A distributed temperature and strain measurement method for OPPC in distribution Internet of Things in electricity based on multilayer feedforward artificial neural network

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Abstract. In order to effectively measure temperature and strain along op ticalphase conductor (OPPC), the multilayer feedforward artificial neural network (ANN) is applied to demodulate the temperature and strain along OPPC composite optical fiber. The basic principle and parameters of ANN for this purpose are introduced. ANN is trained by using the numerically generated Brillouin spectra with different values of signal-to-noise ratio (SNR) and Brillouin frequency shifts (BFS), and the training results are presented. The Brillouin spectra with different values of SNR, temperature and strain along the optical fiber are numerically generated. The temperature and strain along the optical fiber are demodulated by the spectrum fitting method and the ANN method. The results reveal that the multilayer feedforward artificial neural network method has similar accuracy with the spectrum fitting method. However, the computation time of the former is much less than that of the latter.

1. Introduction
With the development of distribution Internet of Things in electricity [1], there are higher and higher requirements for intelligent transmission lines. Using Brillouin scattering technology [2-3], the temperature and strain along opticalphase conductor (OPPC) [4] can be easily monitored. Because the temperature and strain of optical fiber are linear to Brillouin frequency shift (BFS), the key problem of temperature and strain measurement along optical fiber is Brillouin frequency shift estimation.

Brillouin frequency shift can be estimated by the slope-assisted method [5], the similarity matching method [6] and the spectrum fitting method [7]. The slope-assisted method estimates the Brillouin frequency shift based on the gains of one or two working points which results in short spectrum measurement time and low computational burden in Brillouin frequency shift estimation. However, it is overly sensitive to noise. It is more suitable for the cases that has a high requirement on real-time performance. The similarity matching method determines the Brillouin frequency shift according to the correlation between the measured spectrum and the reference spectrum. It has low computational burden, but it requires a small frequency step. Otherwise, the Brillouin frequency shift error increases. The spectrum fitting method uses the least-squares fitting method to establish the objective function and estimates the Brillouin frequency shift by minimizing the objective function. It is the mainstream method of Brillouin frequency shift estimation. It has high accuracy but is relatively slow to compute. Therefore, there is still a lack of a highly accurate and computationally inexpensive algorithm for Brillouin frequency shift estimation.
To fix this problem, a multilayer feedforward artificial neural network (ANN) is applied to distributed strain and temperature measurement of OPPC in distribution Internet of Things in electricity based on Brillouin scattering. The basic principle and parameters of the multilayer feedforward artificial neural network for temperature and strain demodulation along OPPC composite optical fiber are introduced. ANN is trained by using the numerically generated Brillouin spectra with different values of signal-to-noise ratio (SNR) and Brillouin frequency shifts (BFS), and the training results are presented. The Brillouin spectra with different values of SNR, temperature and strain along the optical fiber are numerically generated. The temperature and strain along the optical fiber are demodulated by the spectrum fitting method and ANN method. The results validate the ANN method.

2. Distributed strain and temperature measurement method based on Brillouin scattering

2.1. Optical fiber strain and temperature measurement method based on Brillouin scattering

When a wide pulse light incidents into the optical fiber, the measured Brillouin spectrum follows the Lorentzian model as follows [7].

\[ g_B(v) = \frac{g_0}{1 + (v - v_B) / (\Delta v_B / 2)^2} \]  

(1)

where, \( g_B \) is Brillouin gain; \( v \) is frequency shift; \( g_0 \) is the peak of gain; \( \Delta v_B \) is linewidth; \( v_B \) is the Brillouin frequency shift.

Brillouin frequency shift is linear to the optical fiber temperature and strain as shown in equation (2) [8].

\[ v_B = v_{B0} + C_v \Delta T + C_{v\epsilon} \Delta \varepsilon \]  

(2)

where, \( C_v \) and \( C_{v\epsilon} \) are temperature and strain sensitivity coefficients of Brillouin frequency shift, respectively. \( \Delta T \) and \( \Delta \varepsilon \) are variations of temperature and strain, respectively; \( v_{B0} \) is the Brillouin frequency shift at reference temperature and strain.

Because the temperature and strain cannot be demodulated only according to Brillouin frequency shift, the demodulation is usually carried out in light of the actual situation in practical applications. For example, generally, the temperature along the optical fiber is the same value at the same time. The strain along the optical fiber is the same value when the loose tube optical fiber is used. Then, the change of Brillouin frequency shift along the optical fiber is mainly caused by the change in temperature (such as lightning strike) [9].

2.2. Spectrum fitting method

The spectrum fitting method establishes the objective function and estimates the Brillouin frequency shift by minimizing the objective function. The objective function established based on the Lorentzian model is shown in equation (3).

\[ E = \sum_{n=1}^{N} (g_B(v_n) - g_{meas})^2 \]  

(3)

where \( E \) is the sum of the squares gain errors; \( N \) is the number of sweeps; \( v_n \) is the \( n \)th frequency; \( g_{meas} \) is the measured Brillouin gain at \( v_n \).

Because the method can effectively utilize the whole Brillouin spectrum data, the accuracy is high. However, it is needed to minimize the nonlinear least-square fitting problem by the iterative optimization algorithm. Therefore, it is relatively slow to compute.

2.3. Multilayer feedforward artificial neural network method

The relationship between Brillouin gains and Brillouin frequency shift can be seen as a mapping, which can be approximated by a multilayer feedforward artificial neural network. Single hidden layer
ANN is used because of its strong approximation ability. The input of ANN is the Brillouin gains at the sweep frequencies. Therefore, the number of neurons in the input layer is the number of sweeps. The output of ANN is Brillouin frequency shift. Therefore, the number of neurons in the output layer is 1. The number of hidden layer neurons can be adjusted according to the actual situations. The activation functions of the hidden layer and output layer neuron are set to the Sigmoid and linear functions, respectively. Since the corresponding objective function of ANN training is a nonlinear least-square fitting problem, the Levenberg-Marquardt algorithm [10] is used to minimize the objective function. The optimal weights and thresholds are obtained after the ANN training. BFS of Brillouin spectrum can be easily estimated by the trained ANN with the least computational effort.

3. OPPC distributed strain and temperature measurement method

3.1. Neural network training

Brillouin spectra are numerically generated by the Lorentzian model. The linewidth is 50 MHz; the frequency ranges from 10.625 to 10.775 GHz, the frequency step is 1 MHz; the Brillouin frequency shift changes in the range of 10.675-10.725 GHz with a step size of 1 MHz. The SNR is set to 10 dB, 20 dB and 30 dB, respectively. 1530 Brillouin spectra are numerically generated as the training samples. The number of hidden layer neurons is set to 20, the maximum allowable number of epochs is 100, and the goal is that the mean square error (MSE) of Brillouin frequency shift is less than 0.1 MHz². The other parameters are the same as those in Section 2.3.

Change of training error and training time of ANN with number of epochs is shown in figure 1. For the training samples, Brillouin frequency shift error of the trained ANN is shown in figure 2.

As can be seen from figure 1, the mean square error of ANN decreases rapidly with number of epochs, and it tends to a stable value when the number of epochs is more than 6. The minimum error is only 0.71 MHz², which ensures that the ANN learns the mapping from Brillouin gains to Brillouin frequency shift. In addition, the training times is approximately proportional to the number of epochs. It can be seen from figure 2 that the estimated Brillouin frequency shift is consistent with the accurate value along the optical fiber on the whole, and the difference between them decreases with SNR, which further validates of the ANN training.

![Figure 1. Change of training error, training time with number of epochs.](image)
3.2. **Comparison of ANN method and spectrum fitting method**

Brillouin spectra are numerically generated based on equation (1). The length of OPPC is 8 km, and the Brillouin frequency shift along the optical fiber is displayed in figure 3. The measurement resolution is 10 m, and the SNR is set to 13, 18, 23 and 28 dB, respectively. The Brillouin frequency shift is estimated by using the ANN trained in Section 3.1 and the spectrum fitting method based on the Lorentzian model. The average computation time of a Brillouin frequency shift estimation by the two methods is 70.13 μs and 39.84 ms, respectively. That is to say, the computation time of the former is about 1/560 of the latter. Let $v_{00}$=10.68 GHz, $C_{vT}$ and $C_{vε}$ are set to the typical values of 1.12 MHz/°C and 0.0482 MHz/με, respectively. Assume that the Brillouin frequency shift variations along the optical fiber are only caused by variation in temperature or strain, the corresponding temperature and strain errors are shown in figures 4 and 5, respectively. The statistical results of Brillouin frequency shift error, temperature error and strain error under different SNRs are illustrated in table 1. In table 1, Max and Std mean the maximum value and standard deviation of errors, respectively.

![Figure 2. Calculation results of training samples with different SNRs.](image)

![Figure 3. Brillouin frequency shift along optical fiber.](image)
Figure 4. Temperature error of spectrum fitting method and ANN method at different SNRs.
According to figures 4-6 and table 1, the Brillouin frequency shift error, temperature error and strain error of the ANN method are very close to those of the classical spectrum fitting method. Even if the SNR is only 13 dB, the maximum temperature error is only about 3°C, and the corresponding maximum strain error is less than 80 με, which can meet the accuracy requirements of distributed strain and temperature measurement for OPPC in distribution Internet of Things in electricity. However, the former requires much less computational effort.

4. Conclusion
In this work, the demodulation of temperature and strain in distributed strain and temperature measurement for OPPC in distribution Internet of Things in electricity is investigated, and a multi-layer feedforward artificial neural network method is proposed to estimate Brillouin frequency shift for Brillouin spectra with different SNRs and Brillouin frequency shifts. The results reveal that the ANN method has similar accuracy with the classical spectrum fitting method. However, the computation time of the former is much less than that of the latter.

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