CLASSIFICATION OF VOLTAGE SAG DISTURBANCE SOURCES USING FUZZY COMPREHENSIVE EVALUATION METHOD

Chenyi LI
Jiali YANG
State Key Laboratory of Alternate Electrical Power System With Renewable Energy Sources System, North China Electric Power University – China
1903539506@qq.com

Yonghai XU
Yapen WU
Pengfei WEI
State Key Laboratory of Alternate Electrical Power System With Renewable Energy Sources System, North China Electric Power University – China
yonghaixu@263.net

ABSTRACT

The classification and recognition of voltage sag disturbance sources is the foundation of mitigating voltage sags. This paper analyzed characteristics of various kinds of voltage sags, including sags caused by short-circuit faults, energizing of transformers and starting of large induction motors. According to the features of different sources, an evaluation index set was formed by three-phase voltage unbalance factor, duration ratio and increments of second harmonic. After that, the weight of each element was calculated by Analytic Hierarchy Process (AHP). A novel kind of estimation criterion for fuzzy membership function parameters was proposed, inspired from 95% probability value, based on the method of undetermined coefficient to establish the functions. Consequently, according to it, fuzzy membership functions were created for each index. Further, comprehensive index membership degrees were calculated to judge the disturbance source according to the maximum of the degrees. The presented estimation criterion can efficiently reduce the influence of sample errors and thus improve the accuracy of the whole process, which was verified with the use of data obtained from both simulations and measurements.

INTRODUCTION

It is well-known that voltage sags are mainly caused by short-circuit faults, energizing of transformers and starting of large loads (e.g. large induction motors) [1]. The classification and recognition of voltage sag disturbance sources is the foundation of mitigating voltage sags.

Recently, studies on classification or recognition of voltage sag disturbance sources tend to use frequency domain transform methods (such as S transform, Hilbert-Huang transform, wavelet transform and so on) in order to extract features of voltage sags which followed by adopting different classification strategies to identify the disturbance sources. For instance, as for extraction of features for sags, S transform was applied in [2], wavelet transform in [3-4], and Hilbert-Huang transform in [5]. As for classification strategies, neural network was adopted in [2] and support vector machine (SVM) was used in [3-4]. Similarity analysis between measured signal template and standard template is an alternate. The mentioned frequency domain transform methods are relatively accurate to extract the features, nevertheless, as for the classification strategies, parameters of neural network have great sensitivity to sample data. In other words, the fluctuation of sample data will have great influence on the selection of parameters. In addition, support vector machine is not ideal when dealing with large sample data. What's more, when similarity analysis is used, the selection of the standard template has great influence on the classification results.

However distinct the features are, there's still some fuzziness between them. Fuzzy comprehensive evaluation method can solve fuzzy and uncertain problems, and it has been widely used in many fields. Therefore, this paper employed it to solve the problem of classification and recognition of sag sources. The classification targets are short-circuit faults, energizing of transformers, and starting of large induction motors. Then a novel kind of estimation criterion for fuzzy membership function parameters was proposed, based on which, fuzzy membership functions were created for each index. Further, the validation of the presented method was verified with the use of data obtained from both simulations and measurements.

TYPES OF VOLTAGE SAG DISTURBANCE SOURCE

Short-circuit Faults

Short-circuit faults are one of the main causes of voltage sags. Subjected to the page restriction, illustrations are avoided. According to some relevant studies, the essential features of sags caused by short-circuit faults can be summarized as followings:

- As for sags caused by three-phase balanced faults, the dip of voltage amplitude is nearly the same, whereas for sags caused by unbalanced faults, the voltage amplitude of the faulting phase drops while the amplitude of other phases keeps a constant or swells.

• In the beginning and end of the two transition stage, the voltage RMS value changes abruptly whereas during the sag, the RMS value keeps almost the same.
• There's little increment of harmonics during the sag.

Energizing of transformers

When a transformer is switched without load, a current will emerge which is many times higher than the rated value due to the abrupt change of DC component. The large excitation current can cause voltage sags at points of common coupling (PCC) when flowing through transmission lines. Because there's always 120-degree difference in initial phase angle of three-phase voltages, saturation degree of each phase varies, which results in unbalance of the voltage sag. Fig. 1 is an illustration of this type of sag.

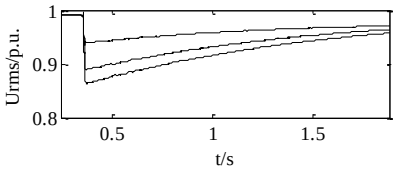


Fig. 1 RMS value of three-phase voltages for a simulated sag caused by energizing of a transformer

The typical characteristics of sags caused by energizing of transformers can be drawn as followings:
• Voltage amplitude of three phases drops rapidly at different values.
• Voltage amplitude recovers immediately after arriving at the minimum value. The recovery is a gradual process, so the time of the end of the sag is not clear.
• There are 2 to 4 and higher harmonics especially 2nd harmonics during the recovery stage.

Starting of large induction motor

When an induction motor is started, the initial speed of the rotor is zero, that is, the slip ratio is considerably large which brings about a high starting current in the stator. Similarly, the large current causes voltage drop on transmission lines and then a sag forms when the voltage magnitude drops below certain level.

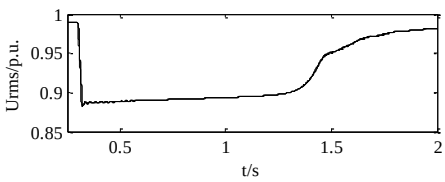


Fig. 2 RMS value of three-phase voltages for a simulated sag caused by starting of an induction motor

The typical features of sags caused by starting of induction motors can be presented as followings:
• Voltage amplitude of three phases drops rapidly at almost the same value.
• The same with the second feature of sags caused by energizing of transformers.
• The three phase voltages are always symmetrical.

CLASSIFICATION OF SAG SOURCES USING FUZZY COMPREHENSIVE EVALUATION

The general steps of fuzzy comprehensive evaluation contain deciding evaluation levels, selecting evaluation indexes, calculating weight factors of each index, establishing of fuzzy membership functions, calculating comprehensive index membership degrees, etc [6]. In this paper the set V of evaluation levels is formed by short-circuit (S), energizing of transformers (T) and starting of large induction motor (M), that is, $V=\{S, T, M\}$.

Selection of evaluation indexes

When selecting evaluation indexes, each of them should highlight the otherness in different features and similarity in the same feature, which can be collectively called "comparability". In this paper, three-phase voltage unbalance factor (U), duration ratio (R) and increments of second harmonic (H) were chose as the indexes.

Index 1 - three-phase voltage unbalance factor *U*

According to IEEE std.112-2004 [7], an easy approach to calculate the three-phase voltage unbalance factor based on phase voltage is shown as:

$$U = \frac{\max(|V_a - V_{pavg}|, |V_b - V_{pavg}|, |V_c - V_{pavg}|)}{V_{pavg}} \quad (1)$$

Where, V_a, V_b and V_c respectively represent the minimum value of the three phase voltage amplitude during the transient process, and V_{pavg} is the average value for them.

As we can know from (1), the range of U falls in (0,1). Theoretically, on the one hand, the value of U for Level S and Level T is quiet large because what mostly happens in practice is asymmetric faults and sags brought about by energizing of transformers are always three-phase unbalanced. On the other hand, contrarily, the value of U for Level M is relatively small for the sake that sags caused by starting of induction motors are symmetric at all time. Therefore, this index is effective to discriminate the sags caused by starting of induction machines.

Index 2 - duration ratio *R*

The duration ratio R was defined as:

$$R = \frac{(t_2 - t_1)}{(t_{\max} - t_1)} \quad (2)$$

Where, t_1 and t_2 ($t_1<t_2$) are the two time points when the voltage amplitude reaches $(0.9\text{-}U_{\min})\times 10\%+U_{\min}$ firstly and secondly; $t_{\max}$ ($t_{\max}>t_2$) is the time point when the voltage amplitude recovers to 0.9 p.u. According to (2), the longer the bottom of the sag is and the higher the recovery speed is, the larger R is, such as the R for Level S. As for Level T and M, the R value is smaller and the latter's is a bit larger than the former's.

Index 3 - increments of second harmonic *H*

It is well known that the energizing of transformers will bring about increments of harmonics especially second ones. Consequently, increments of second harmonic H is adopted as an index to outstand the features caused by energizing of transformers as (3) shows.

$$H = \frac{\sum_{k=n_1}^{n_2} U_{2sag}(k)}{(n_2 - n_1)U_{1sag}(k)} - \frac{U_{2pre}}{U_{1pre}} \quad (3)$$

Where, U_{2sag} is the amplitude of the second harmonic component during the sag; U_{1sag} is the amplitude of the fundamental component; n_1 and n_2 ($n_1<n_2$) are the starting and ending sampling points for calculating when the ratio of amplitude for harmonic to fundamental component reaches the threshold 1%; U_{2pre} and U_{1pre} are the amplitude of second and fundamental component voltage before the sag. Thus, H represents "average" increments of second harmonic. Theoretically, the H of Level T is relatively large whereas that of Level S and M are small. Accordingly, this index can strengthen characteristics of sags caused by energizing of transformers.

Weight calculation of evaluation indexes based on AHP

In the evaluation index system, the importance of each index varies and the weight of each shows difference. AHP was applied to calculate the weight, for it can decompose complex problems into several related factors, making the analysis process clear, concise and practical. The general steps of AHP are as followings:

- Establish a hierarchical structure to describe the characteristics of the system. The target level in this paper is $V=\{S, T, M\}$ and the index level is $B=\{U, R, H\}$.
- Set up judgment matrixes. Compare which element in the index level is more important to the target level two by two and then give them a comparison scale proposed by an American operational research expert A. L. Satty, as Table 1 shows. Then the judgment matrix $\mathbf{A}=(a_{ij})$ under the target level V can be got, where $a_{ij}>0$ and $a_{ij}=1/a_{ji}$ ($i,j=1,2,\ldots,n$).
- Calculate eigenvalues of **A** and the corresponding eigenvectors and normalize the eigenvector $p_{\max}$ referring to the largest eigenvalue $\lambda_{\max}$ by rows, thus the weight vector can be obtained as $w = p_{ij}/\sum_{i=1}^{n} p_{ij}$, where j is the column number of the $p_{\max}$.
- Test the consistency of the weight vector: $CR=CI/RI<0.1$, where $CI=(\lambda_{\max}-n)/(n-1)$, n is the number of the indexes and RI is the average random consistency index, as Table 2 shows.

Table. 1: The definition of comparison scale

Scale value	1	3	5	7	9
Importance	Same	A bit larger	Obviously larger	Strongly larger	Absolutely important
2,4,6,8 is between the above values when the importance is between them. If comparing i to j gets a_{ij}, then comparing j to i can get $1/a_{ij}$.					

Table. 2: Average random consistency index

n	3	4	5	6	7	8	9	10	11
RI	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52

Establishment of fuzzy membership function

The most critical step of fuzzy comprehensive evaluation is the establishment of fuzzy membership function. Among the most frequently used methods, method of undetermined coefficients has the most extensive field of application and a majority of fuzzy membership functions can be constructed by it. Therefore, it was chose to generate the functions.

Steps of establishing membership functions

- Step1: Determine the general shape of the functions, including partial small, partial large and middle type, as Fig. 3 shows.
- Step2: Determine the areas where membership value equals 0 or 1. In this paper, 0 is impossible area whereas 1 is the most possible area.
- Step3: Determine the shape of the transition zone, including the linear and the nonlinear. Further, the nonlinear contains Cauchy distribution, Gauss distribution, k-parabolic distribution, ridge distribution and Z distribution. As for ridge distribution, shown by Fig. 3, the greater the membership value is closer to 1, the more likely it is for a certain level, otherwise, the less likely, which is quite in accordance with reality. Consequently, ridge distribution was chose in this paper.
- Step4: Determine the final structure of the functions and estimating the parameters.

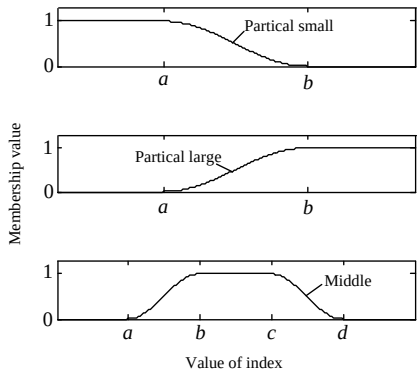


Fig. 3 Diagrams of a ridge type distribution function

A novel estimation criterion for parameters of membership functions

As Fig. 3 shows, it is a and b that need to be determined for partial small and partial large type, and as for the middle type, a, b, c, and d need to be determined. To reduce the errors caused by the fluctuation of sample data, referring to the definition of 95% probability value, a novel estimation criterion for parameters of membership functions was proposed. The specific rules of it are as followings:

- As for the partial large (or small) type, sample data cannot fully reflect the real situation. Thus, in a group of indexes, set the membership value as 0.05 for the minimum (or maximum) index, and similarly, set the membership value as 0.95 for the maximum (or minimum) one. Then bring them into expressions of ridge distribution to get a and b.

• As for the middle type, divide the numeric zone of each index into 100 (a changeable number) equal parts and then count the frequency of the index value falling into each part to get a frequency histogram. After that, starting from the maximum of the frequency, sums the frequency from each side of the maximum. When the summation reaches 0.95, *b* and *c* are respectively the minimum and maximum of the summed elements. Set the membership value as 0.05 for the minimum and the maximum index, and then bring them into the expressions to get *a* and *d*. If *b* (or *c*) equals the minimum (or maximum) index, set *a*=*b* (or *d*=*c*).

VERIFICATION BASED ON SIMULATED AND MEASURED DATA

Models of faults, energizing of transformers and starting of induction motors were established in PSCAD. We changed types and duration of faults, the rated capacity and time of switching for transformers and the rated voltage and current for motors to get 60 groups of every type of sag samples. Afterwards, the indexes, weight of them and parameters of functions were calculated one after another. Finally, some samples were selected randomly for classification.

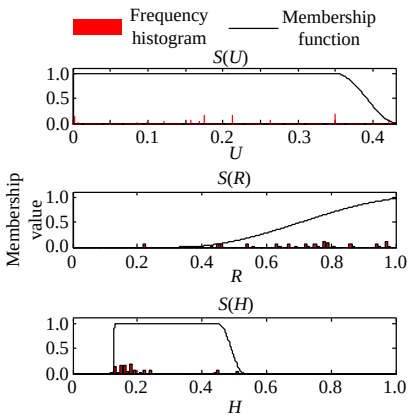
Establishment of fuzzy membership functions

Then the relative parameters are calculated according to the steps proposed above. The results are as Table 3 and Fig. 4 (a)-(c) shows.

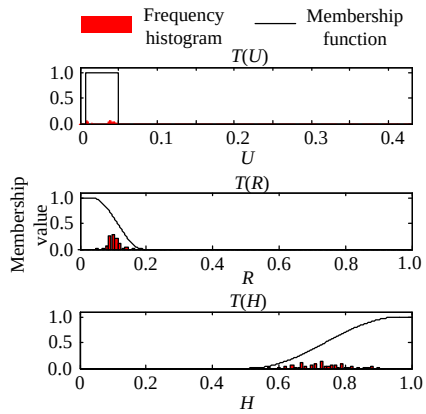
Table 3: The fuzzy membership function parameters

Level	*U*	*R*	*H*
S	a=1.200×10^{-1} b=1.200×10^{-1} c=3.494×10^{-1} d=4.338×10^{-1}	a=3.298×10^{-1} b=1.089	a=1.242×10^{-2} b=1.300×10^{-2} c=4.500×10^{-2} d=5.315×10^{-2}
T	a=7.079×10^{-3} b=7.100×10^{-3} c=4.910×10^{-2} d=4.910×10^{-2}	a=3.520×10^{-2} b=1.913×10^{-1}	a=5.132×10^{-2} b=9.708×10^{-2}
M	a=–1.500×10^{-4} b=9.630×10^{-4}	a=–8.120×10^{-2} b=5.263×10^{-1}	a=2.644×10^{-2} b=2.700×10^{-2} c=3.600×10^{-2} d=3.758×10^{-2}

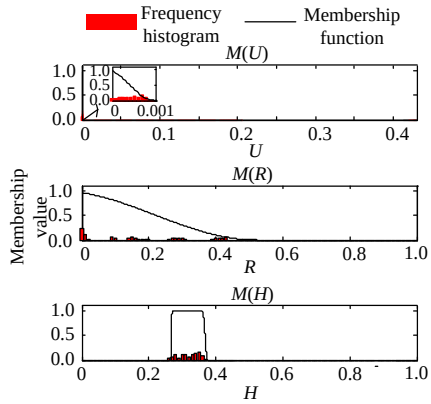
Here, the partial large or small type only has parameter *a* and *b* whereas the middle type has parameter *a*, *b*, *c* and *d*.



(a) Membership functions for Level *S*



(b) Membership functions for Level *T*



(c) Membership functions for Level *M*

Fig. 4 Fuzzy membership functions

Classification of sag sources

By comparing the usage frequency of *U*、*R*、*H* and considering the effect of classification, according to Table 1, the judgment matrix **A** can be got as (4) shows.

$$\boldsymbol{A}=\begin{bmatrix}1 & 2 & 2\\ 1/2 & 1 & 2\\ 1/2 & 1/2 & 2\end{bmatrix} \tag{4}$$

Where, the rank of the indexes is *U*, *R*, and *H*. Then eigenvalues of **A** were calculated and the weight vector was got as w={0.4934 0.3108 0.1958}. The consistency of it satisfied the requirement: $CR=CI/0.52=0.0515<0.1$. The general steps of the process are as Fig. 5 shows.

To verify the efficiency of the presented method, a conventional approach, which is based on wavelet entropy and probability neural network, was applied to compare with it. The accuracy of identifying sag sources by the two methods is shown by Table 4. Obviously, the accuracy of correctly classifying every type of sags using fuzzy method is higher than that by the conventional method. It implies the presented method can efficiently decrease errors of samples compared to probability neural network. At the same time, compared with frequency domain transform methods, it is easier to use fuzzy method when the results have no significant difference.

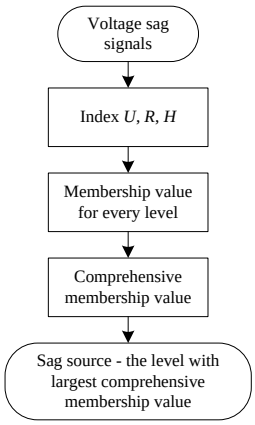


Fig. 5 A flowchart of the method of classifying the sag disturbance source based on fuzzy comprehensive evaluation

Table 4: The accuracy of identifying sag sources

Method	Evaluation level			Average accuracy
	S	*T*	*M*	
Fuzzy	100	100	98.33	99.44
Conventional	91.38	97.07	96.26	94.90

Verification by measured data

The measured data in this paper came from captured sag cases by power quality detection system in some cities and provinces of China. Five groups of data under different conditions were analyzed, among which the group 1 is a three-phase fault, 2 is a two-phase-to-ground fault, 3 and 4 are single -phase-to-ground faults and the later one has swells in other phases, and 5 was obtained from no-load switching of a transformer. The results of recognition are shown by Table 5.

Table 5: The results based on real data

Group	Classification level	Fuzzy method	Conventional
1	S	√	×
2	S	√	√
3	S	√	√
4	S	√	√
5	T	√	√

Where “√” and “×” refer to correctly and wrongly recognizing the sag sources. As Table 5 shows, all of the five groups of data can be correctly recognized by the presented method which is better than the conventional method.

CONCLUSIONS

- This paper employed the method of fuzzy comprehensive evaluation to solve the classification of sag sources. The validity of the whole process was verified by both simulated and measured data.
- Due to the limitation of sample data, a novel kind of estimation criterion for fuzzy membership function parameters was proposed, inspired from the definition of 95% probability value, which can effectively reduce errors of samples.
- Fuzzy comprehensive evaluation is simpler and easier to realize compared to frequency domain transformation, such as, S transform, Hilbert-Huang transform and wavelet transform, when the results have no significant difference.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 51277069).

REFERENCES

[1] Math H. J. Bollen, 1999, *Understanding Power Quality Problems: Voltage Sags and Interruptions*, IEEE Press, Piscataway, USA, 139-140.

[2] C. Venkatesh, D. V. S. S. Siva Sarma, M. Sydulu, 2010, "Classification of voltage sag，swell and harmonics using S-transform based modular neural network", *Proceedings of 14th International Conference on Harmonics and Quality of Power-ICHQP*, Bergamo, Italy, 1-7.

[3] H. Ismail, N. Hamzah, S. Shahbudin, Z. Zakaria, 2010, "Comparative analysis of input parameters using wavelet transform for voltage sag disturbance classification", *2010 IEEE International Conference on Software Engineering and Service Sciences*, Beijing, China, 5-8.

[4] N. Wang, S. Wang and Q. Jia, 2014, "The method to reduce identification feature of different voltage sag disturbance source based on principal component analysis", *2014 IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC Asia-Pacific)*, Beijing, China, 1-6.

[5] M. Manjula, A. V. R. S. Sarma, S. Mishra, 2011, "Detection and classification of voltage sag causes based on empirical mode decomposition", *2011 Annual IEEE India Conference*, Hyderabad, India, 1-5.

[6] J Luo, 1999, *Integrating Fuzzy Logic with Data Mining Methods for Intrusion Detection*, Mississippi State University, Mississippi, USA.

[7] IEEE Std 112-2004 *IEEE standard test procedure for poly-phase induction motors and generators*, IEEE Press, Piscataway, USA, 2004.