Voltage Sags Recognition Based on S Transforms and Neural Networks

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Abstract

Voltage sags, a kind of power quality problems, have become a research focus of power quality problems. The correct identification of disturbance source plays an indispensable role in the prevention and control of voltage sags. According to the real situation of distribution networks, different types of voltage sags disturbance sources are analyzed in this paper. The sources which cause voltage sags could be divided into simple voltage sag disturbance sources and complex voltage sag disturbance sources. This paper uses PSO-BP method to distinguish these voltage sags disturbance source. The experimental results show that the proposed method could achieve a more accurate classification of the disturbance sources.

Keywords: voltage sag, S-transform, PSO, classification, recognition

1. Introduction

The electric power energy is not only economical, clean and pollution-free, but also easy to transform, transport and control. At the same time, it is a special commodity which is generated by the power plants, transmitted by electric power companies and used by customers. It is needed to cooperate among generation, transmission, consumption to guarantee the power quality. High-quality energy plays an important role in economic rapid development, industrial and agricultural production and daily life of people.

A voltage sag detection system has the function of automatic analysis, because it is analyzed and processed for detecting the signal. Disturbance recognition is one of the main tasks of analyzing and processing voltage sags , which are divided into two parts that construct eigenvalue and classification of classifier designs. Many methods are put forward for different types of voltage sags disturbance source identification and classification by domestic and foreign scholars, mainly including short-time Fourier Transform (STFT, Short-time Fourier Transform), Wavelet Transform (WT, Wavelet Transform), S Transform (ST, S-Transform) and Hilbert Huang Transform (HHT, Hilbert Huang Transform), the d-q Transform, Kalman Filter and so on. Selecting intelligence algorithms, such as expert systems, fuzzy recognitions, support vector machines, decision trees, neural networks and etc for the classification and recognition of voltage sags disturbances

In recent years, intelligent algorithms have been applied to the field of temperature prediction by some scholars. Based on the STFT (short time Fourier transform) method, the amplitude, starting and ending time and duration of voltage sags were detected by Zhao Fengzhan and other people in literature [2], and the accuracy is proved by the simulation experiment. The multiple voltage sag disturbance sources are classified and identified according to the difference of the fundamental frequency amplitude curve and the number of the disturbance point, and the voltage sags were detected by hybrid wavelet transforms and energy operate methods in literature [3]. The disturbance signal is decomposed into approximation signal and detail signal by Wavelet Transforms in this method, and the starting and ending time can be located accurately in detail section of signals, the amplitude of voltage sags can be measured precisely by applying an energy operator to approximation signals. Using singularity theory of wavelet transform, voltage transform characteristics are extracted in literature [4], and then each kind of voltage sag disturbance sources is identified.

Many methods are put forward in the voltage sag detection and recognition by domestic and foreign scholars, but the most research in these literatures are about analysis and identification of some simple disturbance sources, such as short circuit faults, induction motor starting and transformer energizing. The study of complex disturbance sources is less, such as a multiple line short circuit fault, induction motor restarting, induction motor starting and transformer energizing interaction. In this paper, the classification and recognition of simple disturbance sources and complex disturbance sources are realized by PSO-BP neural network to construct a classifier.

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2. Analysis of Voltage Sag Source of Disturbance

Voltage sags, a kind of voltage change events, generally refer to the root mean square values of voltage drops suddenly in a short time, and the duration is about 0.5-30 cycles. There are two different definitions for the degree of voltage sag RMS in the world. RMS value of the supply voltage drop from 90% to 10% of the initial value is the voltage sag definition of the International Institute of Electrical and Electronics Engineers (IEEE), but its drop from 90% to 1% is the voltage sag definition of International Electrotechnical Commission (IEC).

The essence of voltage sags is the power system impedance current rises sharply in a short period time, and, sometimes, it is several times or scores times of rating current, leading the source impedance voltage to increase, and making transiency of nearby transformer voltage or a common connection point (Point of common coupling, PCC) voltage drop. It has many reasons which cause voltage sags. In this paper, voltage sag disturbance sources are divided into simple and complex disturbance sources according to its complexity. Voltage sags caused by a simple disturbance including short circuit fault, induction motor starting, transformer energizing and etc; many aspects are likely to cause voltage sags because of disturbance sources existing in a large power system, such as voltage sags caused by line fault, so voltage sags disappear after fault clearing; reclosing unsuccessfully will cause a voltage sag once again, or, otherwise, it will lead to induction motor starting and transformer inrush current. Voltage sags caused by complex voltage sag disturbance sources mainly include short circuit fault, and induction motor starting, both induction motor starting and the transformer energizing interaction

2.1 Voltage Sags Caused by Short Circuit Faults

Short-circuit faults are a more important situation caused the voltage sags of a power system. In process of power system running, many cases are likely to make short circuit faults of a power line, such as lightning, strong wind and bad weather as well human factor. When the short circuit faults happen, the system current increases several times suddenly, leading to the voltage drop of nearby short circuit points. types of faults are divided into two categories, one is symmetrical fault, the other is unsymmetrical fault. Symmetrical fault is caused by a three phase short circuit, but the unsymmetrical fault mainly include three faults, single phase short circuit, two-phase short circuit and double phase-grounded fault. The three-phase voltage sag amplitude is the same for symmetrical short-circuit fault, but the amplitude is not same for unsymmetrical short circuit faults. Therefore, the voltage amplitude may be the same or different for voltage sags caused by short-circuits. Figs 1-2 are original signal and its RMS of voltage sag caused by short circuit fault, respectively.

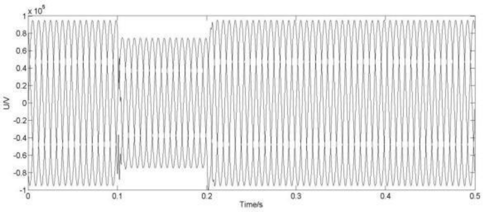


Figure 1: Original signal of voltage sag caused by short circuit faults

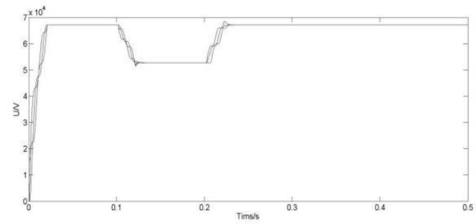


Figure 2: RMS of voltage sag caused by short circuit fault

2.2 Voltage Sag Caused by Induction Motor Starting

There are many induction motors in a distribution network, and the induction motor is one of the common loads. Motor speed rises rapidly to the ratings in a short time when the induction motor starting. In this process, it requires motor to obtain large current from power sources, so it is generally five to six times as much as rating current. This will cause the system impedance voltage increasing and make voltage of public join points drop. Figs 3 to 4 are original signal and its RMS of voltage sag caused by induction motor, respectively.

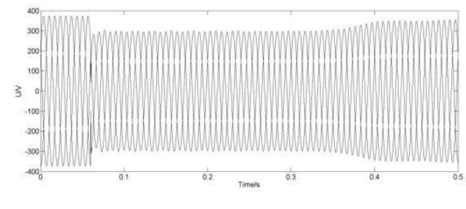


Figure 3: Original signal of voltage sags caused by an induction motor

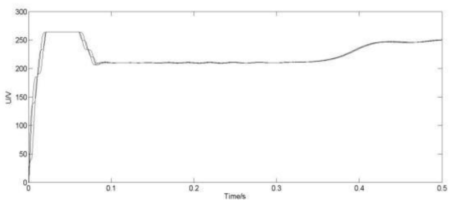


Figure 4: RMS of voltage sags caused by an induction motor

2.3 Voltage Sags Caused by Transform Input

The terminal voltage will change dramatically when transformer energizing, it may produce several times higher inrush current than the rating current because of saturation of core, leading to the voltage of system impedance to increase and causing voltage sags. Figs 5-6 are original waveform and its RMS of voltage sag caused by transform energizing, respectively.

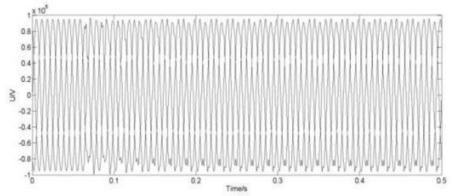


Figure 5: Original waveform of voltage sags caused by transform energizing

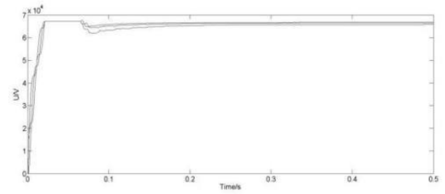


Figure 6: RMS of voltage sag caused by transform energizing

2.4 Voltage Sags Caused by Short Circuit Faults of Multiple Lines

The voltage sag caused by multiple line short circuit faults refers to many short circuit faults occurred on the same transmission line. Generally, the voltage sags caused by short circuit faults will recover when faults are cleared; however, this kind of amplitude of voltage sags will increase when faults are cleared incompletely, it will recover after faults are cleared completely Figs.7-8 are original waveform and the effective value of voltage sag caused by multiple lines short circuit faults, respectively

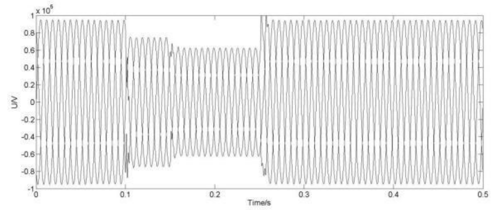


Figure 7: Original waveform of voltage sag caused by multiple lines short circuit fault

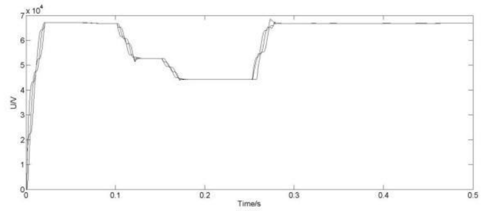


Figure 8: Effective value of voltage sag caused by multiple lines short circuit fault

2.5 The Voltage Sag Caused by Induction Motor Restarting

Induction motor restarting refers that a motor gradually returns to normal work when the fault is cleared; the line short circuit fault occurs when the induction motor under a normal operation, resulting that the grid will stop power supply for a motor, but the motor still works in state of the rating voltage due to the rotor in the role of inertia, and then the rotor slows down; after the fault happens, the voltage sag will have a very small attenuation. It cannot recover initial value gradually until dropping to the minimum value. In Figs 9-10, are original waveform and the effective value of voltage sag caused by induction motor restarting, respectively.

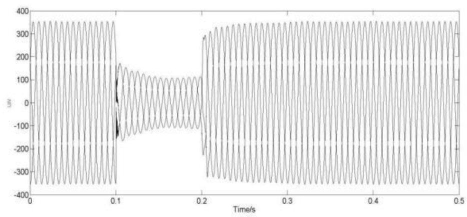


Figure 9: Original waveform by Induction motor restart induced voltage drop

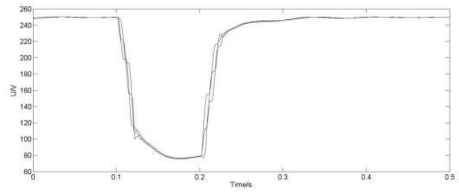


Figure 10: Effective value of voltage sag caused by restarting of induction motor

2.6 The Voltage Sag Caused by Induction Motor Starting and Transformer Energizing Common Action

When induction motors and transformers are put into the power grid simultaneously, the waveform of voltage sags is the addition of all individual effect, and the voltage amplitude dropped is greater than alone. Figs.11-12 are original waveform and the effective value of voltage sag caused by common action, respectively.

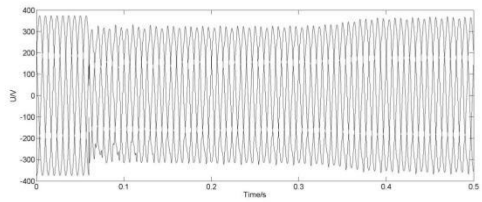


Figure 11: Original waveform of voltage sag caused by common action

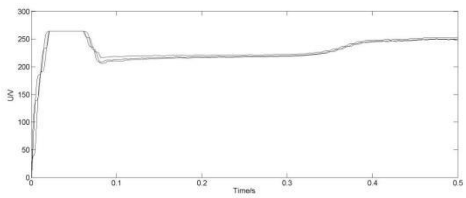


Figure 12: Effective value of voltage sag caused by common action

The above waveforms of six kinds of voltage sag disturbance sources are studied and analyzed. From the waveforms of original signal and the effective value, it is found that the different types of disturbance sources have different forms of expressions in the amplitude, harmonic, and the process of voltage sages. Therefore, different types of voltage sags can be classified and recognized according to signal and characteristic index of voltage sags.

3. S Transform

S transform is a reversible local time-frequency analysis method, and its idea is developed by a continuous wavelet transform and a short time Fourier transform,The S transform is: $S(\tau, f)$ of signal $x(t)$ are defined as follows:

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t)\omega(\tau - t, f)e^{-j2\pi ft}dt \qquad (1)$$

$$\omega(\tau - t, f) = \frac{|f|}{\sqrt{2\pi}}e^{\left|\frac{-f^2(\tau-t)^2}{2}\right|} \qquad (2)$$

where, $\omega(\tau - t, f)$ is Gaussian window, τ is location parameters of controlling Gaussian window in time axis *t*, *f* is frequency, and *j* is imaginary unit. From Formula (1), it is found that S transform is different from a short-time Fourier transform in the height and width of the Gaussian window on frequency changes. Therefore, it overcomes defects of the short-time Fourier transform window on fixed height and width.

After sampling in equal time interval, continuous disturbance signal $x(t)$ can be divided into discrete disturbance signal $x(kT)$, where T is sampling time interval, N is the total sample of sampling, and k=0, 1, 2,..., N-1. Therefore, the discrete Fourier transform of $x(kT)$ is expressed as:

$$X\left[\frac{n}{NT}\right] = \frac{1}{N}\sum_{k=0}^{N-1} x(kT)e^{-i2\pi kn/N} \qquad (3)$$

where, $n = 0,1...,N-1$, $f \to \frac{n}{NT}$ and $\tau \to jT$ .Then the discrete disturbance signals $x(kT)$ corresponding to the discrete transform can be expressed as:

When $n = 0$ (that is zero frequency), the discrete S transform expression is as follows:

$$S[jT,0] = \frac{1}{N}\sum_{m=0}^{N-1} x\left[\frac{m}{NT}\right] \qquad (4)$$

When $n \neq 0$, the discrete S transform expression is as follows:

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} X\left[\frac{m+n}{NT}\right]e^{(-\frac{2\pi^2 m^2}{n^2})}e^{i\frac{2\pi mj}{N}} \qquad (5)$$

where $j,m,n = 0,1,2,...,N-1$. Then collect N point $x[t](t = 0,1,2,...,N-1)$ of discrete signal , and make S transform with Formula (4), (5); the result of S transform is complex time-frequency matrix of $n+1$ rows and m columns called S matrix, where columns represent sampling time points, and rows represent frequencies. The matrix of modulus is regarded as S-modulus matrix, where each row represents amplitude changes of a frequency signal in the time axis, where each column represents the amplitude of the signal at a time of change in the frequency axis. Therefore, each element value is corresponding to the amplitude of time and frequency signal in S modulus matrix. Even though the column vector is the discrete frequency in S modulus matrix, it is not true value of signal frequency; the true value is calculated by the sampling frequency and sampling point. The true frequency of sampling point of discretion is equal to $(f_s / N) \times n$, where f_s is sampling frequency, N is total sampling points, $n = 0,1,...,N-1$.

4. Build Characteristic Index of Voltage Sag Recognition

It is found that the voltage sag signal is mainly based on the power frequency from analyzing different types of voltage sag signals. Due to the effect of transformer inrush current, and the voltage sag signal with higher harmonics caused by transformer energizing, voltage sag signals are processed and analyzed by S transform in order to ensure that the power frequency possess high temporal resolution, and components of higher harmonics have high frequency resolution in this paper

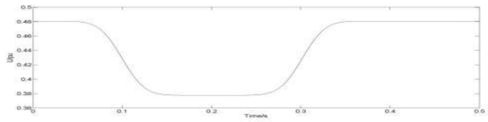
Frequency amplitude curves can be used to detect the amplitude of the voltage sag signal in S modulus matrix. The Expression of fundamental frequency amplitude curves is:

$$S_0(t) = S(jT, f_0) \quad (6)$$

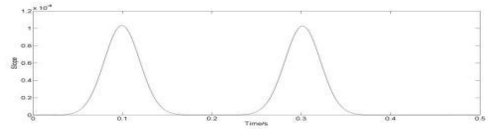
where, $j = 0,1,2,...,N-1, S_0(t)$ is the sequence of fundamental frequency amplitude signal change over time. The expression is as follows:

$$S_k(t) = \left| S_0(t+1) - S_0(t) \right| \quad (7)$$

Six kinds of voltage sag sampling signals are obtained by Simulink simulation, and the sampling signal is made of S transform; according to the Formula (6) and (7), it then gets fundamental frequency amplitude curve and slop curve, respectively, as shown from Fig. 13 to Fig. 18:

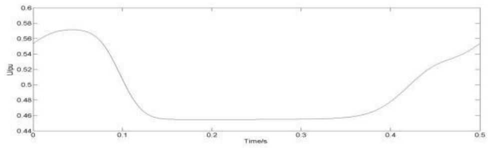


(a) Curve of fundamental frequency amplitude

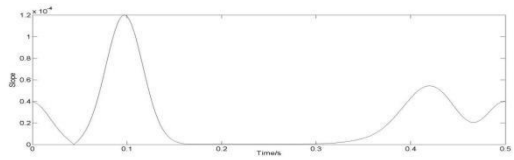


(b) Curve of amplitude slope

Figure 13: Line short circuit fault

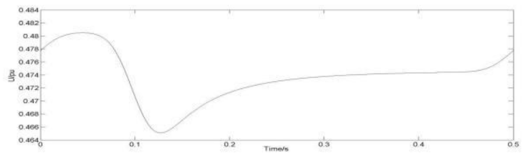


(a) Curve of fundamental frequency amplitude

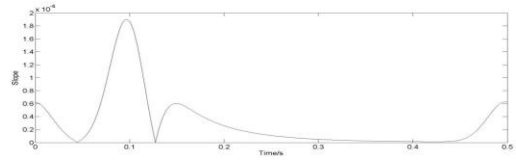


(b) Curve of amplitude slope

Figure 14: Induction motor starting

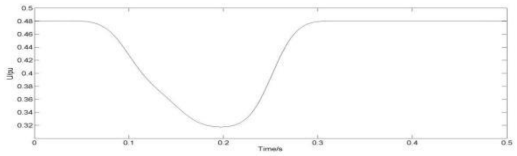


(a) Curve of fundamental frequency amplitude

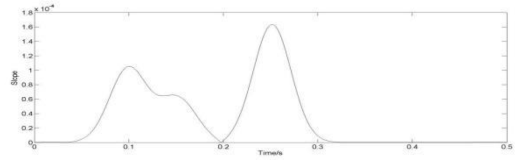


(b) Curve of amplitude slope

Figure 15: Transformer input

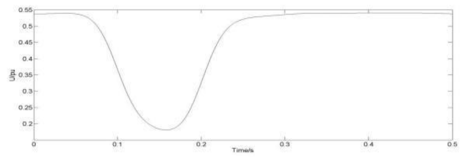


(a) Curve of fundamental frequency amplitude

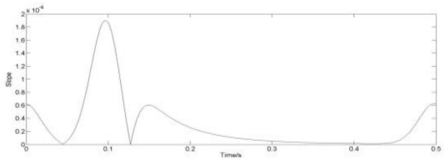


(b) Curve of amplitude slope

Figure 16: Short circuit fault of multiple line

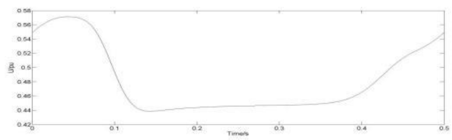


(a) Curve of fundamental frequency amplitude

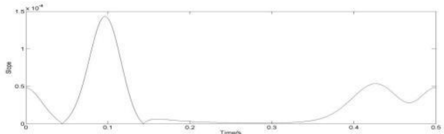


(b) Curve of amplitude slope

Figure 17: Induction motor restarting



(a) Curve of fundamental frequency amplitude



(b) Curve of amplitude slope

Figure 18: Induction motor starting and transformer input interaction

From above figures, it is found that the transform transformer inrush current can generate high harmonics, mainly in the 2-5 harmonic, the voltage sag is based on fundamental frequency components which are caused by a short circuit fault and induction motor starting. Therefore, voltage sags caused by transformer energizing or other conditions are distinguished effectively. According to harmonic components, characteristic index of voltage sags are constructed by statistics, entropy, energy and other aspects in order to classify and recognize the type of voltage sags. Among them, the statistics includes the mean, standard deviation, skewness, kurtosis, rms; entropy contains Shannon entropy and log energy entropy.

1) Mean: Reacting concentration of data. According to the fundamental frequency amplitude curve, F_1 is defined:

$$F_1 = \frac{1}{N}\sum_{k=0}^{N-1} S_0(k) \tag{8}$$

2) Standard deviation: Reacting degree of dispersion of data. According to the fundamental frequency curve amplitude, F_2 is defined:

$$F_2 = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1}\left[S_0(k) - F_1\right]^2} \tag{9}$$

3) Skewness: Reflecting asymmetric level of data distribution. According to the fundamental frequency amplitude curve, F_3 is defined:

$$F_3 = \frac{1}{N-1}\sum_{k=0}^{N-1}\left[\frac{S_0(k) - F_1}{F_2}\right]^3 \tag{10}$$

4) Kurtosis: Reflecting asymmetric degree of data distribution. According to the fundamental frequency amplitude curve t, F_4 is defined:

$$F_4 = \frac{1}{N-1}\sum_{k=0}^{N-1}\left[\frac{S_0(k) - F_1}{F_2}\right]^4 \tag{11}$$

5) RMS: Reflecting the size of effective value of the data in the statistical time period. According to the fundamental frequency amplitude curve F_5 is defined:

$$F_5 = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1}\left[S_0(k)\right]^2} \tag{12}$$

6) Shannon entropy: Reflecting the degree of uncertainty of data. According to the fundamental frequency amplitude curve, twice and 5 times of the amplitude curve, F_6 is defined:

$$F_6(i) = -\sum_{k=0}^{N-1}\left[S_i(k)\log(S_i(k))\right] \tag{13}$$

7) Log energy entropy: Reflecting the degree of sparsity of data energy. According to the fundamental frequency amplitude curve, twice and 5 times of the amplitude curve, F_7 is defined:

$$F_7(i) = \sum_{k=0}^{N-1} log\left[S_i^2(k)\right] \tag{14}$$

8) Energy: Reflecting the size of data. According to the fundamental frequency amplitude curve, twice and 5 times of the amplitude curve F_8 is defined:

$$F_8(i) = \sum_{k=0}^{N-1} S_i^2(k) \tag{15}$$

where in Formula 15, $i = 0,2,5$, $S_0(k), S_2(k), S_5(k)$ represent, respectively, the fundamental frequency amplitude curve, 2 times of the fundamental frequency amplitude curve, and 5 times of the fundamental frequency amplitude curve.

The each phase of voltage sag disturbance signals is made of S transform, respectively, which then get the corresponding mean, standard deviation, skewness, kurtosis, RMS, Shannon entropy, logarithmic energy entropy, and other eigenvalues. However, it is given that the ranges of fluctuation of different eigenvalues are different, and eigenvalues are normalized in order to avoid a large range of digital features covering the small range of digital features and reducing the complexity of computation. The calculation formula is as follows. Finally, normalized eigenvalues are regarded as an eigenvector and put into the classifier to achieve classification of voltage sag disturbance sources:

$$F^* = \frac{F - \min(F)}{\max(F) - \min(F)} \tag{16}$$

5. Simulation Verification

Simulation model of voltage sags in a simple distribution network is shown in Fig. 19. S-tangent function tansig is regarded as a neurons transfer function of input layer, and S-logarithmic function logsig is regarded as a neurons transfer function of output layer. Voltage sag simulation model is built under the MATLAB/SIMULINK simulation software. This is a radiation system that contains 110kV transmission,10KV distribution and 0.4KV consumption.In Fig. 19, the connection mode of transform T_1 and T_2 is YNd11, and the transformation ratio is 110KV/10.5KV; it is given that the iron core saturation characteristics of the transformer T_2, the connection mode of transform T_3 and T_4 is Yyn0, and the transformation ratio is 10KV/0.4KV.

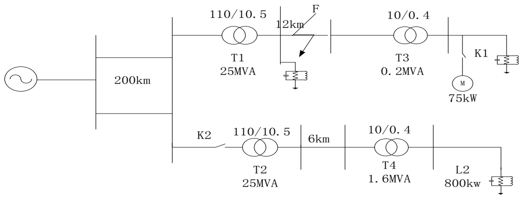


Figure 19: The mode of system simulation

The sampling data of 6 different types of voltage sags are extracted by simulations. For short circuit faults, the sampling data is obtained by changing the location of the fault point, the load of the line, the starting and ending times of fault and the transition resistance; for induction motor starting, the sampling data is obtained by changing the starting time, the line load and the superior transformer capacity; for transformer switching , the sampling data is obtained by changing the start time, the line load and the transformer capacity; for the short circuit fault of multiple line, the sampling data is obtained by changing the location of the fault point, the load of the line, the starting and ending times of faults; for the fault caused by a short circuit to induction motor restarting , the sampling data is obtained by changing the position of the point of failure, line load and the superior transformer capacity; for faults caused by induction motor and transformer interaction, the sampling data is obtained by changing the starting time, the line load and transformer capacity.

In this paper, BP neural network select a 3-layer structure ,and the function tranlm is used for training a network function, where the neurons in the input layer are 14, hidden layer neurons are 29, and the output layer neuron is 1.There are a total of 435 weights and 30 thresholds. Therefore, the number of parameters of the particle swarm optimization algorithm is 465. Through comparing BP network classification using particle swarm optimization with the case using BP network classification, the test results are shown in the following table:

Table 1: Test results of disturbance identification of BP and PSO-BP

Sample signal	Test sample	BP correct number	PSO Correct number	BP correct rate(%)	PSO correct rate(%)
Short circuit fault	30	30	30	100	100
Induction motor starting	30	30	30	96.67	100
Transformer input	30	20	28	66.67	93.33
Multiple line short circuit fault	30	30	30	100	100
Short circuit fault causing motor restart	30	26	26	86.77	86.77
Induction motor and transformer interaction	30	28	28	93.33	93.33
total	180	164	170	91.11	94.44

From the table, it is found that the correct recognition rate of this type of disturbance is 94.44%, where the recognition rate of disturbance sources for voltage sags caused by short-circuit faults and multiple short circuit faults can be up to 100%; this method has good classification ability. At the same time, although the BP network also has the correct recognition rate of 91.11%, the aim cannot be achieved because its performance is not stable and often encounters the situation of local optimal.

6. Conclusion

In this paper, the problems of voltage sags are studied deeply based on the S transform and the related principle of PSO-BP neural network. The amplitude and starting and ending times are detected and located for three simple and three complex voltage sag disturbances in a distribution network commonly. Different types of disturbance sources are identified according to features of disturbance waveform. Conclusions are summarized as follow:

The voltage sag caused by different types of disturbance sources are studied, and causes and characteristics of disturbances are analyzed. Taking into account the complexity and variety of distribution network, voltage sag disturbance sources are divided into six kinds of disturbance types, which are simple disturbance source and complex disturbance source. According to the voltage sag waveform characteristics caused by different disturbance sources, some statistical indexes are presented including mean, standard deviation skewness, kurtosis, RMS value etc, and characteristic indexes are presented including Shannon entropy, log energy entropy and based on S transform. Taking into account the global search ability of PSO algorithm, it can get an optimal value point of infinite approximation, and the connection weights and thresholds of the initial BP neural network are found in this way, Furthermore, weights and thresholds are studied by applying the algorithm of BP neural network, so to find the optimum solution; types of voltage sag disturbance sources are classified by PSO-BP algorithm. Experiments show that PSO-BP algorithm is comparable with the traditional BP algorithm in accuracy, but PSO-BP algorithm has advantages of fast convergence and more stable in process of training.

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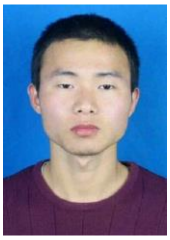

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