Measurement of crude oil water content based on cross-correlation method

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Abstract: In order to measure the proportion of each phase flow of oil-water mixture in practical application and improve the accuracy of crude oil moisture measurement, a method for measuring the water content of crude oil based on cross-correlation method is proposed. The capacitive array sensor is used for measurement to reduce the influence of the flow pattern on the measurement accuracy. The Particle Swarm Optimization BP Neural Network is used to accurately and nonlinearly fit the relationship between the voltage value and the water content to effectively improve the accuracy of the water content measurement.

1. Introduction

Crude oil water content [1] is an important measurement parameter for predicting oil well life, controlling crude oil dehydration, storage and transportation process. Accurate detection of crude oil water content and subsequent data processing is of great significance to the development and progress of the contemporary petroleum industry.

In the online moisture measurement method [2], the capacitive [3] sensor uses the difference of the dielectric constant [4] of the oil-water mixture as the measurement principle. Due to its simple structure, convenient installation and high precision, it has been widely used. However, the mineralization degree of water in the mixture is generally high, and its conductivity is good. When the water content is gradually increased, the measurement accuracy of the sensor is lowered, and Mohamed [5] uses coplanar guided wave detection technology (Coplanar waveguide, CPW), time-domain transmission method, through the eigenvalue decomposition, the measurement signal can reflect the capacitance and its electrical conductivity [6] of the measured substance, and the radio frequency admittance technology also has the same function. These studies measure the oil-water mixture from two angles of capacitance and conductance [7], which improves the accuracy of the water content measurement and expands the measurement range. At the same time, the equivalent dielectric constant of crude oil is not only related to water content, but also affected by temperature [8] and flow pattern [9,10]. Existing sensors mostly use temperature compensation circuit or multi-sensor information fusion technology [11] to reduce the measurement error caused by temperature. In terms of the identification of flow patterns, Ren L., Chen XG et al. [12] classified and identified both water-in-oil and oil-in-water conditions by means of pattern recognition, but in practical applications, the flow pattern is complex and variable. It is not yet possible to accurately determine the flow pattern, which brings difficulties to the selection of the corresponding signal interpretation model.
corresponding to flow pattern [13]. Moreover, the moisture content of crude oil measured by existing sensors is mostly the water holdup of crude oil, that is, the pipe cross-sectional area ratio of each phase in crude oil. However, due to the existence of the phase interface in the multiphase mixture which randomly varying in time and space. There is actually a non-negligible relative velocity between the phases, so that the phase flow ratio through the pipeline is not equal to the pipe cross-sectional area ratio.

In this paper, we make improvement to the sensor which measures capacitance and conductance at the same time, by using the array sensor, we can reduce the effect of the flow pattern on the measurement result. When the spacing of the sensing electrodes is a certain value, performing fast Fourier transform and cross-correlation analysis on the measured signals to obtain the time taken for the oil sample to flow through the two sensing electrodes, so that we can calculate the velocity and volume of flow, and the relationship between capacitance value, conductance value, temperature and water holding rate is fitted accurately by artificial neural network, which further improves the measurement accuracy.

2. Capacitive array sensor

In this paper, we make improvement based on the capacitive sensor that can measure capacitance and conductance at the same time, the sensor device is illustrated in Figure 1, the instrument has a cylindrical housing, and the built-in electrode of the sensor is improved from the original single electrode pair to the flat sensor array. A plurality of sensors is positioned vertically in a pipeline. The array sensor divides the original pipeline fluid into five layers of local fluid for measurement, thereby reducing the effect of the flow pattern on experimental measurements.

![Figure 1. Capacitive array sensor housing](image1)

In Figure 2, each labeled electrode group is composed of two sensing electrodes with a spacing of 1 cm, and transmitting electrode includes galvanic transmitter electrode and capacitive transmitter electrode, the tool measures water content with alternating current from two transmitter electrodes driven in quadrature. Both the transmitting electrode and the receiving electrode surface are coated with an insulating film to avoid the corrosion effect of the oil sample. The measured capacitance and the conductance signal are converted into corresponding voltage values $V_c$ and $V_r$, after being amplified by the measuring circuit and processed by the phase detector.

![Figure 2. Array sensor cross section schematic.](image2)

![Figure 3. Schematic diagram of the sensor receiving electrode plate.](image3)

![Figure 4. Schematic diagram of the sensor emitter electrode plate.](image4)
3. Signal processing

3.1. Particle Swarm Optimization BP Neural Network

The particle swarm algorithm [14] was proposed by Eberhart and Kennedy. The combination of BP network and particle swarm optimization algorithm can avoid the problem of gradient disappearance. It has the characteristics of global search optimal solution and improves the performance of BP neural network, making it difficult to fall into local minimum value. In this paper, the temperature value of the temperature sensor output, voltage signal $V_c$ and $V_r$, a total of three variables are used as the input of the network. After experiment comparison, the number of hidden layer neural units has been selected as 7, and the water holdup of the oil sample is used as the output. The basic structure of the network is shown in Figure 5.

![Figure 5. Neural network structure](image)

The formula for calculating the fitness function of a particle is:

$$I_i = \frac{1}{n} \sum_{i=1}^{n} (Y_i - y_i)^2$$  \hspace{1cm} (1)

Where $Y_i$ is the true water content value and $y_i$ is the neural network prediction value. The particle swarm algorithm flow is as follows:

| Table 1. Particle Swarm Algorithm |
|-----------------------------------|
| **Input:** conductive voltage, temperature, capacitive voltage | **Output:** water holdup |
| **Step 1.** Initialize a group of particles (the population size is N, this experiment takes N=160), including random position and speed, and set the training batch. | |
| **Step 2.** Evaluate the fitness of each particle according to Equation (1). | |
| **Step 3.** For each particle, compare its fitness value to its own best position pbest, and if it is better, use it as the current best position pbest. | |
| **Step 4.** For each particle, compare its fitness value to swarm’s best position gbest, and if it is better, use it as the current best position gbest. | |
| **Step 5.** Adjust the particle speed and position according to Equation (2) and Equation (3). | |
| $$x_i = x_i + v_i$$  \hspace{1cm} (2) |
| $$v_i = w \times v_i + c_1 \times (pbest_i - x_i) + c_2 \times (gbest_i - x_i)$$  \hspace{1cm} (3) |
| In Equation (2) and Equation (3), pbest and gbest represent the local and global optimal position of the particle group respectively. | |
| **Step 6.** If the training batch is not reached, go to step 2. | |

3.2. Fast Fourier Transform

Fast Fourier transform is an efficient and fast calculation method for calculating discrete Fourier transform. When mapping time domain problem to frequency domain, finite-length sequence can discretize its frequency domain into finite length sequence through discrete Fourier transform.

The sampling frequency is set to 500Hz, the sampling point is set to 512. The discrete aperiodic sequence obtained by sampling is denoted as $x(n)$. Let the length of the sequence $x(n)$ be $N = 2^v$ ($v = 9$), then the Fourier transform of the sequence $x(n)$ is:
\[ X(k) = \sum_{n=0}^{N-1} x(n)e^{-j\frac{2\pi nk}{N}} \quad k = 0,1,2,\ldots,N-1 \]  \hfill (4)

For the sake of simplicity, let the exponential factor \( W_N = e^{-j\frac{2\pi}{N}} \), then the Equation (4) can be written as:

\[ X(k) = \sum_{n=0}^{N-1} x(n)W_N^{nk} \quad k = 0,1,2,\ldots,N-1 \]  \hfill (5)

The sequence \( x(n) \) is extracted into two subsequences, each subsequence is \( N/2 \), the first sequence is composed of even items, and the second sequence is composed of odd items. Then the Equation (5) can be written as:

\[ X(k) = \sum_{l=0}^{N/2-1} x(2l)W_N^{lk} + W_N^k\sum_{l=0}^{N/2-1} x(2l+1)W_N^{lk} \quad k = 0,1,\ldots,N-1 \]  \hfill (6)

Let the first term and the second term in (6) be \( G(k) \) and \( H(k) \) respectively. It is obvious that \( G(k) \), \( H(k) \) is a Fourier transform sequence of length \( N/2 \), and its period is \( N/2 \), then:

\[ G(k + N/2) = G(k) \]  \hfill (7)
\[ H(k + N/2) = H(k) \]  \hfill (8)

Use the symmetry of \( W_N^k \):

\[ W_N^{k+N/2} = -W_N^k \]  \hfill (9)

Then Equation (6) can be expressed as:

\[ X(k) = G(k) + W_N^kH(k) \quad k = 0,1,2,\ldots,\frac{N}{2}-1 \]  \hfill (10)
\[ X \left( k + \frac{N}{2} \right) = G(k) - W_N^kH(k) \quad k = 0,1,2,\ldots,\frac{N}{2}-1 \]  \hfill (11)

Similarly, sequence decomposition can be continued. In this paper, 256 signals are collected as a sequence, which needs to be decomposed 9 times. The fast Fourier transform utilizes the sequence decomposition and the symmetry and periodicity of the exponent factor \( W_N \) to meet real-time requirements for data processing.

### 3.3. Cross-correlation analysis

The cross-correlation function is generally used to represent the degree of correlation between two series [15]. The cross-correlation function is used to analyze the correlation degree of adjacent electrode signals in the electrode group. When the correlation reaches the maximum, the corresponding time difference \( \tau \) is the time required for the crude oil flows through the interval between two electrodes. The signals of two adjacent electrodes in the electrode group are written as: \( x(t), y(t) \). Then its cross-correlation function can be expressed as:

\[ R_{xy}(\tau) = R_{xy}(-\tau) = \int_{-\infty}^{\infty} x(t)y(t-\tau)dt = x(\tau) * y(-\tau) \]  \hfill (12)

The convolution theorem establishes the corresponding Fourier transform relationship between time domain convolution and frequency domain multiplication:

\[ x(\tau) * y(-\tau) \leftrightarrow X(k)Y(-k) \]  \hfill (13)

\( X(k) \) and \( Y(k) \) are the electrode signal sequences after fast Fourier transform. When the cross-correlation function takes the maximum value, the value of \( \tau \) is the time required for the crude oil flows through the interval between two electrodes. When the electrode spacing \( d \) is constant, the flow rate of the oil sample is:

\[ \nu = \frac{d}{\tau} \]  \hfill (14)

The stratified cross-sectional area of the array sensor is denoted as \( S \), and the flow velocity of each layer of the five-layer fluid is denoted as \( \nu_i \) (\( i = 0,1,2,\ldots,5 \)). The temperature value and the output voltage of each layer of electrodes in the array sensor are input into the neural network model to obtain the layered water holding capacity \( \sigma_i \) (\( i = 0,1,\ldots,5 \)), and the proportion of water flow in the crude oil is:
\[ \sigma = \frac{S \sum_{i=1}^{5} \sigma_i v_i}{S \sum_{i=1}^{5} v_i} = \frac{\sum_{i=1}^{5} \sigma_i v_i}{\sum_{i=1}^{5} v_i} \]  

(15)

4. Experimental analysis

The experiment is carried out in a multi-phase flow test circuit. The experimental device includes an oil storage tank and a water storage tank that can regulate the flow rate by an external valve. The true water content value can be obtained from the known water flow rate and oil flow rate. The experimental site is shown below:

Figure 6. multi-phase flow test circuit

The specific steps of the experiment are:

1. The oil and water with a known volume percentage are mixed uniformly, and then placed in the pipe, and the output voltage value is measured. Temperature and the average value of the five sets of electrode output voltages \( V_c \) and \( V_r \) are input to the particle swarm optimization BP neural network model, and the water holdup is the output. 700 sets of experimental data are used as training sets to train the neural network. The training error is shown in the figure below:

Figure 7. Neural network training errors

2. Perform performance tests on the trained neural network model. The following table shows some experimental test data:
It can be seen from the experimental test data that the BP neural network after particle swarm optimization has a water content prediction error of less than 1% in the full range, indicating that the particle swarm optimization BP neural network fits the electrode output voltage value, temperature and water holdup of the oil sample well, which proves its superior performance and improves the measurement accuracy to some extent.

(3) The unmixed oil and water are directly placed in the pipeline, and the flow rate can be controlled by an external valve. The oil-water mixture will form different flow patterns in the pipeline flow without uniform stirring. The voltage signal outputted by the sensor is subjected to fast Fourier transform and cross-correlation analysis to obtain the flow rate. The water holdup of each layer of oil sample is obtained by the neural network. So the water content of crude oil can be calculated by Equation (15). The experimental data are shown in the following table:

| Index | Vc(V) | Vr(V) | Temperature(℃) | True water holdup(%) | Neural network prediction(%) | Absolute error(%) |
|-------|-------|-------|----------------|----------------------|----------------------------|-----------------|
| 1     | 4.319 | 2.237 | 50.9           | 100.000              | 100.000                    | 0.000           |
| 2     | 4.318 | 2.359 | 12.9           | 85.587               | 85.267                     | 0.319           |
| 3     | 4.318 | 2.291 | 45.6           | 93.343               | 93.599                     | -0.256          |
| 4     | 4.319 | 2.514 | 51.1           | 70.170               | 70.544                     | -0.373          |
| 5     | 4.319 | 2.658 | 39.7           | 58.516               | 59.299                     | -0.783          |
| 6     | 4.318 | 2.959 | 26.8           | 41.215               | 40.843                     | 0.372           |
| 7     | 3.470 | 3.625 | 10.7           | 26.203               | 27.246                     | -1.043          |
| 8     | 1.555 | 4.294 | 51.1           | 15.777               | 16.284                     | -0.507          |
| 9     | 1.407 | 4.411 | 51.7           | 7.563                | 7.935                      | -0.372          |
| 10    | 2.388 | 3.980 | 45.6           | 23.246               | 23.985                     | 0.739           |
| 11    | 1.276 | 4.515 | 35.6           | 0.000                | 0.002                      | -0.002          |

The experimental results show that the improved capacitive array sensor can minimize the influence of flow pattern on measurement accuracy. The cross-correlation method can simultaneously measure the stratified flow velocity and flow rate of oil sample, and the water holdup of crude oil is measured by the particle swarm optimization BP neural network algorithm, so we can get the water content of the oil sample eventually. The experiment proves that the method has good measurement accuracy in practical application and has high practical value.

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