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Electrical Energy Loss Analysis for Low-Voltage Distribution Network Based on Measured Data Features

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ABSTRACT

In order to more accurately analyze electrical energy loss for the low-voltage distribution network, the feature of "virtual line resistance" is calculated based on the measured data when the topology of the distribution network and the data of a single user's meter are unknown. Then, combined with the measured power supply and sale, current, and statistical line loss as the features, the isolated forest algorithm is used to detect the data outliers. After removing the abnormal values of the data, the regression analysis method in machine learning is adopted for a large amount of measured data to establish an actual line loss estimation model. The results show that the fitting effect for the actual line loss estimation model based on the features of the measured data is better than based on the non-measured data such as "transformer district information" in previous studies, and provides a reference of the electrical energy loss management for the low-voltage distribution network.

Keywords: low-voltage distribution network, electrical energy loss, measured data, actual line loss

1. INTRODUCTION

The electrical energy loss of the low-voltage distribution network is mainly manifested as the loss of the line. At the same time, the line loss is an important indicator reflecting the management level of the distribution network, and it is also the main content of the performance evaluation of the power grid enterprise. However, due to the large power consumption of low-voltage transformer districts, complex distribution lines, and weak file management in transformer districts, it is very difficult to calculate the actual line loss for the low-voltage distribution networks.

At present, many documents focus on the research on the load side, hoping to start from the load side, and calculate the actual line loss through the forward-back method [1]. There are also documents that focus on the mean and variance of the load, and correcting the actual line loss rate to improve the accuracy of the actual line loss calculation [2]. However, these methods all need to have the correct network topology and a large number of load-side users' power consumption data. When the low-voltage distribution network is more complicated or the construction is early, it may not be possible to obtain the actual topology and obtain the data of each user. With the development of the artificial intelligence, researchers have also tried to calculate the actual line loss using neural networks, clustering and other methods [3-5]. The general idea of these methods is: select some features of the transformer district information, such as the power supply radius, the total length of the low-voltage line, the load rate, etc. Based on these features, the various low-voltage station areas are clustered, and their own neural network regression model is established based on each category to obtain the actual line loss value. However, these methods are all based on the fitting of statistical methods, discarding the physical model of the power grid, and the interpretability needs to be further strengthened.

According to the characteristics of the power supply system of the low-voltage distribution network, based on the physical model, this paper calculates the "virtual line resistance" through the measured data. Isolated forest algorithm is used to detect data outliers. The regression analysis method in machine learning is used to establish actual line loss estimation model for a large number of measured data, and then the actual line loss estimation is carried out. This method gives consideration to both interpretability and accuracy, and provides reference for electrical energy loss management of low voltage distribution network.

2. CALCULATION FOR FEATURE OF MEASURED DATA

2.1 Physical model

Once the low-voltage platform area is built, when the user load is all connected, the line resistance can be regarded as unchanged, but when the daily load is not the same, the line resistance will be different.The load connection condition and the line resistance both lead to different distribution of power flow. In order to describe the above phenomenon, it is necessary to use a variable "virtual line resistance" in different day to equivalently "different line losses caused by different load access conditions in different days". At the same time, a "total load equivalent resistance" is used for daily load to facilitate the solution of the circuit. The build model is shown in Figure 1.

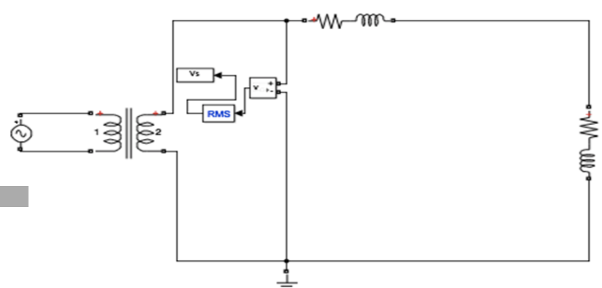

Fig 1 A phase line model

Because the three-phase load imbalance is more obvious in the low-voltage distribution network, the three-phase is modeled separately. Figure 1 only shows the model of A phase, and the models of B and C phase are the same as A phase.

2.2 Mathematical model

Take "day" as the unit, and similarly, use phase A to establish a model for solution. Know the three-phase voltage, current and power factor of the low-voltage side of the transformer for 24 hours in the day, as well as the total daily power supply, total power sales, and statistical line loss rate. During the day, the "total load equivalent resistance" will change once every hour, which are marked as $R_{0\_A}, R_{1\_A} \ldots R_{23\_A}$, and the value of "virtual line resistance" is R_{line_A} unchanged, but the value of "virtual line resistance" varies from day to day.

Under this model, the active power loss of the “total load equivalent resistance” of A phase on that day is the A phase power sale on that day:

$$W_{con\_A} = \int_0^{23} I_{t\_A}^2 R_{t\_A}\, dt \qquad (1)$$

Among them, the relationship between the A phase power sale and the three-phase total power sale meets the proportional relationship of the three-phase total power supply as follows:

$$W_{sup\_A} = \int_0^{23} U_A I_A cos\varphi_A\, dt \qquad (2)$$

$$W_{con\_A} = \frac{W_{sup\_A}}{W_{sup\_A}+W_{sup\_B}+W_{sup\_C}} W_{con\_all} \qquad (3)$$

Where W_{sup_A} is the A phase total power supply, W_{con_A} is the A phase total power sale, and W_{con_all} is the three-phase total power sale.

Then establish the equations for the hourly voltage, current and power factor as follows:

$$\begin{cases} U_{0\_A} cos\varphi_{0\_A} = I_{0\_A}(R_{0\_A} + R_{line_A}) \\ U_{1\_A} cos\varphi_{1\_A} = I_{1\_A}(R_{1\_A} + R_{line_A}) \\ \ldots \\ U_{23\_A} cos\varphi_{23\_A} = I_{23\_A}(R_{23\_A} + R_{line_A}) \end{cases} \qquad (4)$$

Combining equation (1) and equation (4) together and sorting them out, the equation of resistance R is:

$$\begin{bmatrix} 1 & 0 & \ldots & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & 0 & 1 & 1 \\ I_{0\_A}^2 & I_{1\_A}^2 & I_{2\_A}^2 & I_{23\_A}^2 & 0 \end{bmatrix} \bullet \begin{bmatrix} R_{0\_A} \\ R_{1\_A} \\ \ldots \\ R_{23\_A} \\ R_{line_A} \end{bmatrix} = \begin{bmatrix} \frac{U_{0\_A} \cos\varphi_{0\_A}}{I_{0\_A}} \\ \frac{U_{1\_A} \cos\varphi_{1\_A}}{I_{1\_A}} \\ \ldots \\ \frac{U_{23\_A} \cos\varphi_{23\_A}}{I_{23\_A}} \\ W_{con\_A} \end{bmatrix} \qquad (5)$$

The R equation has a full rank and has a unique solution. The “virtual line resistance” of A phase on that day and the “total load equivalent resistance” per hour of A phase can be solved.

3. OUTLIER DETECTION BASED ON ISOLATED FOREST

The isolated forest algorithm is a method suitable for unsupervised outlier detection. It is different from other algorithms that use quantitative indicators to describe the degree of alienation between samples. This algorithm uses a binary search tree structure called iTree to isolate samples. Compared with traditional algorithms such as K-means, the isolated forest algorithm has better robustness. The algorithm is divided into training phase and evaluation phase.

In the training phase, ψ sample points are randomly selected from the training data set X to construct an iTree. If T is a node of the iTree, there are two situations for T: (1) As an external node without child nodes. (2) As an internal node with two child nodes (Tl, TR). The judgment condition at node T is composed of a randomly designated attribute q and a randomly designated split point p. The sample point with q<p belongs to Tl, otherwise it belongs to TR. Repeat this way until the depth of the tree reaches the specified value, or there is

only one sample under each node. The path length h(x) of the sample point x in the isolated tree is the number of edges that the sample point x passes from the root node of the iTree to the leaf node.

In the evaluation stage, let each data point traverse each iTree, calculate the height h(x) of the point in the tree. Then calculate the outlier score which is closer to -1, the more likely it is an abnormal sample and which is closer to 0, the more likely it is a normal sample.

In the detection, the cutoff score "offset" (default is -0.5) for distinguishing normal and abnormal can be fixed, or it can be selected by percentile.

4. ACTUAL LINE LOSS ESTIMATION MODEL

After removing the outliers, the regression analysis method was used to establish an actual line loss estimation model.

Randomly select 80% of the data as the training set and 20% of the data as the test set. In the training process, the "virtual line resistance" value obtained in 2.2 is used as feature X, the actual line loss rate Y is linearly fitted, and 20% of the test data is substituted into the fitted straight line for testing, and the error is analyzed.

5. EXAMPLE ANALYSIS

According to the measured data of a typical transformer district from November 2018 to June 2019 for a total of more than 200 days, the calculation method in 2.2 is used to obtain the change of the average value of the three-phase virtual line resistance as shown in Figure 2:

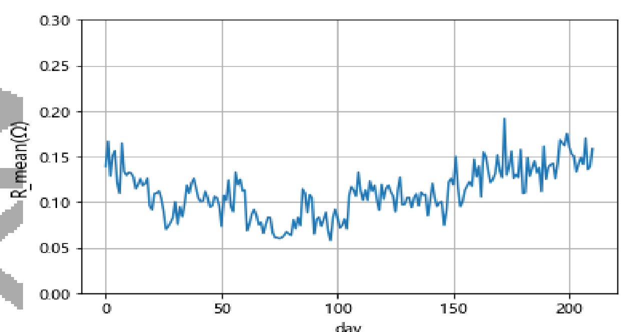

Fig 2 Change of the average value of the three-phase virtual line resistance

Select the 10% quantile as the cutoff score "offset". Figure 3, 4, 5, 6 are respectively the outlier detection results for four groups of different features as power sale, average current, average load equivalent resistance and average virtual line resistance.

After eliminating the abnormal points, there are 190 data points left. The statistical line loss at the normal point is considered as the actual line loss. The relationship between actual line loss rate and virtual line resistance is shown in Figure 7.

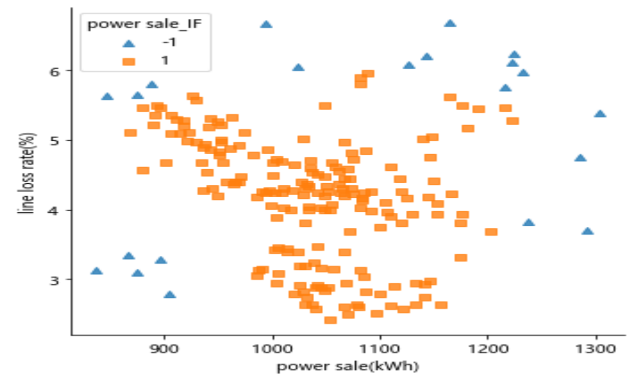

Fig 3 Line loss rate vs power sale

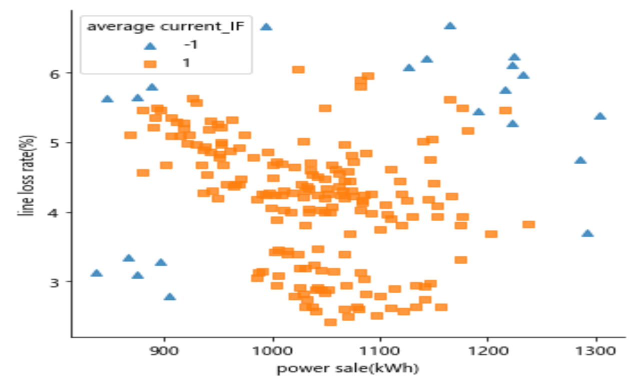

Fig 4 Line loss rate vs average current

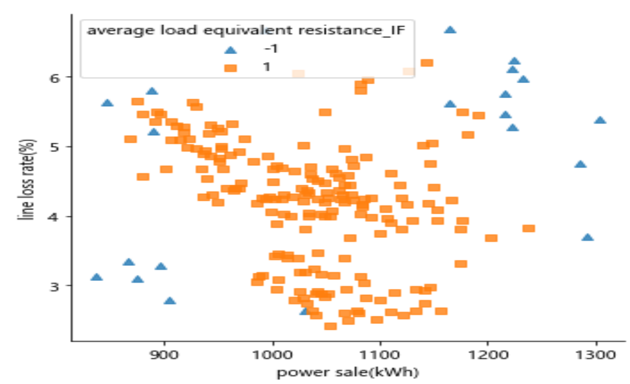

Fig 5 Line loss rate vs average load equivalent resistance

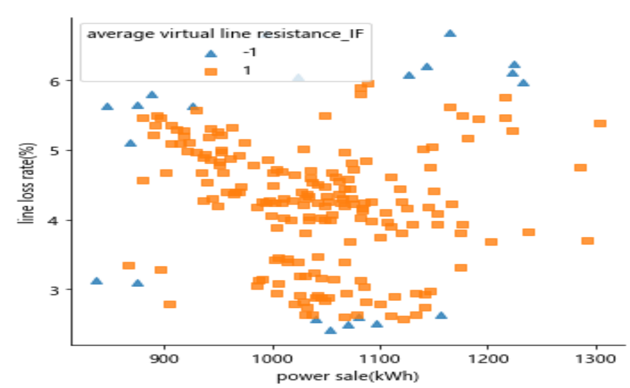

Fig 6 Line loss rate vs average virtual line resistance

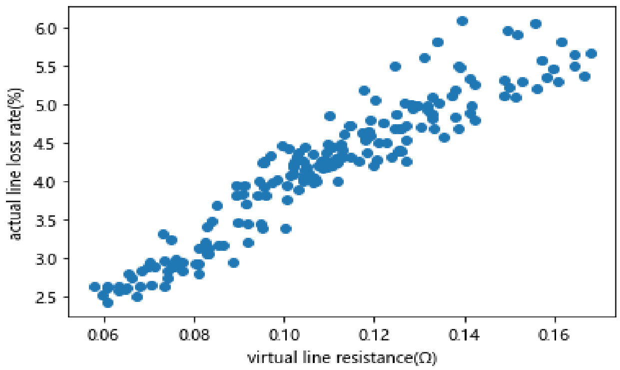

Fig 7 Relationship between theoretical line loss rate and virtual line resistance

It is found that the actual line loss rate and the virtual line resistance basically satisfy the linear relationship, so a linear fitting is performed with keras API. First, the 190 data points are divided into a training set containing 150 data points, and a test set containing 40 data points. Then, the training set is used for fitting, and the fitting result is obtained: Weights= 3.119455, biases= 0.783609. The test set is substituted into the trained model for evaluation, and the fitting effect and relative error are shown in Figure 8 and Figure 9.

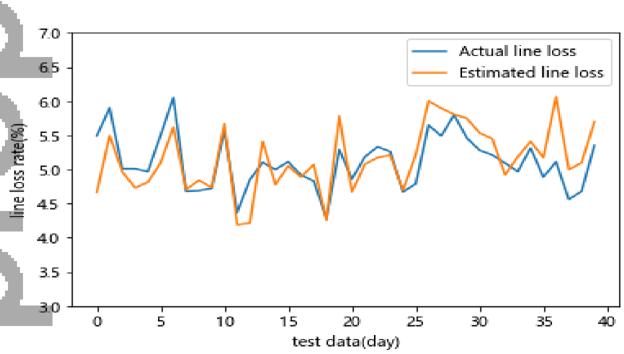

Fig 8 Fitting result of actual line loss on test set

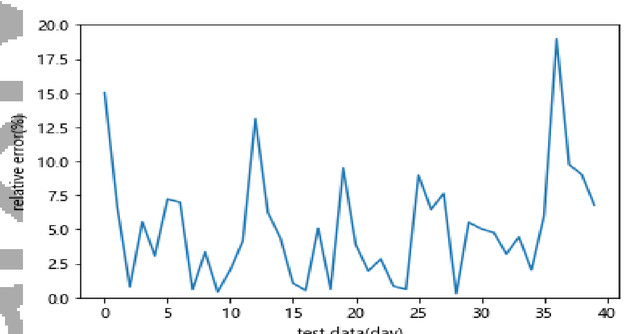

Fig 9 Relative error of actual line loss fitting

It can be easily obtained from Figure 9 that the relative errors of all the predicted values and the true values are within 20%, and except for the relative error of 3 data points greater than 10%, the relative errors of the remaining data points is within 10%.

6. CONCLUSION

In order to analyze electrical energy loss of the low-voltage distribution network, this paper proposes an analysis method for calculating the actual line loss based on the measured data features. Based on the feature of the "virtual line resistance" calculated by the measured data, combined with the features of the measured data, the isolated forest is used to eliminate outliers, and then the actual line loss estimation model is established through regression analysis. The calculation is carried out with the measured data of more than 200 days in a typical transformer district, which verifies the accuracy of the method, and the fitting effect is better than that based on non-measured data such as "transformer district information" in previous studies.

This conclusion also means that with the further enhancement of the informatization for the low-voltage distribution network in the future, more measured data will be more conducive to the analysis and research of the electrical energy loss for the low-voltage distribution network.

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