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Synthesis of Ultra High Molecular Weight HPAM and Viscosity Forecast by BP Neural Network

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Hydrolyzed polyacrylamide (HPAM) is widely used to increase the sweep efficiency of water phase in oil reservoirs. It is very important to select proper polymer for the reservoirs. In this study, a series of ultra-high molecular weight HPAMs were synthesized and characterized by FT-IR analysis. Their physical properties were tested under reservoir condition. BP neural network (BPNN) was employed to forecast the viscosity of high molecular weight HPAM in produced water. The input indices including molecular weight, solid content, degree of hydrolysis, water-insoluble residue, polymer concentration, temperature of reservoir and salinity of produced water. The results show that all physical properties fulfill the requirements of Q/SY DQ1059-2005. This BPNN can predict the viscosity of ultra-high molecular weight HPAM accurately. It is proposed that this BPNN can be used to screen proper polymers for enhance oil recovery.

Keywords: ultra-high molecular weight HPAM, BP neural network, viscosity, oil-displacing agent.

1. INTRODUCTION

Polymer flooding is a quite advanced technique for enhancing oil recovery [1]. Water-soluble polymer, such as hydrolyzed polyacrylamide (HPAM), is now becoming a class of prospective candidates as thickeners to improve the mobility ratio in the flooding process [2].

It has been shown that the higher molecular weight of HPAM is, the thicker the solution will be [3]. Moreover, the solution viscosity depends not only on the molecular weight of HPAM, but also on many physical properties and the test conditions, such as filter factor, insoluble residue, hydrolysis degree, temperature, salinity and so on [4]. Since there are many factors can affect the viscosity of HPAM, it is very hard to forecast the viscosity of HPAM. However, the viscosity of HPAM forecast is of great significant for polymer flooding, especially for engineers to screen polymer. So, it is necessary to find a reliable method to forecast the viscosity of HPAM based on some common factors, which is tested under specified and rigid conditions and can be supplied by every company. However, there is few researches that focus on this field.

As a forecasting technique, artificial neural network (ANN) has been widely used in many different domains. Compared with other forecast methods, ANN methods are advantageous in terms of high data error tolerance, easy adaptability to online measurements. A Back Propagation Neural Network (BPNN) is a typical ANN. It is essentially a mapping function from the input vector(s) to output vector(s) without knowing the correlation between the data. It can implement any complex nonlinear mapping function proved by mathematical theories, and approximate an arbitrary nonlinear function with satisfactory accuracy. After learning the data trends from historical data, BPNN can be used effectively to forecast new data [5–7]. So, BPNN might be able to forecast the HPAM viscosity.

In this work, a series of HPAM was synthesized and characterized by Fourier Transform Infrared spectroscopy (FT-IR). The molecular weight, viscosity, solid content, degree of hydrolysis, water-insoluble residue et al. was tested. Then BPNN was employed to forecast the viscosity of HPAM under reservoir conditions. The accuracy of forecasting results was also tested.

2. EXPERIMENTAL DETAILS

2.1. Materials

Acrylamide, urea, potassium persulfate, sodium bisulfite, sodium formate, sodium hydroxide were analytical grade chemicals. Deionized water was used in solution preparation. The produced water was from Dagang oilfield.

2.2. Synthesis of HPAM

A 500 ml beaker was charged with 60 g acrylamide, 240 g deionized water and 3 g urea. The mixture was stirred until a homogeneous phase appears in the solution. Temperature was adjusted at 10 – 13 °C. The mixture was poured into a heat insulation beaker equipped with a cork of thermometer and a nitrogen inlet/outlet and purged with nitrogen for at least 40 min. Potassium persulfate initiator, sodium bisulfite and sodium formate, were dissolved in water respectively, and were injected into the reaction mixture. After 8 h and temperature is over the maximum (around 65 °C), the reaction is finished. The product has the aspect of a gel. It was cut into pellet smaller than

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1.0 cm. Then hydrolysis reaction was performed by mixing a solution of 11.4 g sodium hydroxide in 50 ml of water with these pellets until one obtains a homogeneous phase which is gel-like. A dialysis bag filled with this phase is put into an excess of water at 90 °C for 2.5 h. After hydrolysis process, the product was cut again into pellets of 1.0 cm size, and dried under vacuum, the temperature being kept below 60 °C. The dried pellet is finally broken into powder.

2.3. FT-IR

The FT-IR spectroscopy was carried out on a Perkin Elmer FT-IR using Spectrum software version 10.3.2. The FTIR spectrum of the HPAM was recorded in the region $4000-650\ cm^{-1}$ by using KBr pellet technique. The spectrum was recorded at room temperature, with scanning speed of 10 cm^{-1} per minute and the spectral resolution of 4.0 cm^{-1}.

2.4. Properties measurements of HPAM solution

The property's measurements of HPAM solution was according to Q/SY DQ1059-2005, including viscosity, molecular weight, insoluble residue and so on. The concentration of polymer used in viscosity test was 1000 mg/L.

3. RESULTS

3.1. Characterization

The HPAM (molecular weight = 32.18 million) was selected as an example, and its structure was confirmed by FT-IR spectroscopy showed in Fig. 1. The peaks of 3337 and 3178cm-1 are the characteristic absorbing peaks of the amide group. The peaks of 1651, 1553, and 1448 cm^{-1} indicated the existence of C=O, C-N and N-H bonds [9].

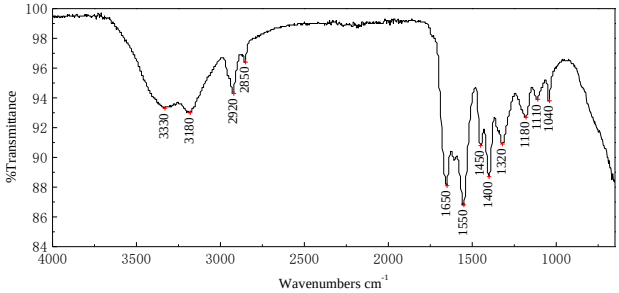

Fig. 1. FT-IR spectra of HPAM

3.2. Physical properties of HPAM

HPAM physical properties are given in Table 1 and Table 2. The results show that the molecular weight is between 28 million, and 37 million and the viscosity is between 60 and 75 mPa·s. All physical properties are fulfilling the requirements of Q/SY DQ1059-2005.

3.3. BPNN

As the BPNN is used as a baseline method in this study, we briefly describe it in this section. This network is a three-layer network: the input layer, a hidden layer and the output layer. The seven nodes in the input layer represent the molecular weight, hydrolysis degree, insoluble residue, solid content, temperature, concentration and salinity. Seven nodes were chosen as the input layer is based on experience and extensive experiments: the seven nodes can describe the physical properties of HPAM and the reservoir condition basically.

Table 1. Polymers physical properties tested results at 40 °C

No.	Solid content, %	Molecular weight, million	Hydrolysis degree, %	Insoluble eesidue, %	Salinity, $mg\cdot L^{-1}$	Viscosity, mPa·s
1	88.40	32.98	27.85	0.08	5090	70.6
2	88.95	29.98	26.44	0.10	5117	68.0
3	89.64	28.88	27.84	0.16	5112	70.0
4	89.11	31.63	28.11	0.18	5101	66.7
5	88.91	29.85	25.35	0.22	4964	63.3
6	88.93	29.67	28.83	0.10	4937	66.8
7	89.80	28.96	27.50	0.32	5178	65.5
8	89.10	32.18	27.63	0.30	5174	69.5
9	89.16	33.59	27.72	0.04	4995	69.0
10	89.44	32.26	27.44	0.24	4902	67.3
11	89.93	28.20	27.00	0.28	5105	65.6
12	88.94	32.36	27.72	0.14	5089	65.5
13	89.03	29.66	27.80	0.12	5122	71.6
14	88.92	29.59	27.83	0.20	4953	67.5
15	89.67	29.89	27.83	0.18	5134	66.8
16	89.04	34.00	27.47	0.04	5021	72.4
17	88.83	33.10	24.92	0.14	5091	68.2
18	89.67	32.61	26.69	0.14	4952	66.0
19	89.67	33.62	26.81	0.18	5056	67.9
20	89.44	36.70	27.39	0.26	5085	70.5
21	89.51	31.48	27.71	0.30	4948	72.3
22	88.72	32.91	27.75	0.18	4903	72.1
23	88.97	31.50	27.53	0.14	5107	70.5
24	88.92	32.35	27.63	0.22	4950	70.5
25	89.69	34.02	26.48	0.14	5182	71.0
26	89.14	33.62	27.34	0.10	4907	67.8
27	89.62	32.33	26.97	0.06	5023	72.0
28	89.10	32.53	27.70	0.12	5163	74.5
29	88.49	31.99	27.34	0.08	5048	73.4
30	89.25	31.72	27.65	0.12	4959	71.6

When the input layer has seven nodes, the forecast result is much better compared to other cases. The only one node in the output is the HPAM viscosity. Since the hidden layer affects the robustness of the neural network, Hecht-Nelson [10] method was employed to determine the node number of the hidden layer for better prediction result: when the node number of the input layer is n, the node number of the hidden layer is 2n + 1.With seven input neurons, fifteen hidden neurons, and one output neuron, as shown in Fig. 2, the training process of BP network can be described as follows [7]: Study process is formed by two parts: signal forward-propagating and error signal reverse dissemination. When forward-propagating, the input sample spreads from the input layer, coped with by hidden layers, passing on to the output layer. Neuron condition in one layer only influences next layer's neuron. If expected output cannot be obtained from the output layer, then system turns to error signal reverse dissemination stage, which makes outlet error back propagate to the input layer through hidden layer, and shares error with all units of each layer, thus obtains error signal of each unit, which be regarded as the basis of revising weight value. This kind of signal forward-propagating and error back-propagating is to go round and round. The process of weight continual readjustment is the network study training process. The

process carries on when the network output error-reducing to acceptance degree or arriving at preset study number.

Table 2. Polymers physical properties tested results at 50 °

No.	Solid content, %	Molecular weight, million	Hydrolysis degree, %	Insoluble residue, %	Salinity, mg·L^{-1}	Viscosity, mPa·s
1	89.07	32.40	27.61	0.18	5125	67.1
2	89.28	32.44	27.07	0.16	5187	66.0
3	89.12	34.86	27.76	0.12	5147	72.6
4	88.77	30.57	25.92	0.14	4942	65.5
5	89.52	36.32	27.95	0.10	5031	71.8
6	88.72	28.29	27.37	0.26	5176	71.8
7	89.23	28.07	27.57	0.20	5162	66.9
8	88.53	30.82	27.74	0.08	5115	64.7
9	89.41	35.53	27.16	0.18	5068	72.7
10	89.81	30.91	27.59	0.10	4963	68.1
11	88.95	32.06	27.53	0.08	5106	65.2
12	89.41	33.94	27.28	0.10	4925	69.0
13	88.77	33.52	27.03	0.12	4953	67.8
14	89.57	32.66	27.37	0.26	4986	68.5
15	90.08	29.78	26.44	0.32	5090	68.1
16	89.19	30.68	26.34	0.06	5055	63.4
17	89.15	31.73	28.03	0.20	5067	65.4
18	89.23	30.10	28.10	0.08	5164	64.4
19	88.65	29.68	27.28	0.10	5034	63.4
20	89.11	36.31	29.67	0.12	5183	69.3
21	89.53	36.69	28.75	0.24	4913	65.7
22	89.14	33.16	27.12	0.10	5054	65.7
23	88.62	34.26	28.63	0.26	5084	62.8
24	89.27	32.09	27.92	0.06	5034	67.0
25	90.07	32.06	27.92	0.14	4927	68.1
26	89.75	28.65	27.57	0.14	4952	60.2
27	89.08	31.58	27.63	0.10	4982	69.8
28	89.48	28.22	27.45	0.10	4907	65.9
29	89.78	31.72	26.41	0.10	5134	62.1
30	89.20	34.08	27.46	0.08	5067	64.6

To ensure the quality of forecast results, we adopt normalized method to treat the input and output data in advance of training the network, the formula is as follow:

$$X = 2 \times \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} - 1, \quad (1)$$

where $X_{\min}$ and $X_{\max}$ are the minimum and maximum value of input array or output vectors, and X_i denotes the real value of each vector.

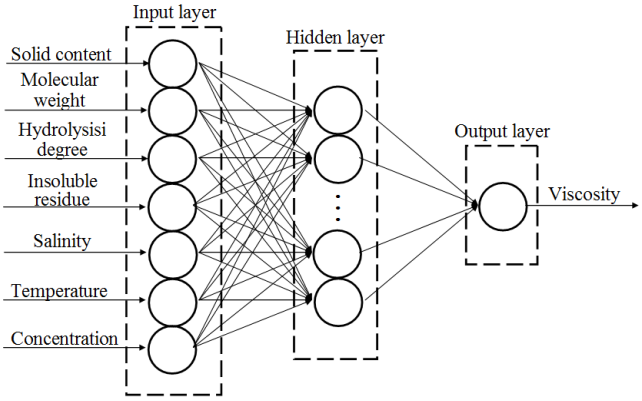

Fig. 2. PSO-BP neural structure

3.4. BPNN optimized by Particle Swarm Optimization algorithm

The BPNN optimized by Particle Swarm Optimization algorithm is also called PSO-BP algorithm, it takes the weights and biases of neurons trained as one particle for PSO algorithm. The fundamental idea of PSO-BP algorithm can be described as follows:

1. Normalize the training dataset and the testing dataset into [-1, 1].
2. Randomly initialize a group of m particles with the number is m, including positions and speed velocities.
3. Compute every particle's fitness value: referring to a complexity of training dataset, LM algorithm or the Conjugate gradient algorithm is used to train the BP neural network. When the dataset is simple, the LM algorithm is used; otherwise Conjugate algorithm is chosen. Update the weights and biases of each neuron using current gbest value. The performance function selects the MSE function: where MSE denotes the mean sum of squares of the network errors.
4. Update particles' speed and position using the following Eq.:

$$V_i^{t+1} = \omega^t V_i^t + c_1\tau_1(pbest^t - x_i^t) + c_2\tau_2(gbest^t - x_i^t); \quad (2)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1}, \quad (3)$$

where V_i^t is the velocity of particle i at iteration t. As V_i^t is uncontrollable, a particle will cycle beating in the problem space, in order to inhibit the erratic beating, the speed is often limited to a value within $[-v_{\max}, v_{\max}]$; X_i^t represents the position of i particle i at iteration t; τ_1 and τ_2 are two uniform random number from [-1, 1]; c_1 and c_2 are learning factor that also called acceleration constants as they control how far a particle can move in a single iteration. Generally, $c_1 = c_2 = 2$ were used. $pbest^t$ and $gbest^t$ are the individual best position and the global best position of all particles at iteration t respectively. The variable ω^t is inertia weight at iteration t that is defined by Eq. below. A larger inertia weight led to the global exploration and a smaller inertia weight tends to facilitate the local exploration to fine-tune the current search area.

$$\omega^t = \omega_{max} - (\omega_{max} - \omega_{min}) \times \frac{iter}{it_{max}}, \quad (4)$$

where $\omega_{\max}$ and $\omega_{\min}$ are maximum and minimum of inertia weight respectively, which are suggested to be 0.9 and 0.4 respectively; $iter$ is the iteration t; $it_{\max}$ is maximum of iteration number.

5. If the end condition is not satisfied, go to step 2 again, or else, go to (6). The end station usually is set to a previously determined $it_{\max}$ or adapts fitness value.
6. Update the weights and biases of BPNN by PSO algorithm and the network can be used for forecasting.
7. Renormalize the forecasting results from [-1, 1].

3.5. Optimal parameters selection for BPNN based on particle swarm optimization

The fitness (objective) function is taken to be MSE shown in Eq. 5, where $y_{\text{k-real}}$ is the real output value, $y_{\text{k-forecast}}$ is the forecasting output, and Q is the total number of cases used. The minimum value of the fitness function corresponds to the best nest (solution) [11].

$$F_k = \frac{1}{Q}\sum_{k=1}^{Q}\left(y_{k-forecase} - y_{k-real}\right)^2. \quad (5)$$

Table 3. Test and forecast results

No.	Solid content, %	Molecular weight, million	Hydrolysis degree, %	Insoluble residue, %	T/°C	Salinity, $mg \cdot l^{-1}$	Real viscosity, mPa s	Forecast viscosity, mPa s	Forecast error, %
1	86.59	25.23	29.82	0.26	40	5106	63.0	63.1	0.16
2	87.60	30.12	28.72	0.18	40	4925	74.1	73.9	-0.27
3	87.56	25.33	29.18	0.12	40	4953	66.1	66.4	0.45
4	89.21	31.69	28.11	0.30	50	4986	68.7	69.1	0.87
5	89.07	34.98	27.57	0.25	50	5090	72.3	72.3	0.00
6	88.68	34.35	28.55	0.20	50	5055	73.5	73.2	-0.41
7	91.08	30.58	26.78	0.25	60	5067	63.3	63.1	-0.32
8	89.20	31.20	26.10	0.10	60	5164	64.2	64.2	0.00
9	89.03	32.67	26.42	0.21	60	5034	70.8	71.1	0.42

After optimized the BPNN by Particle Swarm Optimization algorithm, the algorithm parameters are configured as follows: $\alpha = 1$, max iteration number = 1000, network error = 0.0001. $\alpha > 0$ is the step size which should be related to the scales of the problem of interest. In most cases, $\alpha = 1$ [11]. When the topology structure and initial parameters of BPNN has been optimized by PSO-BP algorithm, the BPNN is successfully established.

3.6. Simulation results of the case study

The error training curves of BPNN and under the setting is shown in Fig. 3. It is obvious that this BPNN have a fast convergence rate and high accuracy, and the network trains successfully.

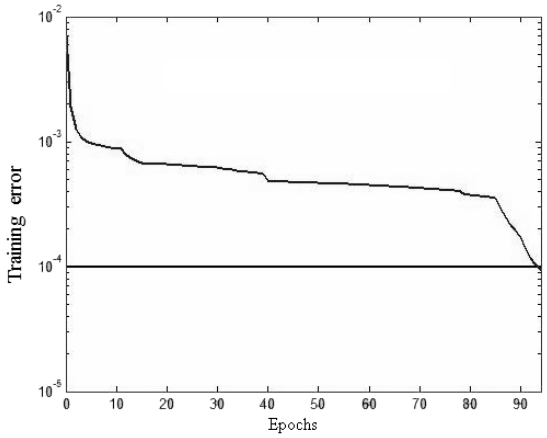

Fig. 3. BPNN error training curve

3.7. Forecast by BPNN

MATLAB Neural Network Toolbox was employed to configure the BPNN. Another 9 HPAM were synthesized and their physical properties were tested as described above. The test and forecast results are shown in Table 3.

Through analyzing error of the predicted results, it can be seen that the network is trained in good condition. The fluctuations of the prediction value are in a small range around the actual value. Since the input layer did not include the data of HPAM viscosity at 60 °C, it is likely that the BPNN has a wider application area.

4. CONCLUSIONS

1. A series of ultra-high molecular weight HPAM were synthesized and characterized by FT-IR.
2. A BPNN was successfully established. Considering the actual conditions of oilfield and the typical physical properties, proper set of indices was selected as the inputs of the network. This BPNN can be used to forecast HPAM viscosity. Errors satisfy the requirement of practical application.
3. This BPNN has omitted to take into consideration the viscosity of copolymers and the temperature higher.

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