reduce the weight of the sample with good training effect and the weak classifier weight of the weak learning ability [19].

In this paper, the algorithm flow of Adaboost based SVM weak classifier is shown in Figure 1.

```
Ada-SVM algorithm
Begin
Input：Sample training set, SVM weak classification algorithm, cycle number M, kernel function parameter σ, C;
Output：SVM Strong Classifier;
1: Initialize training sample weight is 1/n, and the initialization iteration number is m=0;
2: According to the weight distribution of training samples, RBF-SVM weak classifier is trained;
3: Calculated the prediction error of RBF-SVM weak classifier ;
4: Adjust the training sample weights and RBF-SVM weights of weak classifiers;
5: if  Number of iterations=m
6: Get the final strong classifier;
7:    else
8: Number of iterations: m=m+1，return step 4, 5;
9:    end if
End
```

Figure 1. Pseudocode of Ada-SVM algorithm

C. Fault level prediction

The feature selection method for power outage fault level prediction is divided into four stages: data preprocessing, feature extraction, feature selection and fault class classification verification. The implementation process is shown in Figure 2.

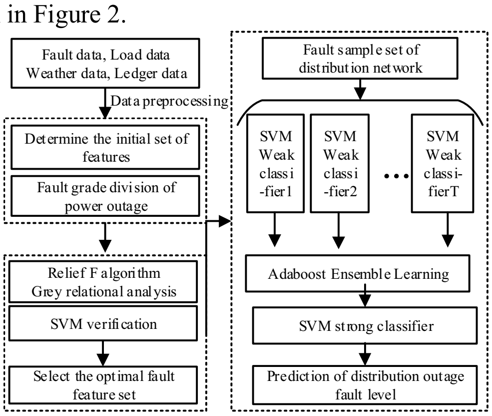

Figure 2. Flow chart of fault level prediction

V. CASE STUDY

In this paper, the data of 18 months' fault data, operation data, weather data and other data of the 120 feeder lines of a local distribution network are tested. 1800 pieces of fault data are analyzed with month unit, 1016 pieces as training sample data and 254 pieces as test sample data, of which a class of sample data is 604 pieces, two sample data is 376 pieces, and three classes of sample data are 290 pieces.

The experimental platform consists of two parts: hardware configuration and software environment. The hardware is Intel (R) Core (TM) I3 processor, PC machine in 2GB memory, and Weka3.8.2 and MATLAB R2015a in software environment.

A. Feature extraction

The failure of different months in different feeders is calculated, and the average monthly failure number and the number of monthly mean faults are calculated. The monthly mean fault and the monthly average fault distribution of the 19 feeder zones in the 12 months of the city are shown as shown in Figure 3. The abscissa represents the number of 12 months and 19 feeder areas, and the vertical coordinates represent the monthly average failure times and the monthly average faults of the feeder respectively.

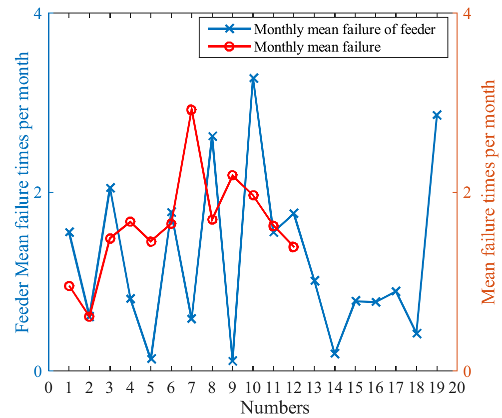

Figure 3. Distribution diagram of twelve-month average fault

Figure 3 show that the average number of failures is the highest in July, and the lowest in February. Taking "time grading" as the unit of month as fault feature. There are great differences in monthly average fault numbers in different feeder areas, that is, there are regional characteristics of failure occurrence. "Regional classification" as a fault feature. After analysis, the fault characteristics of distribution network are preliminarily identified, as shown in Table 3.

TABLE III. FAULT FEATURES OF DISTRIBUTION NETWORK

Label	Fault feature	Label	Fault feature
f 1	Time classification	*f 15*	Maximum sustained wind speed
f 2	Regional classification	*f 16*	Rainfall days
f 3	Average temperature	*f 17*	Average delivery time of segmented cable
f 4	Average high temperature	*f 18*	Transformer number
f 5	Extreme high temperature	*f 19*	Fuses average delivery time
f 6	Average low temperature	*f 20*	Number of segmented insulated conductors
f 7	Extreme low temperature	*f 21*	Fuse number
f 8	Average wind speed	*f 22*	Monthly mean load of feeder
f 9	Foggy days	*f 23*	Average loading time of load switch
f 10	Gale day	*f 24*	Cable length
f 11	Relative humidity	*f 25*	Average delivery time of insulated conductors
f 12	Fog and haze days	*f 26*	Transformer average delivery time
f 13	Precipitation	*f 27*	Length of segmented insulated wire
f 14	Thunderstorm Day	*f 28*	Average delivery time of branch lines

B. Feature selection

The characteristics of the initial fault are selected based on Relief-F, in which the sample sampling number is set to 20, the nearest neighbor sample number is set to 5, the repeated calculation is 20 times, and the feature weight is shown as Figure 4.

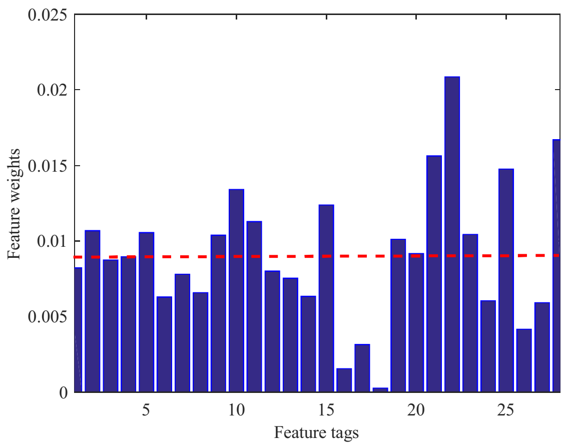

Figure 4. Distribution diagram of twelve-month average fault

After sorting features according to the weight from big to small, the rate of change of classification accuracy is verified by SVM, as shown in Figure 5.

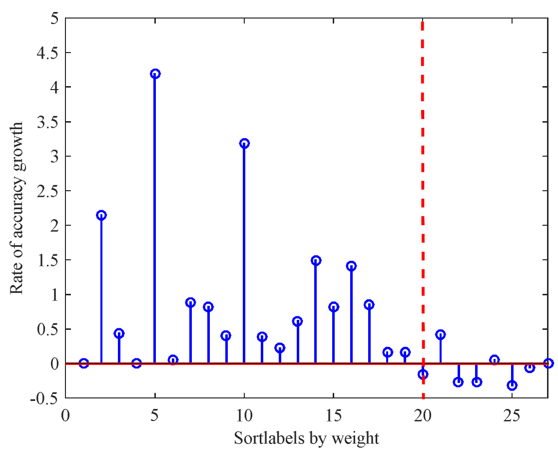

Figure 5. Fault class classification accuracy growth rate

Figure 5 show that the accurate rate of growth is negative for the first time when twentieth features are calculated, then the accuracy rate of fault classification forecasting begins to decline. Although the later features have contributed to the accuracy, the weight is far below average of 0.009. The threshold value of the feature weight is set 0.008. Based on grey relational analysis, the characteristic correlation degree matrix is calculated, and the P value is 0.5, correlation threshold is 0.8. Through calculation, correlation degree between *f3, f4* and *f*5 is greater than the threshold value. After analyzing, redundant fault features *f*3 and *f*4 are eliminated. Finally, the optimal set of fault risk features of distribution network is {*f2 f14 f5 f11 f13 f22 f23 f16 f18 f20 f*21 *f*19 *f*10 *f*17 *f*6 *f7 f*1}.

C. Results and analysis

1) Comparison of different feature selection methods

Based on different feature selection algorithms, SVM classification prediction model is built. The PC algorithm is evaluated according to the main component analysis and transformation of the data. The CSE algorithm evaluates the predictive ability of each feature and the correlation between them, and the GAE algorithm is evaluated according to the gain ratio of each attribute related to the classification. Among them, GAE and PC algorithm adopt Ranker search algorithm, and CSE adopts BestFirst search algorithm to feature selection. The comparison of classification results of different feature selection methods is shown in Table 4. M-error represents Mean absolute error.

TABLE IV. COMPARISON OF CLASSIFICATION RESULTS OF DIFFERENT FEATURE SELECTION METHODS

Evaluator	Number	Label Accuracy (%)	Kappa	M- error
—	28	78.05	0.2684	0.2741
PC	12	78.33	0.267	0.2728
CSE	9	79.17	0.3237	0.1774
GAE	20	79.44	0.3693	0.2698
Relief F+G	17	81.72	0.4158	0.1544

Table 4 show that the classification accuracy of the Relief F+G feature selection method is 81.72%, the Kappa is the highest, and the M-error is 0.1544, which is better than the other feature selection methods. PC and CSR feature selection method performs better in feature dimension reduction. The size of feature subset after selection is 12 and 9 respectively, but the classification accuracy is low. The results show that the feature selection method can select the subset of fault features with the best feature size and the best classification performance.

2) Comparison of the results of different classification algorithms

Using Decision Tree, BP Neural Network, SVM and the Ada-SVM algorithm of distribution network fault risk level prediction, prediction of four cases of accuracy and recall as shown in table 5. Level 1 represents the fault level of distribution network 1, that is, it is slight; grade 2 represents important; grade 3 represents severe.

TABLE V. COMPARISON OF THE RESULTS OF DIFFERENT CLASSIFICATION ALGORITHMS

Method	Index (%)	Level 1	Level 2	Level 3	Accuracy (%)
Decision Tree	Precision	75.0	90.9	73.7	78.9
	Recall	100	58.8	85.7	-
BP Neural Network	Precision	82.6	83.3	85.0	84.2
	Recall	90.5	78.4	80.9	-
SVM	Precision	83.0	86.4	85.7	85.1
	Recall	92.9	78.4	85.7	-
Ada-SVM	Precision	92.9	88.2	85.7	89.5
	Recall	92.9	88.2	85.7	-

Table 5 show that the accuracy and recall rate of the Ada-SVM algorithm in this paper are 92.9%, 88.2% and 89.5%

respectively, the comprehensive classification performance is obviously superior to decision tree, BP neural network and SVM algorithm. Although the decision tree algorithm has a predictive recall rate of 100% for rank 1, the recall rate for grade 2 is 58.8%, indicating that grade 2 is very poor in adaptability. The experimental results show that the classification performance of the fault level prediction method is better than the decision tree, the BP neural network and the SVM algorithm. It has good prediction accuracy and adaptability, and the validity of this method is verified.

VI. CONCLUSION

In this paper, a fault grade prediction method of distribution network based on feature selection and ensemble learning is proposed. Through Relief-F algorithm and grey correlation analysis method, the optimal selection of distribution network fault characteristics is achieved, which improves the efficiency of fault risk prediction in distribution network. The SVM algorithm based on Adaboost is superior to BP neural network and SVM algorithm for prediction of distribution network fault level, prediction accuracy and generalization ability. It verifies the validity and correctness of the prediction method of distribution network fault risk based on Ada-SVM algorithm, which can provide a basis for operation and maintenance of distribution network. With the development of data mining technology and the accumulation of fault sample data, the correlation analysis and grade prediction of different time scales can be further carried out for different feeder zoning, and the prediction accuracy will also be improved continuously.

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