A Measuring Method of DOM Components Based on Fiber SPR Sensor and ICPSO-BP Neural Network

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ABSTRACT As the single sensor is not competent for the variation of the total amount and components of DOM in a large range, according to the cross-sensitivity between fiber SPR sensors with different structures, a measuring method of DOM components is proposed by combining the deep learning algorithm with the fiber SPR sensors based on the regulation of metal film thickness. We exploit an improved cooperative particle swarm optimization algorithm (ICPSO) aiming at the problem of particle diversity loss caused by premature convergence of particles which not only considers the optimization information of single particles, the global particles and particles in the groups, but also considers the proportion of shared information. Then, the ICPSO is used to optimize the weights and thresholds of back propagation neural network (BPNN) to establish ICPSO-BP network, so as to construct three classifiers consists of ICPSO-BP (wave length), ICPSO-BP (spectral width), ICPSO-BP (light intensity). By comprehensive training of the resonance wavelength, spectrum width and light intensity of SPR effect for the measured water, five DOM components (tyrosine protein, tryptophan protein, fulvic acid, dissolved microbial metabolites and humic acid) and their concentrations in four water samples, namely, Inner canal (A), Hongze lake (B), Park lake (C) and Campus lake (D), have been effectively predicted. The prediction accuracy is more than 80%, among them, the highest prediction rate of tryptophan protein and its concentration in Hongze lake (B) which can reach 86%. Therefore, the dynamic range of SPR measurement is effectively expanded and better measurement accuracy and sensitivity are maintained, which verifies the feasibility of the proposed method in DOM measuring and provide a new idea for DOM component testing.

INDEX TERMS fiber SPR sensor array, surface plasmon resonance effect, artificial neural network, dissolved organic matter, premature convergence, particle swarm optimization

I. INTRODUCTION Among different water pollutants, the adverse effect of dissolved organic matter (DOM) on water quality is particularly prominent. Excessive concentration of DOM is one of the important factors causing water eutrophication [1]-[2], which not only releases toxins through the explosive growth, death and degradation of algae, but also affects the self-cleaning ability of water body through a series of complex and changeable biochemical processes, resulting in the accelerating deterioration of water quality [3]-[4]. Relevant studies have shown that the impact of DOM is related not only to its total amount, but also to its components. In various of indicators representing water quality, the identifications of total amount and components of DOM play prominent roles [5]. However, the complexity of organic structure puts forward higher requirements for the effective measuring method of DOM components.

At present, the common measuring methods of DOM in water mainly include electrochemical method, absorption spectroscopy, fluorescence spectroscopy and biological detection.

Electrochemical method [6] mainly reflects the total amount of DOM, which is the main DOM measuring method in environmental monitoring, but it is difficult to reflect the components and relative proportion of DOM. Moreover, its
measurement and analysis process are completed in the laboratory environment after chemical pretreatment, which often take hours or even days, resulting in the lack of timeliness. In addition, the chemical pretreatment of water samples reduces the reliability of the measurement results due to the secondary pollution.

Absorption spectroscopy and fluorescence spectroscopy [7]-[8] belong to physical methods using optical technology, which can reflect the changes of total amount and components of DOM by dielectric properties. The changed dielectric characteristics will produce the modulation of the absorption characteristics, fluorescence emission and optical transmission characteristics of the samples to the detection light, and the measurement purpose will be realized by demodulating the optical characteristics of the detection light after comparing with the water samples. The optical measurement methods abandon the chemical pretreatment process in the electrochemical method, which have no calibration and maintenance requirements caused by the performance of the measurement equipment in the electrochemical method. However, to better meet the requirements of water quality monitoring, there are still some important basic problems to be studied and solved. Among them, fluorescence spectroscopy, especially three-dimensional fluorescence spectroscopy [9], use different characteristic fluorescence wavelengths to complete the determination of DOM components, which need to be carried out in the laboratory with large equipment. So, there are two problems: first, when the intensities of different characteristic peaks are greatly different in the same measured water, there will be an intensity masking effect in the fluorescence measurement, which may make it difficult to detect the fluorescence characteristic peaks of substances with weak intensity and DOM components with low concentration, the weak fluorescence intensity may also be shielded, which limits the measurement accuracy and sensitivity.

Biological detection methods [10] generally require a long time to screen biological species and to establish a relatively stable and significant corresponding relationship between the total amount and components of DOM. Its process is complex and generally used for qualitative analysis and obviously insufficient in quantitative analysis.

It can be seen that these common measuring methods can determine the total amount of DOM, but there are always bottlenecks in the determination of DOM components [11]-[12]. It has important theoretical significance and practical value to find a more effective method to measure the total amount and components of DOM.

In fact, water bodies from different sources have a great impact on the content and properties of DOM components, which lead to the components are very complex. In the face of measuring tasks of DOM components, the proportion of each component cannot be achieved by a single sensor, the sensors with different characteristics are required to respond to their component one by one and are analyzed to get respective component information. The component information just like the sour, sweet, bitter, spicy and other complex taste information felt by the human taste system, which can be accurately identified through the different responses of the taste buds of human tongue. Based on this, the electronic tongue (ET) method [13] suitable for identifying different component information is applied to the testing process of DOM components. In addition, the research results of fluorescence spectrum show that the main components of DOM are tyrosine proteins, tryptophan proteins, fulvic acid, soluble microbial metabolites and humic acid [14]. Different components have different characteristic luminescence spectrum, which shows that when different kinds of DOM are dissolved in water, it will show different dielectric properties, its refractive index will change in a wide range [14]-[15]. The relative content of different DOM component plays a decisive role in the refractive index of water body. So, the DOM components and their relative content can be determined based on the measurement of refractive index. The higher the measurement accuracy of refractive index, the more accurate the measuring of DOM components and relative content.

In recent years, with the extensive application of surface plasmon resonance (SPR) technology, the combination of SPR with fiber sensor has attracted more and more attention [16]-[17]. Because of its portability, miniaturization and easy integration, the sensor has great application potential in biomedicine, health care, environmental pollution detection, industrial production monitoring and other fields [16]-[18]. As the fiber SPR sensing technology combines the excellent sensing accuracy and test sensitivity of refractive index, it is very suitable for the measuring of DOM components. So, the sensor array is established by fiber SPR sensing probes in the paper. The sensing probes generate taste bud-like response to different DOM components, which then are processed by the deep learning algorithm. Thus, the characteristics of DOM components are obtained, and the effective detection of DOM components and their relative concentrations are completed.

In the paper, a measuring method of DOM components is proposed by combining the deep learning algorithm with the fiber SPR sensors based on the regulation of metal film thickness. The effective prediction of five DOM components and their concentrations in four kinds of water is realized using fiber SPR sensor array and artificial neural network optimized by improved particle swarm algorithm (ICPSO). It realizes the high-sensitivity measurement of DOM components within a large dynamic range. So, the novelty of this work is providing a new idea for DOM component testing. The main contributions of this paper can be summarized as follows:

- We propose the fiber SPR sensing probes with different optimum refractive index by multimode fiber and gold film with 7 different thickness of 55-85 nm. The optimum
refractive index of each probe is effectively distributed in the range of 1.33 to 1.43 RIU corresponding to the measured water.

- We propose an ICPSO algorithm aiming at the problem of particle diversity loss caused by the premature convergence of particles. By dividing subgroups, the subgroup information and the information between subgroups are introduced to improve the optimization effect.

- By constructing the ICPSO-BP network optimized by ICPSO, we propose three classifiers as the intelligent algorithm of the fiber SPR sensor array to realize the effective prediction of five DOM components and their concentrations in four kinds of water.

II. THE PRINCIPLE OF MEASUREMENT FOR DOM BASED ON FIBER SPR SENSOR ARRAY

The basic structure of fiber SPR sensor consists of three layers: the core, the metal film and the medium. In practice, the terminal reflected structure is often used by coating metal film on the end of the core [19]. The measurement structure and principle of the terminal reflected fiber SPR sensor are shown in Fig. 1.

![Image](image1)

**FIGURE 1.** The measurement structure and principle of the terminal reflected fiber SPR sensor.

When the incident light is emitted from the light dense medium (the core) to the light sparse medium (the cladding), the light will be fully reflected while the incident angle is greater than the total reflection angle. Evanescent wave will be generated at the interface between the core and the cladding, which will penetrate into the metal film and couple with the free electrons on the surface of the metal film to produce surface plasma wave (SPW). The resonance occurs while the frequency of SPW is equal to that of evanescent wave. The free electrons on the metal surface will absorb the energy of the incident light, which result in a large reduction of the reflected light energy, and a resonance peak is shown in the reflection spectrum. When the refractive index of the metal film changes, the resonance peak will also change. So, the medium refractive index can be obtained by the position of the resonance peak.

The amplitude of SPW decays exponentially along the direction perpendicular to the interface [19]. The propagation constant of SPW is determined by the metal and medium which shown in formula (1) [20]:

\[
K_{SP} = \frac{\omega}{c} \left( \frac{\varepsilon_2 \varepsilon_3}{\varepsilon_2 + \varepsilon_3} \right)^{1/2}
\]

where \(\varepsilon_2\) and \(\varepsilon_3\) are the dielectric constant of the metal and medium, respectively. \(\omega\) is the angular frequency of excitation light. \(c\) is the velocity of light in vacuum.

The evanescent wave will appear while total reflection occurs which propagation constant \(K_x\) is given by formula (2) [18]

\[
K_x = \frac{\omega}{c} \sqrt{\varepsilon_1 \sin \theta}
\]

where \(\varepsilon_1\) is the dielectric constant of the core. \(\theta\) is the incident angle.

When the propagation vector of the evanescent wave matches the SPW, plasma resonance occurs at a specific excitation angle \(\tilde{\theta}\). Its resonance condition is as shown in formula (3) [19]-[20].

\[
K_x = K_{sp}
\]

That is, the resonance angle \(\tilde{\theta}\) of incident light meets:

\[
\sin \tilde{\theta} = \sqrt{\frac{\varepsilon_2 \varepsilon_3}{\varepsilon_2 + \varepsilon_3}} / \sqrt{\varepsilon_1}
\]

According to the theory of Maxwell [20], Equation (5) can be deduced from Equation (4) by substituting the dielectric constant and refractive index of the medium:

\[
\sin \theta = \sqrt{\frac{\varepsilon_2 n_1^2}{\varepsilon_2 + n_1^2}} / \sqrt{n_1}
\]

So, the relationship between the resonance angle \(\tilde{\theta}\) and the refractive index of medium \(n_1\) can be calculated by Equation (5) while the refractive index of the fiber \(n_2\) and the metal film \(\varepsilon_3\) are fixed. Because the propagation constant of SPW strongly depends on the refractive index of medium, so as to result in the shift of the resonant peak position by the change of the medium. Thus, the relationship between resonant wavelength (or angle) with the measured refractive index is established. For the change of the measured refractive index is closely related to the measured medium, the medium properties detection can be completed by fiber SPR sensor.

The fiber SPR sensing system can realize high-precision and high-sensitivity refractive index measurement [19]-[20]. However, the resonance absorption principle of SPR determines the limited dynamic range of the corresponding sensing system, and its best measurement effect is mainly shown in the point-measurement of refractive index. Therefore, when the structure of sensing probes is given, it has good measurement sensitivity and accuracy for the specific point of refractive index determined by its parameters of structure and geometric size, but for the tested object which refractive index deviate from the optimal
measurement point, the center absorption wavelength, the light intensity and spectral width will show obvious nonlinear degradation with the deviation of the measured refractive index [20]. In the case of single sensing probe, when the resonant absorption wavelength is used as the response to the change of measured refractive index, this obvious degradation is a bottleneck for the dynamic range of the measuring system. From another point of view, the more serious this nonlinear degradation is, the stronger the response of the sensing probe to the deviation of the measured object is. For the traditional linear system, this strong nonlinear degradation cannot support the design principle of the sensing system. However, the significant nonlinear degradation itself is also an available sensing information, which is the response of the given sensing probe to the change out of its dynamic range. The higher the degree of degradation, the more sensitive the sensing probe is. Therefore, the fiber SPR sensing probes with different structures are selected to form a sensor array taking advantage of its excellent optical transmission characteristics. In addition to the point-measurement performance with good linearity in its dynamic range, each sensing probe has a certain sensitive nonlinear response to the refractive index out of the dynamic range.

Through the effective arrangement of the optimal refractive index interval of each sensing probe, it can ensure that the measurement performance of a sensing probe is in good agreement with the measured refractive index in large variation range, so as to carry out the refractive index measurement with good linearity. For other sensing probes, due to the varying deviation between the endogenous optimal measurement point and the measured refractive index, it will take the light intensity and spectral width at the resonance point as the characteristic quantities which correspond to different nonlinear deterioration, the different degrees of deterioration of each sensing probe are processed together with the perception of the probe at the best point by deep learning algorithm, therefore, the measured response information similar to taste buds can be obtained.

After the structure of the fiber SPR sensor is given, the response of the refractive index of the measured water can be realized through the resonant wavelength, spectral width and the light intensity at the absorption peak. Owing to the structural parameters of the sensing probes are different, such as the refractive index, diameter and film thickness of the fiber core, the above three parameters characterizing the absorption spectrum have different responses for the same refractive index. By the responding of these three parameters to the change of refractive index of the measured water, more abundant cross-sensitivity information between the sensing probes can be obtained in theory.

In the implementation process, firstly, the measured water samples were prepared, then, to determine the fiber SPR sensor array. The fiber sensing probes were selected with different structures to make them have different central absorption wavelengths for the refractive index of the same measured object, and the refractive index range of the measured liquid corresponding to the optimal absorption wavelength of each sensing probe is consistent with the target dynamic range of the detection system. Secondly, the data processing algorithm was determined. The BP Network optimized by ICPSO was selected as processing algorithm to construct a three-layer network. The number of the input layer was determined by the number of sensing probes in the sensor array (7 sensing probes), and the output corresponded to five DOM components of the measured water which were determined by three-dimensional fluorescence spectroscopy technology. In order to verify the function of fiber SPR sensor array, the following experimental processes are designed: preparation of DOM samples with different components and concentration, determination of DOM components in water samples, implementation of fiber SPR sensor array, measurement of SPR effect of water samples, artificial intelligence network training and result verification.

III. THE PREPARATION OF WATER SAMPLES

In the implementation, for the water samples with different mixing ratios, the DOM components of the samples were measured by the three-dimensional fluorescence spectrum technology. The SPR resonance absorption parameters of sensing probes were measured by the fiber spectrometer and Abbe refractometer, so as to obtain the training data which were handed over to ANN. Likewise, similar SPR spectral measurement and three-dimensional fluorescence analysis for other step points of the measured water were carried out, the obtained results were taken as the validation data.

The water samples with different components and concentrations are not only the measured objects, but also the necessary condition to confirm the testing function. From the perspective of water quality measurement, DOM components which be concerned mainly include tyrosine proteins, tryptophan proteins, fulvic acids, dissolved microbial metabolites and humic acids [11]-[12]. Unlike commercial synthetic organics, there are not standardized industrial products of DOM components. So, to ensure the universality of the fiber SPR sensor array, four water samples with different natural environments were selected as the measured objects, namely, Inner canal (A), Hongze lake (B), Park lake (C) and Campus lake (D), which are the representatives of waters samples with different degrees of pollution.

A. OVERVIEW OF THE STUDY AREA

Hongze lake (33°06' ~ 33°40' N, 118°10' ~ 118°52' E), which located in Huai’an and Suqian cities in the north of Jiangsu province. It is in the middle and lower reaches of the Huaihe and Yihe rivers, which is the fourth largest freshwater lake in China with length of 60 km, maximum
width of 58 km, maximum water depth of 4.75 m. Affected by natural and human factors, the water quality of Hongze Lake is seriously polluted in the southwest and southeast, and is in the state of slightly eutrophic nutrition as a whole. Compared with other lakes in the five freshwater lakes of China, the research on Hongze Lake is relatively weak; The Beijing-Hangzhou Grand Canal is the longest canal in the world, stretching a length of 1794 km, which start from Hangzhou in the south and Beijing in the north. The section from Yangzhuang in Huai’an City to liuweikou of the Hangzhou in the south and Beijing in the north. The Beijing-Hangzhou Grand Canal is the longest canal in China, the research on Hong ze Lake is relatively weak; "

B. SAMPLE COLLECTION AND PRETREATMENT

In May 2020, 500ml samples at the depth of 0.5m above the surface of the measured waters were collected and stored at low temperature. The three-dimensional fluorescence spectrum analysis of DOM and SPR parameter measurement were completed within 2-3 days after the sampling.

For all kinds of collected samples, insoluble granular substances were removed using pre-burned 0.22 μm filter membrane. NF270 commercial nanofiltration membrane was used to filter some inorganic salts and other substances. The obtained filtrate was divided into two parts: one part was directly stored in brown glass bottle and stored at 4°C for standby, the other part was placed in an open brown glass bottle and concentrated by natural evaporation at room temperature in a clean and dark environment. The purpose of avoiding light and room temperature is to avoid biochemical reaction in the concentration process, which can destroy the relative contents of DOM in the samples. For the concentrated samples, filtered again by 0.22 μm filter membrane after burning, and the obtained filtrate was stored in a brown glass bottle and stored at 4°C for standby. Four samples after concentration were grouped with marks of A, B, C and D. Regarding the concentrated samples as the pure solutions, 50 samples with different concentrations were prepared with the concentration step of 2% which numbered A1-50, B1-50, C1-50, D1-50. The corresponding data are used for the training of ANN. Then, 34 samples with different concentrations, numbered a1-34, b1-34, c1-34 and d1-34, were prepared with the step of 3% as validation data.

Due to the close relationships between the refractive indexes and the substances in water, the refractive indexes of different water were measured for a short time. The data were collected in Huai’an City in May 2020 by Abbe refractometer, and the temperature was about 25°C. Repeat the measurement of each water for 3 times every day and take the average value to reduce the error. The measurement range of Abbe refractometer is 1.3000~ 1.7000, and its accuracy is 0.0001. The short-term refractive indexes of different water in 30 days are shown in Fig.2.

IV. THE DETERMINATION OF DOM IN SAMPLES

According to the function of fiber SPR sensor and the requirements of ANN, the components and relative contents of DOM in samples should be known. In this paper, they were determined by three-dimensional fluorescence spectrum measurement. The fluorescence spectrum is usually divided into five regions according to the relationship between continuous excitation wavelength and emission wavelength [21], as shown in Table 1.

| Region | Organic type                | Excitation wavelength (Ex)/nm | Emission wavelength (Em)/nm |
|--------|-----------------------------|-------------------------------|-----------------------------|
| I      | Tyrosine proteins           | 200 ~ 250                     | 260 ~ 320                   |
| II     | Tryptophan protein          | 200 ~ 250                     | 320 ~ 380                   |
| III    | Fulvic acid                 | 200 ~ 250                     | 380 ~ 550                   |
| IV     | Dissolved microbial metabolites | 250 ~ 450                     | 260 ~ 380                   |
| V      | Humic acid                  | 250 ~ 450                     | 380 ~ 550                   |
Hitachi's F-7000 fluorescence spectrophotometer was used to measure the three-dimensional fluorescence spectrum of the samples. The corresponding parameters of spectrophotometer: emission wavelength (EM) is 280-550 nm; Slit width is 5 nm. Excitation wavelength (Ex) is 200-550 nm; Slit width is 5 nm. Scanning speed is 2400 nm/min. In the measurement, it is necessary to subtract the blank spectrum from each sample, so as to eliminate the influence of Raman scattering. Therefore, while the three-dimensional fluorescence spectrum data of all samples were obtained, the types and relative components of DOM can be obtained by using the three-dimensional spectral region integration method [21]. The specific implementation is as follows: calculate the specific regional standard volume and the overall standard volume of DOM measurement needs to have good measurement sensitivity and linearity in the range of 1.33-1.43 RIU. To investigate the structure of fiber sensing probe and the selection of fiber type, the influence of gold film thickness at different excitation wavelength. 

\[
\Phi_{i,n} = M_{i,n} \sum_{i=1}^{N} I(\lambda_{exc}, \lambda_{em}) \Delta \lambda_{exc} \Delta \lambda_{em} 
\]

\[
\Phi_{T,n} = \sum_{i=1}^{N} \Phi_{i,n} 
\]

\[
P_{i,n} = \frac{\Phi_{i,n}}{\Phi_{T,n}} \times 100\% 
\]

where \(\Delta \lambda_{exc}\) and \(\Delta \lambda_{em}\) are the wavelength intervals of excitation and corresponding fluorescence, respectively. \(I(\lambda_{exc}, \lambda_{em})\) is the fluorescence intensity corresponding to different excitation wavelength. \(P_{i,n}\) is the relative content of different fluorescent substances. \(M_{i,n}\) is the multiplication coefficient corresponding to different regions of the three-dimensional fluorescence spectrum, which are 20.4, 16.4, 4.81, 8.76, 1.76 for five regions.

For the four samples selected in this paper, The DOM components in the samples were calculated by the regional integration method, as shown in Table 2.

| Component | Inner canal (A) | Hongze lake (B) | Park lake (C) | Campus lake (D) |
|-----------|----------------|----------------|--------------|-----------------|
| P1 (%)    | 20.7           | 18.54          | 24.46        | 22.26           |
| P2 (%)    | 35.98          | 44.32          | 32.98        | 33.48           |
| P3 (%)    | 11.35          | 12.66          | 12.67        | 13.09           |
| P4 (%)    | 26.75          | 19.16          | 24.66        | 25.67           |
| P5 (%)    | 5.22           | 5.32           | 5.23         | 5.457           |

Notice: P1, P2, P3, P4, P5 are five components of DOM, respectively (tyrosine protein, tryptophan protein, fulvic acid, dissolved microbial metabolites and humic acid).

V. IMPLEMENTATION OF FIBER SPR SENSOR ARRAY

According to the principle of SPR effect, the fiber SPR sensing probe with single-mode, multimode and tapered structure can achieve theoretical measurement effect at the best measuring points. However, the dynamic range of high sensitivity can be kept very small, which is limited for the applications with large refractive index range. Relatively speaking, the sensor array can realize high sensitivity measurement in a large range. Its basis is that each sensing probe has cross-sensitivity which measurement requirements are as follows. First, the best measuring points of each sensing probe are evenly distributed within the measurable refractive index range as much as possible. Second, as many sensing probes as possible have sensitive responses to the measured refractive index and its changes, regardless of linear or nonlinear. The third is to make the resonant wavelength, spectral width and light intensity as sensitive as possible to the measured refractive index and its changes. Therefore, the premise of forming fiber SPR sensor array is to select the appropriate sensing probes. According to the refractive index variation range of the measured water, the SPR sensor array for the purpose of DOM measurement needs to have good measurement sensitivity and linearity in the range of 1.33-1.43 RIU. To investigate the structure of fiber sensing probe and the selection of fiber type, the influence of gold film thickness at three different refractive indexes of the measured object was studied by using single-mode and multimode fiber SPR. The theoretical model of fiber SPR is used for modeling, analysis and simulation [20]. The experimental results are shown in Fig. 3.
The results show that there is an optimal metal film thickness when the measured refractive index is given in both single-mode and multi-mode, and the optimal film thickness increases with the increase of the refractive index. At the same refractive index point, the optimal film thickness of multimode fiber sensor is greater than that of single-mode fiber. The increasing extent of the resonant wavelength and spectral width of multimode fiber is smaller than that of single-mode fiber. When the measured refractive index deviates from the optimal measuring point corresponding to the film thickness, the resonance characteristics deteriorate in varying degrees.

Compared with the multimode fiber, single-mode fiber has better resonance characteristics at each optimal film thickness. However, when the measured refractive index deviate from the optimal measuring point determined by the structure of fiber sensing probe, the degradation speed of the resonance characteristics is higher than that of multimode fiber. Therefore, the measurement effect of the adjacent area by the single-mode fiber sensing probe are not ideal and its coverage characteristic and cross-sensitivity are poor, which is caused by the small core size and less leakage mode.

Combined with the cross-sensitivity requirements of each sensing probe in the sensor array, it can be seen from Fig. 3 that multi-mode fiber probes have better cross-sensitivity characteristics than the single-mode fiber probes around its best measuring point. That is, in a large refractive index change range, it has better response to the change of refractive index through the changes of resonance wavelength, spectral width and light intensity. Although for each sensing probe, three characteristic response is not linear when it deviates from the best measured refractive index, but the nonlinearity can be effectively eliminated through ANN. Therefore, we select multimode fiber plated with gold film of different thickness to form SPR sensing probes. By controlling the thickness of the gold film, the optimal refractive index measuring point of each sensing probe is effectively distributed within the range of 1.33-1.43 RIU. The film thicknesses are shown in Table 3.

| Sensor probe | Sensor 1 | Sensor 2 | Sensor 3 | Sensor 4 | Sensor 5 | Sensor 6 | Sensor 7 |
|--------------|----------|----------|----------|----------|----------|----------|----------|
| Metal film thickness (nm) | 55 | 60 | 65 | 70 | 75 | 80 | 85 |
| Best measuring point (RIU) | 1.33 | 1.3442 | 1.3586 | 1.373 | 1.387 | 1.4012 | 1.4153 |
| Resonance wavelength (nm) | 560 | 590 | 619 | 645 | 667 | 692 | 701 |
| Spectral width (nm) | 26 | 28 | 29 | 32 | 34 | 36 | 38 |
| Normalized light intensity (%) | 21 | 26 | 28 | 30 | 32 | 35 | 38 |

Notice: normalized relative light intensity is the ratio of SPR resonance light intensity to the light intensity without SPR effect.
index of the measured object deviates, its sensing performance is severely degraded, even lead to resonance failure. The resonance wavelength sensing characteristics of single-mode and multi-mode fiber sensing probes with different gold film thickness are shown in Fig. 4.

From Fig. 4, except for the sensing probe with the best measuring point of 1.33 RIU, each multi-mode fiber probe has better wavelength response characteristics than that of the single-mode fiber, especially in the area which is less than the best measuring point. Therefore, the multi-mode fiber SPR sensor array can effectively extract the refractive index information in a large range. To further illustration, the simulation results are obtained of the sensing characteristics represented by wavelength, spectral width and light intensity of multimode fiber probes with different gold film thickness, which are shown in Fig. 4 (b), Fig. 5 (a) and Fig. 5 (b).

VI. THE SPR EFFECT MEASUREMENT OF WATER SAMPLE BASED ON FIBER SPR SENSOR ARRAY

The multimode quartz fiber with core diameter of 600 nm, numerical aperture of 0.3 and core refractive index of 1.468 RIU was selected as the experimental object. In the preparation process of fiber SPR sensing probe, it needs to go through several processes: cutting, end surface grinding, cleaning, drying and coating. The fiber was cut by the optical brazing cutter, and the end surface are worn smoothly. The fiber cladding was stripped by the corrosion of hydrofluoric acid, cleaned by ultrasonic wave of ultrasonic cleaning instrument (SCQ-250B) and blow dry by nitrogen. The gold film was prepared by vacuum magnetic sputtering instrument (JSD560-V). The length of the sensing area is 15 mm and the thickness of the gold film is 55-85nm. The main equipment and fiber SPR sensing probe after coating are shown in Fig. 6. Due to the large number of probes and large amount of data, to simplify the experimental process, the open-loop structure was adopted which is shown in Fig. 7.
FIGURE 6. The main equipment and fiber SPR sensing probe after coating.

Light guiding fibers L1 → Y-coupler → Light guiding fibers L0 → Broadband light source → Spectrum analyzer → Computer

FIGURE 7. The testing structure of DOM of fiber SPR sensor array.

Seven sensing probes share the coupler, light source, spectrum analyzer and computer analysis software, which were connected to the fiber through manual switching on the left. Each fiber probe is terminal reflective. The broadband light source is coupled to L0, and then connected to the Y-coupler. The other branch of coupler is connected to the fiber sensing probe by L1. By using its terminal mirror effect, the measured signal spectrum is reflected to the Y-coupler through the same path L1, and then sent to the spectrum analyzer through L2. The spectrum signal is identified by the analyzer and converted into electrical signal which is transmitted to the computer through L3 finally. Among them, L0, L1 and L2 are light guiding fibers, L3 is cable. The spectrum data of the measured water is obtained by switching different probes to the measuring circuit, so as to obtain corresponding component information. During the test, after each acquisition, the SPR sensor need to be separated from the measured medium and stand in the air for about 5 minutes until the formant disappears before the next measurement.

To investigate the stability of the fiber SPR sensing probe, relevant experiment was designed. Sensor 1 in Table III was selected as the measuring sensor which metal film thickness is 55 nm. The glycerol solution with refractive index of 1.33 was prepared as measured liquid by Abbe refractometer (2WAIJ). The effect was measured every 10 minutes after starting the measurement for 5 minutes. The results are shown in Fig.8. It can be found that the sensing probe remains relatively stable except for slight fluctuations in wavelength. There are also some reasons for the influence of room temperature, to explore the specific impact of temperature change on the measurement effect, we carried out the experiment of temperature. Sensor 3 in Table III was selected as the measuring sensor which metal film thickness is 65 nm. The glycerol solution with refractive index of 1.358 was prepared as measured liquid by Abbe refractometer (2WAIJ). The sensor was placed in the vacuum thermostat which temperature was increased from 30°C to 55°C, the step is 5°C. Heat preservation was conducted for 10 minutes after each temperature rising. Multiple measurements were carried out at the same temperature point, and the average value of the measured resonance wavelength was calculated to reduce the influence of random factors in the experiment, so as to improve the robustness of the experimental results. The results are shown in Fig.9.
the sampling values and temperature was fitted. The errors between the sampling values and the reference values at different temperatures were calculate by $\Delta x = x_0 - x_2$, while $x_0$ is the optimal response corresponding to fiber SPR sensing probe (true value). In the actual test process, according to the current temperature, the influence of temperature fluctuation can be corrected by plus the error to the actual sampling value of the sensor.

This paper describes the temperature characteristics of fiber SPR sensing probe. The correction method is relatively simple. Later, we can adopt specific compensation circuit or parameter modeling compensation which will also be the focus of our research in the future.

For the water samples prepared with relative concentration step of 2%, 7 sensing probes are used to measure the SPR resonance respectively according to the experimental structure in Fig. 7 which results are the training data of ANN. In addition, the testing data of 3% concentration is selected as for the validation data, which is used to test the effect of ANN.

VII. ARTIFICIAL INTELLIGENCE NETWORK TRAINING

At present, pattern recognition methods in related fields include ANN [22], principal component analysis (PCA) [23], etc. PCA can reduce the dimension of data and eliminate repeated information, which is often used to find a comprehensive index to judge something or phenomenon as an intermediate step. ANN is an algorithm simulating human brain [22], which is realized by the interconnection of a large number of neurons, its basic neurons are nonlinear signal processing units. Due to the large number of neurons, it has large information capacity and strong uncertain information processing ability. So, ANN is very suitable for the quantitative analysis of fiber SPR sensor array with more testing data. Based on this, a distributed fiber SPR sensor based on neural network is applied to the detection of DOM components and their concentrations.

A. BP NEURAL NETWORK OPTIMIZED BY ICPSO

Compared with other neural networks, the basic BP network is more mature in performance. However, the basic BP algorithm has the following problems [22]: (1) S-type excitation function makes the network easy to enter the saturation area; (2) To ensure stability, the learning rate is often small, which result in slow convergence of the network; (3) the unevenness of the error function surface and the maximum speed descent learning algorithm make it slide into the bottom, resulting in the local minimum point of the network training. Therefore, many scholars have proposed improved algorithms, but these algorithms are still local searching algorithms in essence, which can't guarantee to obtain the global optimal solution. The swarm intelligence optimization algorithm represented by particle swarm optimization (PSO) [23] is global optimization algorithm. Combining PSO with ANN can not only realize the generalization ability of ANN, but also improve its convergence speed and learning ability, so as to improve the identification ability of nonlinear system.

B. PSO AND ITS OPTIMIZATION

PSO was proposed by Kennedy and Eberhart and later developed in Shi et al [24]. The algorithm is initialized as a group of random particles and the optimal solution is found using iterations. Its advantages are fast convergence speed and easy realization. In the past few years, it has attracted the attention of many researchers. However, researchers soon found that the premature convergence will occur in the optimization process, as stated in Rashmi et al [25] and NIU et al [26]. The main reason is the loss of the diversity of the particles. To improve the diversity, some scholars introduced random signals to avoid particles falling into local optimum, as in ARUMUGAM et al [27]. Some scholars increase the diversity by adjusting the weights and acceleration coefficients, as in RATNAWEERA et al [28]. However, these methods generally depend too much on the experimental design and lack theoretical guidance. So, some researchers propose dividing particles into subgroups and mine more profound information for each subgroup separately to increase the diversity. For example, in the stochastic cooperative particle swarm optimization proposed in ZHAO et al [29], which takes into account the importance of subgroup information, each subgroup particle randomly chooses the optimal location found by other subgroup, and updates its velocity and optimal value. In Jin et al [30], a corresponding improvement scheme is also proposed that uses the optimal position of other subgroups to retain the optimal value of each subgroup. Therefore, an improved cooperative particle swarm optimization algorithm (ICPSO) with dynamic information adjustment and controllable speed is proposed in this paper. By introducing the subgroup optimal information and the number of iterations to dynamically control the role of the subgroup and the global information, so as to realize the guidance of the global information in the early stage of optimization, the subgroup optimal information will gradually improve with the deepening of the optimization process. So, the particle diversity is maintained.

The original PSO algorithm proposed by Kennedy and Eberhart uses formula (9) to update the particle state [30]:

$$v_{r+1} = \omega \cdot v_r + c1 \cdot r1 \cdot (p_i - x_r) + c2 \cdot r2 \cdot (p_g - x_r)$$

$$x_{r+1} = x_r + v_{r+1}$$  \hspace{1cm} (9)

where $v_{r+1}$, $x_{r+1}$ represent the $mth$ velocity and position of the $ith$ particle in the $(t+1)th$ iteration respectively. $P^i$, $P^g$ are the self-optimum and the global optimum of the $ith$ particle in the $ith$ iteration. $\omega$ is the inertial factor. $c1, c2$ are the acceleration factors. $r1, r2$ are random numbers from 0 to 1.

The ICPSO algorithm proposed in this paper combines the best values of the particles themselves, the global particles
and the particles in the subgroup dynamically. It adjusts the proportion of shared information dynamically in the current optimization stage. Because the algorithm shares the information of the individual optimum, global optimum and subgroup optimum, it has stronger ability to determine the global optimum and local optimum. In addition, to increase the diversity and obtain a more appropriate convergence rate, this paper proposes a scheme to dynamically adjust the convergence rate using the grouping coefficient which further improve the performance of the algorithm, and shown in formula (10):

$$\begin{align*}
x_{t+1} &= x_t + v_{t+1} \\
v_{t+1} &= \omega \cdot v_t + c_1 \cdot r_1 \cdot (p_t - x_t) + 1 \cdot c_2 \cdot r_2 \cdot (p_g - x_t) + (1 - 1) \cdot c_2 \cdot r_2 \cdot (p_r - x_t) / r
\end{align*}$$  

(10)

where \( r \) is the number of groups. \( P_{g_r} \) is the optimal value of each subgroup. \( t \) is the current number of optimizations. The other parameters are the same as above.

To better illustrate the moving principle from \( x_t \) to \( x_{t+1} \) of the particles, the vectors is given in Fig. 10

![FIGURE 10. Particle moving process of ICPSO algorithm.](image)

In Fig. 4, the ICPSO divides all the particles into \( r \) groups to search the optimal values of \( P_{g_r} \) in each group separately which participates in the global decision-making. The algorithm updates the particles' velocities and positions by four information: the current velocity \( v_t \) of the particle; the direction \( p_t \) of the particle; the direction \( P_g \) of the particle; the direction \( P_{g_r} \) of the particle. In the iterative process, each particle into the parameter calculation of BP network. To realize the dynamic regulation of the above information, the number of iterations \( t \) is added to update formula (10). In the early stage \( (t \) is small), the particles mainly share the global optimum; as \( t \) increases, it share better values of each group. Because the algorithm can dynamically adjust the shared information, it has better global and local optimization abilities. In addition, the coefficient \( 1/r \) used in the updating formula is the convergence rate-controlling factor, which can guarantee that \( 1/r \) is in the middle of \([0,1]\) when the number of groups \( r \) is in the middle of \([1, \infty]\). Therefore, the convergence rate can be adjusted by \( r \) to achieve more suitable convergence accuracy.

C. IMPLEMENTATION OF BP NEURAL NETWORK

OPTIMIZED BY ICPSO

ICPSO is introduced to optimize the weights and thresholds of BP network. The specific process is as follows:

**Step 1**: construct and initialize the three-layer BP neural network.

The number of network layers is designed as 3 layers (input, output and hidden). 7 input nodes represent the testing data of 7 sensing probes to obtain the cross sensitive information of DOM. The number of hidden nodes is 15. 5 output nodes represent each component of DOM, namely, P1.n, P2.n, P3.n, P4.n, P5.n (that is tyrosine proteins, tryptophan proteins, fulvic acid, dissolved microbial metabolites and humic acid).

Using the mean squared error as the fitness function which is defined as follows:

$$f = \frac{1}{t} \sum_{j=1}^{3} \sum_{k=1}^{n_t} (y_{ki} - t_{ki})^2$$  

(11)

where \( t \) is the number of training samples. \( n_t \) is the number of output node. \( y_{ki} \) is the actual output. \( t_{ki} \) is the target output.

**Step 2**: initialize ICPSO.

The parameters are determined by simulation. The acceleration coefficient \( c_1 = c_2 = 2.05 \). The inertia factor \( \omega = 0.9 \). The number of particles \( N = 160 \). The number of iterations \( k_i = 100 \). The random numbers \( r_1, r_2 \) are from 0 to 1. The number of subgroups \( r \) is set to 2, 4, 6 and 8, respectively. The output with the highest accuracy is taken as the weights and thresholds of the network. The particle dimension is designed as \( d = P + n_t + q + n_3 \), where \( P \) is the number of input-implied layer connection weights. \( q \) is the number of implied-output layer connection weights. \( n_2 \) is the number of threshold of hidden layer. \( n_3 \) is the number of thresholds of output layer.

**Step 3**: the fitness function is used to calculate the individual optimum, global optimum and subgroup optimum.

Initialize the position and velocity of each particle as a random number. At the same time, divide particles into two groups, substitute the connection weights or thresholds of each particle into the parameter calculation of BP network. Calculate the output of hidden and output layer respectively, and calculate the mean square error between the actual output and the target output. Finally, the global optimum \( P_{g_r} \),
individual optimum $p_i^*$ and subgroup optimum $P_i^*$ are obtained by comparison during the initialization.

**Step 4:** update the current speed and position of particles.

Update the velocity $v_{t+1}$ and position information $s_{t+1}$ of each particle.

**Step 5:** update the optimal value.

According to the fitness function, the individual optimal, the subgroup optimal are compared, if the current optimal is better than any of these parameters, it will be replaced.

**Step 6:** check the end condition.

If the number of iterations $k$ is greater than the maximum $k$, or the error is greater than the given value, the program will stop and turn to step 7, otherwise, the program turns to a new round of particle state updating (step 4).

**Step 7:** save the global optimal values.

**Step 8:** check the end condition of grouping.

If the number of groups is 8, go to step 9, otherwise, go to step 4 after adding 2 to the number of groups $r$.

**Step 9:** the positions of global optimal particle of each group are compared according to the fitness function, the best global optimal positions are mapped into the weights and thresholds of BP network.

The parameters of SPR effect and the relationship between DOM components belong to high nonlinear relationship. So, the deep learning and large number of samples are needed for model training. However, the number of training samples is usually limited. To make full use of the information, a multi-classifier integrated system is adopted based on the BP network optimized by ICPSO. The refractive index measurement based on SPR effect and the classification of DOM components are realized by comprehensive training of resonance wavelength, spectral width and light intensity. The specific methods are as follows:

7 sensing probes are used to detect the resonance wavelength, spectral width and light intensity of the diluted water. ICPSO-BP is used to construct three primary classifiers: ICPSO-BP (wave length), ICPSO-BP (spectral width), ICPSO-BP (light intensity). The structure of each classifier is the same which is shown in Fig. 11.

From Fig. 11, in the training stage, 7 SPR sensing probes are used to measure the parameters of SPR, which are used as the input of respective network. The DOM component data determined by refractive index testing and three-dimensional fluorescence spectrum analysis are used as the output of network. The ICPSO-BP networks are trained to obtain the structure parameters that meet the error requirements. In the testing stage, the SPR testing data are input into the neural network trained successfully to obtain the output of their DOM components. Finally, the DOM components are determined by average method according to the output of classifiers.

The implementation process is shown in Fig. 12.

**FIGURE 11.** Schematic diagram of classification system based on ICPSO-BP.

**FIGURE 12.** Schematic diagram of SPR sensor classification process based on ICPSO-BP.

From Fig. 12, the training samples is processed in two aspect, one is true value measurement, which is the output of ICPSO-BP, the other is to obtain spectral information of measured water by SPR sensor which are the input of ICPSO-BP. Then, train the ICPSO-BP network by the input and output data, and the measurement model is successfully established while the training is over. On the other hand, the prediction samples also need to complete the above processing. By inputting the resonance wavelength, spectral width and light intensity into ICPSO-BP model, the corresponding output of DOM components are obtained. The feasibility of the network is verified by comparing it with the true value.

**VIII. EXPERIMENTAL RESULTS AND ANALYSIS**

The first 30 measured and predicted data of water A are selected to classify and test the five components and
concentrations of water A. The main parameters of ICPSO-BP network are as above.

After the training, the SPR test data of A sample with concentration step of 3% are used as the verification data. The statistical data of predicted value and reference value obtained by ICPSO network and three-dimensional fluorescence spectrum are shown in Table 4. The implementation of ANN structure design and training process are based on MATLAB 6.0.

To better illustrate the classification and prediction effect of ICPSO-BP, the correlation diagram of predicted and reference concentration of DOM components in water A are shown in Fig. 13.

![Relationship between reference and predicted concentration of P1.n](image1)

\[ y = 0.9954x + 0.1458 \quad R^2 = 0.9674 \]

![Relationship between reference and predicted concentration of P2.n](image2)

\[ y = 1.0045x + 0.1411 \quad R^2 = 0.9933 \]

![Relationship between reference and predicted concentration of P3.n](image3)

\[ y = 0.9687x + 0.5045 \quad R^2 = 0.847 \]
The correlation between relative concentration and reference concentration of P1.n to 5.n components in A.

From Fig. 13, the fitting degree of P1.n is 0.9674, the root mean square error (RMSE) of P1.n is 0.980258; the fitting degree of P2.n is 0.9933, RMSE is 0.8680; the fitting degree of P3.n is 0.847, RMSE is 1.247; the fitting degree of P4.n is 0.9822, RMSE is 0.940; the fitting degree of P5.n is 0.3547 and RMSE is 1.994. From the fitting degree and RMSE, ICPSO-BP has the best prediction accuracy and correlation for P2.n, the prediction effect for P1.n and P4.n is the same, P3.n is the third, and P5.n is the worst. Overall, ICPSO-BP has relatively strong modeling and fitting ability, which is suitable for the classification and concentration prediction of most DOM components in water A.

In order to verify the influence of different combinations of sensing probes on the prediction effect and further investigate the generalization ability of the fiber SPR sensor and ICPSO-BP, in subsequent experiments, more water bodies are selected to complete the prediction research. 7 sensing probes are divided into three cases, that is, the case of odd array sensing probes, which is recorded as F1 = {1, 3, 5, 7}, the case of even array sensing probes, which is recorded as F2 = {2, 4, 6}, when all probes are used, it is recorded as F3 = {1, 2, 3, 4, 5, 6, 7}. Network training and verification are carried out for four measured water, namely, Inner canal (A), Hongze lake (B), Park lake (C) and Campus lake (D). The input nodes of ICPSO-BP network are 4, 3, 7 respectively according to the specific situation, and other settings are the same as before. In addition, to better describe the prediction effect, the prediction accuracy $\beta$ is defined as follows:

$$\beta = \frac{\text{the samples number correctly predicted}}{\text{total number of samples}}$$

(12)

Where the samples number correctly predicted is the number of sample when the relative prediction error is less than 1%. The prediction effect of ICPSO-BP network in 3 cases is obtained, as shown in Fig. 14:

![Figure 14](image-url)
P2.n and P5.n in the two measured water are 48.32% and 5.22% respectively, which are the highest and lowest concentration in five components of different water, that is, the higher the component concentration, the higher the detection rate. But there is no such performance for the combination of F1, F2, the accuracy of both is much lower than that of F3. The maximum prediction accuracy of F1 is 79% which appears at P2.n of Hongze lake (B), and the minimum is 57%, which appears at P5.n of Inner canal (A). The maximum prediction accuracy of F2 is 75%, which appears at P2.n of park lake (C), the corresponding DOM component is 36.99, the minimum is 40% at the P5.n of Inner canal (A). The results of three different combinations show that the testing effect of P5.n component is the worst, which is closely related to the low concentration. In other words, it is difficult to sense the subtle changes for the sensing probe while the components are too little. In addition, it can also be seen that F1 and F2 are vague for DOM components of different concentrations. That is, when the difference of type and content in various components are small, the difference of result is also close which is difficult to distinguish for F1 and F2.

Generally speaking, the testing effect of F3 is far better than that of F1 and F2 for four water. The main reason is that the number of sensing probes used in F1 and F2 is limited which can perceive narrow information. Relatively speaking, F3 sensor array can provide more testing information. That is, the more sensing probes with different structures, the more related parameters can be perceived by each sensing probe. When the parameters of all sensing probes cover the refractive index range of the measured water, it will be consistent with the target dynamic range of the detection system. Therefore, compared with single or a few probes, this multi-sensor array can obtain more information of the measured water and effectively extract useful information by intelligent algorithm, so as to ensure the high-sensitivity measurement in a larger dynamic range.

2) Comparing the effects of F1 and F2, their effects are the same for C and D, but are very different for A and B. In addition, the prediction accuracy of F2 is far lower than F1, that's because, the refractive index of best measuring points of sensing probe 2, 4, 6 are 1.3442, 1.373 and 1.4012 respectively, while the refractive index of measured water of A and B are distributed between 1.4216- 1.3359 and 1.4032-1.3343 respectively. Therefore, the sensing probes do not cover the measured water, which result in too little sensing information can be used by the classifiers, and sharp decline in accuracy.

Overall, the prediction effect of F3 is the best, F2 is the worst, and F1 is between the two. the reason can be attributed to the different selection of sensing probes. In F3 case, 7 sensing probes completely cover the refractive index range corresponding to the four samples, for the basic data of F3 are comprehensive and the ICPSO-BP network is appropriate, therefore, it has better prediction effect. For F2, the refractive index range corresponding to three sensing probes are concentrated in the middle of the ranges of the four samples, the SPR sensing information corresponding to the larger and the smaller measured refractive index has not been effectively obtained, therefore, the prediction results for the same training network are not satisfactory due to the lack of comprehensive basic data. In F1, the sensor array corresponds to the whole range of the refractive index of samples, but its density is not enough, which lead to the cross-sensitive information between sensing probes is not enough, so, the prediction effect is also poor. Therefore, regardless of the specific structure of the intelligent system, the design of the sensor array is the premise of the effectiveness of the system. The lack of network design may make the prediction results unsatisfactory, and the defects in the sensor array will lead to the complete failure of the system.

In addition, for four different samples, the prediction effect of high concentration is better than that of low concentration. which can also be attributed to the information acquisition ability of the sensor array. For the SPR sensing probe with a given structure, its response sensitivity to the change of refractive index of the measured object is also determined. For samples with high DOM concentration, the refractive index value and its gradient with concentration are also higher than that of low concentration. So, the selected sensing probes with different structures are required to cover the whole refractive index change of the samples, and to be measured as evenly as possible.

**IX. CONCLUSION**

The fiber SPR sensing probes based on metal film thickness regulation are used to form the sensor array. Aiming at the loss of particle diversity caused by premature convergence, the ICPSO algorithm is proposed. A three-classifier integration system is constructed by using the BP network trained by ICPSO. Thus, the structure of fiber SPR sensor array is designed which can realize the comprehensive training of resonance wavelength, spectrum width and light intensity of SPR effect in measured water. Five DOM components (tyrosine protein, tryptophan protein, fulvic acid, dissolved microbial metabolites and humic acid) and their concentrations in four water, namely, Inner canal (A), Hongze lake (B), Park lake (C) and Campus lake (D), have been effectively predicted. The prediction accuracy is more than 80%, and the measurement of SPR effect of measured water in a wide range is realized, which verify the correctness of the fiber SPR sensor array in the process of DOM measurement and the feasibility in practice.

This work provided a new idea for DOM component testing. The measurement method focuses on the cross-sensitivity of the sensors. The selected sensors should not necessarily have excellent measurement accuracy at the optimal measuring point, instead, they should have better performance in the area near the optimal measuring point.
The measurement information from the sensors not only reflect the value of one measured quantity, but also reflect the superposition of multiple quantities of the measured object. In the measurement scheme, the deep learning algorithm (ICPSO-BP) with excellent performance is introduced to mine a certain measured information from the mixed information superimposed by different measured quantity. Especially, for the introduction of deep learning algorithm, the hidden measured information can be mined from the mixed information, which is the essence of deep learning algorithm and the core of the measuring method, it plays an important role in the realization of test function.

CONFLICTS OF INTEREST

All authors declare that no conflict of interest exists. We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work.

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