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Intelligent Detection of the Location of Voltage Flicker in Active Distribution Networks Using ANN

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Abstract

This paper proposes a novel approach for identifying the location of voltage flicker sources in active distribution networks. The method is based on measuring and sampling bus voltages, from which a voltage flicker detection index is extracted using information related to voltage amplitude and frequency variations. The extraction of this index relies on the S-transform, a time–frequency analysis technique that effectively captures non-stationary characteristics of voltage signals and enables accurate detection of flicker phenomena. The derived flicker index is subsequently utilized to train an artificial neural network (ANN) designed to identify the location of the polluting load within the network. In the proposed framework, the input to the neural network consists of the measured voltage flicker indices at selected buses, while the output represents the flicker occurrence status of all buses in the system. This structure allows the neural network to intelligently map flicker measurements to their corresponding source locations. The effectiveness of the proposed method is evaluated using a standard 14-bus distribution network. Voltage flicker disturbances are simulated using the EMTP/ATP software to generate realistic flicker scenarios under various operating conditions. The simulation results demonstrate that the proposed approach can accurately identify buses or network areas containing flicker-producing loads. Moreover, the results indicate that by optimally selecting measurement locations, reliable flicker source localization can be achieved with a relatively small number of voltage measurements. This significantly reduces measurement requirements, computational burden, and system complexity, making the method suitable for practical implementation in active distribution networks. Overall, the proposed S-transform–based flicker detection combined with neural network classification provides an effective and intelligent solution for locating voltage flicker sources, contributing to improved power quality monitoring and mitigation strategies in modern distribution systems.

1. *Introduction*

The discussion of evaluating power quality and improving its related specifications is one of the topics that has been discussed in recent years due to the increasing growth of power electronic devices and non-linear loads in power networks. One of the most unwanted power quality phenomena in distribution

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networks is the "voltage flicker" phenomenon. According to the definition of the International Electrotechnical Commission (IEC), voltage flicker refers to periodic or random voltage fluctuations with an amplitude of ±10% and a frequency between 0.5 and 25 Hz [1]. In addition to the problems that this phenomenon creates for various equipment such as electronic controllers, protective devices, etc., with the effect it has on the light of the lamps, it causes their light to vibrate, which is easily felt and causes dissatisfaction of the customers. Using high-power fluctuating loads in the power grid, such as impulse loads, can cause voltage fluctuations and flicker, which may damage electrical equipment. This type of power quality disturbance cannot be ignored and has attracted more and more attention [2-6]. Considering the competition in electricity markets, eliminating or reducing the effects of this phenomenon is very important. The first step in this field is to determine the location where the polluting load affects the network so that by identifying the source of flicker production and installing appropriate equipment or by upgrading the network, it is possible to eliminate or reduce these disturbances. Accurate detection of voltage fluctuations and flickering is the basis of assessing their risks and effectively dealing with them. Voltage flicker signal tracking and amplitude modulation wave detection are the main problems of voltage flicker signal detection.

In recent years, some innovative research results on voltage flicker signal characteristics and flicker location detection have been published [7-19]. In [7], the demodulation characteristics of energy operators were studied, and a fast and accurate flicker location signal extraction method was developed based on the improved k-value energy operator. In [8] a hybrid approach was presented to evaluate voltage fluctuations using an algorithm based on synchronization transformation. First, the characteristics of the voltage fluctuations were shown through the exact extraction of the measured voltages by Hilbert transform, then the synchronization transforms and an unsupervised clustering method was applied to determine the number of frequency components and the corresponding frequencies. In [9], an improved Teager energy operator error correction factor was developed to reduce the errors of online extraction of voltage flicker location. In [11], a method to detect flicker parameters based on the Teager-Kaiser energy operator and Blackman-Harris triple spectrum line interpolation was proposed. To detect time-varying signals, the time-frequency analysis method is suitable and approved, and the use of wavelet transform in this field has become a research topic [12-14]. Furthermore, the short-time Fourier transform is a classical time-frequency linear analysis method. Its result is directly related to the signal spectrum and has a good application in diagnosing power quality disturbances [15, 16]. In [17], a method was presented that by knowing the impedance of the short circuit and measuring the current, the feeder where the polluting load is located is detected.

In [18, 19], a method was introduced that determines the direction of the source causing the flicker relative to the measurement point by measuring the voltage and current and calculating a parameter called flicker power. Despite the simplicity of this method, in large networks, determining the location of the polluting load requires multiple measurements, on the other hand, since the phenomenon of voltage flicker is usually a periodic phenomenon and not a permanent one, it will take a lot of time to find the location of flicker generation.

In this paper, a method is presented, in which the voltage in a limited number of network buses is analyzed using a neural network, and the bus or the area where the polluting load is located is detected. The index that was used to train the neural network is the index obtained from the S transformation. This transformation is derived from the wavelet transformation, in which a coefficient is used to correct the phase, and by it, the amplitude and frequency spectra of the signal can be obtained. The S-transform of a signal containing disturbance provides contours that are very similar to the disturbance waveform. In [20-23], this feature was used to identify and separate different power quality phenomena. In these references, various indices such as the standard deviation of frequency-time contours, amplitude factor, etc. have been used, but no suitable index has been presented for flicker evaluation. In this article, using a new index obtained from the "time-domain" contour, the location of the polluting load in the network is detected. The structure of the article is as follows: Section 2 introduces the S-Transform and its related equations. In Section 3, the model employed to simulate voltage flicker is presented, in the following, the introduced model will be examined utilizing S transformation and the used index will be explained. In Section 4, the neural network and how to train it is expressed. The simulation results of the mentioned method are presented in Section 5. Finally, conclusions are given in Section 6.

2. The generalized wavelet transform: S-transform

The Fourier transform of the signal *h(t)* is defined as follows:

$$H(f) = \int_{-\infty}^{+\infty} h(t) e^{-i2\pi ft} dt \quad (1)$$

If the signal *h(t)* is multiplied by the window function *g(t)*, the resulting spectrum will be as follows:

$$H(f) = \int_{-\infty}^{+\infty} h(t) g(t) e^{-i2\pi ft} dt \quad (2)$$

The continuous S-Transform is obtained by defining the special window function in the form of the following normalized Gaussian function:

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(t^2/2\sigma^2)} \quad (3)$$

Where the width of the window σ is proportional to the frequency response and is chosen as follows:

$$\sigma(t) = \frac{1}{a + b|f|} \quad (4)$$

If in Equation (4), *b*=0, then *H(f)* represents the short-time Fourier transform and if *a*=0, it represents the S-Transform. The sample values for *b* are chosen between 0.333 and 5 to achieve different levels of frequency accuracy. For low frequencies, large values of *b* are chosen and small values of *b* are selected for high frequencies to obtain proper frequency accuracy. By substituting Equations (3) and (4) in Equation (2), the continuous S-Transform of the signal *h(t)* is obtained as follows:

$$S(\tau, f) = \int_{-\infty}^{+\infty} h(t) g(t-\tau, f) e^{-i2\pi ft} dt \quad (5)$$

As it is clear from Equation (5), the S transformation of a signal *h(t)* is a function with two parameters, frequency *(f)* and time shift *(τ)*, and this Equation shows the time-frequency feature of the transformation. The S transformation of the signal *h(t)* is a complex matrix according to these two parameters, which can be shown as follows:

$$S(\tau, f) = A(\tau, f) e^{i\varphi(\tau, f)} \quad (6)$$

In this Equation, *A(τ,f)* is the amplitude of the S spectrum, and *φ(τ,f)* is its phase. The discrete S-transform can be calculated in a similar way using the fast Fourier transform (FFT) and the convolution theorem. The discrete Fourier transform of the sampled signal *h(KT)* for *K*=0, 1, ..., N-1 is equal to:

$$H\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{K=0}^{N-1} h(KT) e^{-i(\frac{2n\pi k}{N})} \quad (7)$$

The S transformation of the signal *h(KT)* is defined as follows, considering *f≈n/NT* and *τ≈jT*:

$$S\left(jT, \frac{n}{NT}\right) = \frac{1}{N} \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] G(m,n) e^{i(\frac{2n\pi j}{N})} \quad (8)$$

Where *G(m,n)* is equal to:

$$G(m,n) = e^{-(\frac{2\pi^2 m^2 \alpha^2}{n^2})} \quad (9)$$

and for α we have:

$$\alpha = 1/b \quad (10)$$

In Equation (8), *N* is equal to the total number of samples and *j*, *m*, *n*=0, 1, ..., *N*-1. The output of S transformation is a complex matrix whose rows are frequency values and its columns represent the time values of the signal, so each column represents the local spectrum of the corresponding time.

3. Voltage Flicker

The presence of high-power fluctuating loads such as impulse loads can cause voltage fluctuations and flicker, which may damage electrical equipment. This type of power quality disturbance cannot be ignored and has attracted a lot of attention, which has been modeled in the following.

3.1. Thermodynamic analysis

Accurate modeling of flicker to test the proposed algorithms is a complicated process. In a simplified form, flicker can be modeled as a signal with a modulated amplitude along with a series of harmonic components. The modulated signal is equivalent to the sum of the sinusoidal components with random amplitude and frequency. First, for the simplicity of the proposed method, signal harmonics are omitted, and then in the next steps, their effect on the mentioned method is investigated. Mathematically, if the harmonics are ignored, the flicker signal can be modeled as follows:

$$h(t) = \left(A_0 + \sum_{i=1}^{M} (A_i(t)\cos(\omega_i t + \emptyset_i)) \right) \cos(\omega_0 t + \emptyset_0) \tag{11}$$

Where A_0, ω_0, and $\emptyset_0$ are the amplitude, frequency, and phase angle of the fundamental signal, respectively, and A_i is the amplitude of the voltage flicker with frequency ω_i and phase $\emptyset_i$. Equation (11) in the discrete state can be expressed in the following form:

$$h(n) = \left(A_0 + \sum_{i=1}^{M} (A_i(n)\, cos(\omega_i n + \emptyset_i)) \right) cos(\omega_0 n + \emptyset_0) \tag{12}$$

This equation will be used to simulate the load that creates a flicker in the power network.

3.2 Investigation of voltage flicker in S-transformation

According to the proposed model for flicker in Section 3.1, the waveform of a signal infected with flicker with a fluctuation amplitude of 10% and a frequency of 5 Hz changes was shown in Fig. 1. The three-dimensional representation of matrix S along with the "time-amplitude" contour is given in Figs. 2 and 3. It should be noted that other contours, including "time-frequency" and "amplitude-frequency" contours, can be obtained from the matrix S, which is presented in [20-22].

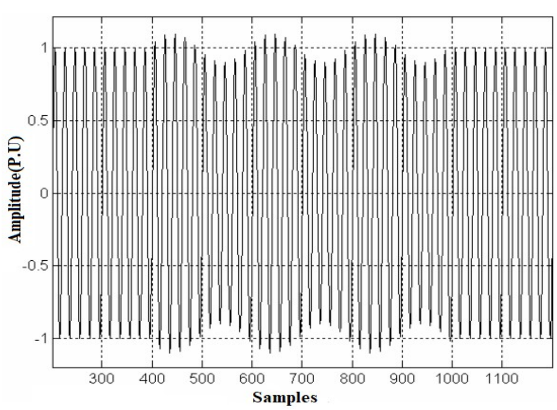

Fig. 1: Flicker-infected sinusoidal waveform with 5 Hz frequency changes and 10% amplitude fluctuations

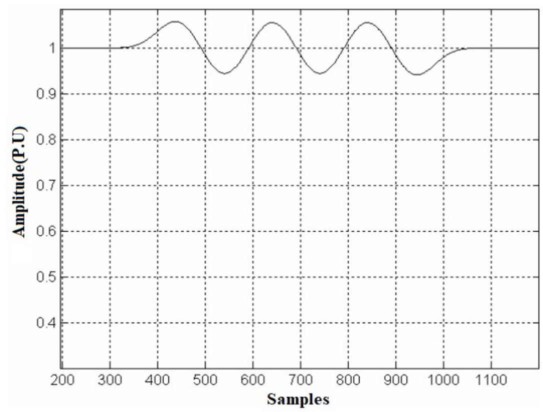

Fig. 2: The "time-amplitude " contour of the matrix S

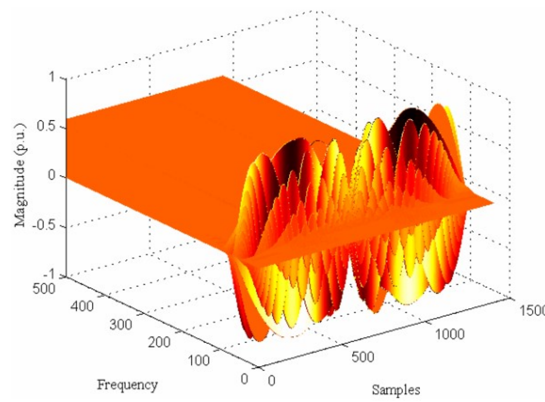

Fig. 3: 3D representation of matrix S

Since the flicker phenomenon contains low frequencies, for a better analysis of the signal in the frequency domain, the α used in this article is chosen as 0.27. As can be seen, there is a close relationship between the "time-amplitude" contour and the fluctuations caused by voltage flicker. In the flicker phenomenon, the frequency of fluctuations is variable and random depending on the working point of the load, and on the other hand, the "time-amplitude" contour according to Equation (5) is both dependent on the frequency and dependent on the amplitude, so to eliminate the effect of changes a new index is used in the output of the S transformation, which is defined as follows:

$$Voltage\ flicker\ index = \max_i \left(\max_j |S_{i,j}| \right) - \min_i \left(\max_j |S_{i,j}| \right) \tag{13}$$

Where *S(i,j)* is the element of the *i-th* row and *j-th* column of the complex transformation matrix. This index is calculated for the voltage samples in the time interval of flicker occurrence and then the index vector is normalized to its maximum and the obtained index is used as an input for neural network training.

3.3 Choosing the number and location of measuring devices in voltage flicker detection

To determine the optimal number and location of measurements in the network, voltage measurements are performed as follows: during the simulation, they are performed on all buses of the network. To identify the most sensitive network buses in terms of voltage flicker detection, the introduced index is calculated for all measurements. After that, the standard deviation of the obtained indices is calculated for each measurement in different simulation modes, and the sensitive buses are arranged in descending order of standard deviation. Based on this, at each step, the input is added to the neural network, and flicker detection is checked for the polluting bus using the neural network. Adding measurements as input to the neural network continues until the polluting bus is correctly detected. In this way, the number and optimal location of measurements are determined.

4. Neural network

To intelligently identify the location of the polluting source according to the index obtained in Section 3.3, a multilayer perceptron (MLP) neural network is used as shown in Fig. 4. The number of neural network inputs is equal to the number of measurements in the network, and the number of outputs is equal to the number of network buses. The Marquardt-Levenberg error back-propagation algorithm was employed to train the neural network, and gradient descent with momentum weights and biases was used to update the weights. The transfer function of neural network nodes was selected as the logarithmic sigmoid function in the first step and the hyperbolic tangent sigmoid function in the next steps. The outputs of the network are considered zero and one in the training phase, and the bus where the source of the flicker is located is indicated by one. To detect the polluting bus, the output of the neural network is examined. If there is only one maximum greater than 0.5 among the outputs, that bus is selected as a polluting one, but if the output of more than one bus is greater than 0.5, then those buses are also selected as suspicious ones. Therefore, in a large network, the investigation to find the polluting bus is limited to two or three buses, and in this situation, the main location of flicker occurrence can be easily identified by the methods presented in [17, 18].

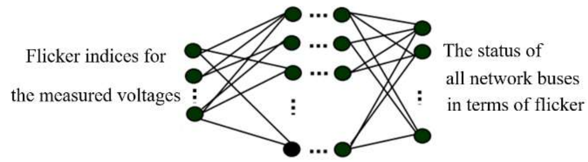

Fig. 4: Selected neural network

5. Simulation results

To show the effectiveness of the proposed method in this article, a sample 14-bus network was selected according to Fig. 5 and simulated in EMTP/ATP software, the required information of the network parameters is given in [25]. To model the flicker in the network, a resistance bank whose resistance changes according to Equation (12) has been used. The selected model is based on the model that is considered for electric arc furnaces, which are the main cause of flicker in power grids [23, 24]. According to the method presented in Section 3.3, buses 1, 3, and 4 were selected for measuring and sampling the voltage.

The used neural network is a two-layer perceptron network with 3 neurons in the input layer and 16 neurons in the hidden layer. To train the neural network, flicker is simulated in three different amplitudes of 2%, 5%, and 10% in different buses of the system and for the oscillation frequency of 8 Hz and is trained by the obtained indices of the neural network. Since the effect of frequency in the change of "time-amplitude" contour has been eliminated according to the discussion in Section 3.2, there is no need to train the neural network for different frequencies, and the simulated results prove the truth of this.

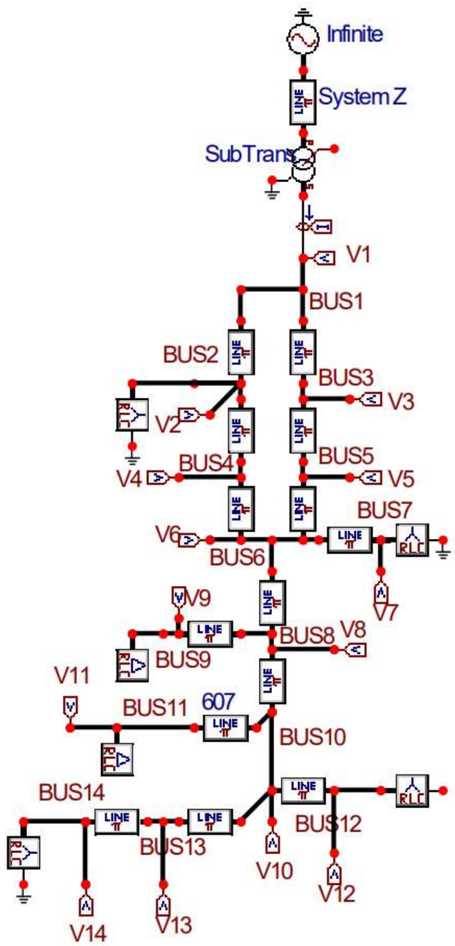

Fig. 5: The 14-bus network under study

In 14-bus network, the indices obtained for neural network training in three different voltage fluctuation modes are given in Table 1. The network test results for flicker modes with 2%, 6%, and 8% amplitude at 8 Hz frequency are given in Table 2. As can be seen, when the polluting load is located in buses 1, 2, 3, 4, 13, and 14, the proposed algorithm is fully capable of identifying the polluting bus. If the polluting load is located in other buses, then the algorithm shows some other buses as candidates for the polluting bus in addition to the actual polluting one. These cases occur when the buses of the network are located at a close distance from each other (such as buses 8 and 9) or in cases where there is symmetry in the network (such as buses 11 and 12 compared to bus 10). In these cases, according to the mentioned contents, some buses are identified as polluting ones.

Table 1: *Calculated indices for neural network training*

Amplitude			Measur	Num of polluting bus	Amplitude			Measure	Num of polluting bus
10%	5%	2%			10%	5%	2%		
0.695	0.691	0.692	V1	8	0.900	0.893	0.893	V1	1
0.773	0.771	0.772	V3		0.908	0.902	0.902	V3	
1	1	1	V4		1	1	1	V4	
0.808	0.7997	0.799	V1	9	1	1	1	V1	2
0.938	0.937	0.937	V3		0.996	0.996	0.996	V3	
1	1	1	V4		0.986	0.985	0.985	V4	
0.699	0.688	0.688	V1	10	0.695	0.687	0.688	V1	3
0.776	0.768	0.768	V3		0.773	0.768	0.768	V3	
1	1	1	V4		1	1	1	V4	
0.696	0.692	0.696	V1	11	0.826	0.816	0.815	V1	4
0.774	0.772	0.771	V3		1	1	1	V3	
1	1	1	V4		0.866	0.858	0.857	V4	
0.694	0.692	0.694	V1	12	0.6981	0.692	0.693	V1	5
0.7723	0.771	0.773	V3		0.775	0.771	0.772	V3	
1	1	1	V4		1	1	1	V4	
0.692	0.691	0.693	V1	13	0.617	0.603	0.602	V1	6
0.771	0.771	0.772	V3		0.6537	0.641	0.639	V3	
1	1	1	V4		1	1	1	V4	
0.694	0.692	0.694	V1	14	0.694	0.692	0.694	V1	7
0.772	0.772	0.773	V3		0.772	0.772	0.7723	V3	
1	1	1	V4		1	1	1	V4	

Tables 2: *The output of the trained neural network for different flicker amplitudes at a frequency of 8 Hz*

Amplitude of flicker oscillations			Polluting bus	Oscillation frequency	Amplitude of flicker oscillations			Polluting bus	Oscillation frequency
8%	6%	2%			8%	6%	2%		
Selected bus in the ANN output					Selected bus in the ANN output				
8, 9	8, 9	8	8	Flicker with 8% oscillations	1	1	1	1	Flicker with 8 Hz oscillations
8, 9	9	8, 9	9		2	2	2	2	
10, 11, 12	10, 11, 12	10, 11, 12	10		3	3	3	3	
10, 11, 12	10, 11, 12	10, 11, 12	11		4	4	4	4	
10, 11, 12	10, 11, 12	10, 11, 12	12		5, 6, 7	5, 6, 7	5	5	
13	13	13	13		5, 6	6	5, 6	6	
14	14	14	14		7	6, 7	7	7	

To show the effectiveness of the method in covering different flicker frequencies, the aforementioned network was also tested for flicker with different amplitudes and frequencies of 4 and 15 Hz, the results of which are given in Tables 3 and 4, respectively. Also, to check the robustness of the algorithm to the harmonics that exist in the network along with flicker, the flicker source was modeled in the network along with a harmonic current source that contains 3rd and 5th harmonics with amplitudes of 20% and 15% of the rated current of the flicker source.

Table 3: *The output of the trained neural network for different flicker amplitudes at a frequency of 4 Hz*

Amplitude of flicker oscillations			Polluting bus	Oscillation frequency	Amplitude of flicker oscillations			Polluting bus	Oscillation frequency
8%	6%	2%			8%	6%	2%		
Selected bus in the ANN output					Selected bus in the ANN output				
8, 9	8, 9	8	8	Flicker with 4% oscillations	1	1	1	1	Flicker with 4 Hz oscillations
8, 9	9	8, 9	9		2	2	2	2	
10, 11, 12	10, 11, 12	10, 12	10		3	3	3	3	
10, 12	10, 11, 12	10, 11	11		4	4	4	4	
10, 11, 12	10, 11, 12	10, 12	12		5, 6	5, 6	5	5	
13	13	13	13		5, 6	6	5, 6	6	
14	14	14	14		7	6, 7	7	7	

Table 4: *The output of the trained neural network for different flicker amplitudes at a frequency of 15 Hz*

Amplitude of flicker oscillations			Polluting bus	Oscillation frequency	Amplitude of flicker oscillations			Polluting bus	Oscillation frequency
8%	6%	2%			8%	6%	2%		
Selected bus in the ANN output					Selected bus in the ANN output				
8, 9	8	8	8	Flicker with 15% oscillations	1	1	1	1	Flicker with 15 Hz oscillations
8, 9	9	8, 9	9		2	2	2	2	
10, 11, 12	11, 12	10, 12	10		3	3	3	3	
10, 12	10, 11, 12	10, 11	11		4	4	4	4	
10, 11, 12	10, 11, 12	10, 11, 12	12		5, 6, 7	5, 6	5	5	
13	13	13	13		5, 6	6	5, 6	6	
14	14	14	14		7	6, 7	7	7	

The obtained indices were tested in the trained neural network and the results are shown in Table 5. It can be seen that the proposed method can detect the bus or area of flicker in different situations.

Table 5: *The output of the trained neural network for different flicker amplitudes at the frequency of 8 Hz along with harmonics*

Amplitude of flicker oscillations						Polluting bus	Oscillation frequency
10%	8%	6%	4%	2%	1%		
Selected bus in the ANN output							
1	1	1	1	1	1	1	Flicker with 8 Hz oscillations along with harmonics
3	3	3	3	3	3	2	
5	5, 6, 7	5, 6, 7	5	5	5	5	
7	7	6,7	7	7	7	7	

5. Conclusion

The purpose of this article is to provide a method to identify the location of the load causing flicker in distribution networks. In this method, by sampling the network voltage in the appropriate buses and using the neural network, it is possible to determine the location of the flicker. When the buses are close to each other or there is symmetry in the network, the proposed method can limit the choice to a few buses in a wide network. Also, the simulation results show that the selected index has little sensitivity to the harmonics that generally exist along with flicker, and it can be applied in actual distribution networks that often have harmonics.

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