# Forecast on Water Locking Damage of Low Permeable Reservoir with Quantum Neural Network

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**Abstract**. It is of great importance in oil-gas reservoir protection to timely and correctly forecast the water locking damage, the greatest damage for low permeable reservoir. An analysis is conducted on the production mechanism and various influence factors of water locking damage, based on which a quantum neuron is constructed based on the information processing manner of a biological neuron and the principle of quantum neural algorithm, besides, the quantum neural network model forecasting the water locking of the reservoir is established and related software is also made to forecast the water locking damage of the gas reservoir. This method has overcome the defects of grey correlation analysis that requires evaluation matrix analysis and complicated operation. According to the practice in Longxi Area of Daqing Oilfield, this method is characterized by fast operation, few system parameters and high accuracy rate (the general incidence rate may reach 90%), which can provide reliable support for the protection technique of low permeable reservoir.

**Keywords.** quantum neural network; water locking damage; forecast; low permeable reservoir; Longxi Area.

## 1. Introduction

Tectonic location of Longxi Area is situated in the Central Depression of the Northern Songliao Basin [1]. The logging for Fu-yang Reservoir shows well, but the actual output is not high. According to the fine analysis on data of reservoir physical property, components of clay minerals and formation water salinity in Longxi Area, the rock minerals of this area mainly consist of quartz, feldspar and rock debris, the reservoir rock cement mainly includes the limy and muddy with few siliceous. Clay minerals mainly exist in the form of illite-montmorillonite mixed-layer, chlorite and illite. The porosity is generally lower than 10%, the permeability of most samples is lower than 10 × 10-3μm2, and therefore, it belongs to the type of low porosity, low permeability and low pressure. Because of narrow porous channel, the capillary effect is quite obvious, when the oil and water percolate in the blowhole, water drip is blocked while flowing through the pore throat, which leads to low permeability of oil phase or water phase; this is the water locking damage [2-3]. Given the above, it is of great significance to research the influence factors of water locking effect and quickly forecast the water locking damage in protecting the oil-gas reservoir of this area.

Forecast on water locking damage is a multivariable nonlinear system, while the neural network has its unique advantages in solving the nonlinear problem. The quantum neural network (QNN) integrating quantum computation and neural computation may forecast the uncertain and unstable data in a better way, which improves the defect that the previous neural network model easily falls into local approach and slow convergence rate[4-5], and can effectively forecast the water locking damage of low permeability sandstone reservoir.

## 2. QNN Forecast Model

### *2.1. Quantum Neuron Model*
Quantum neuron model includes input, parallel, excitation, feedback and output. In the quantum theory, the weight value and activity value in the network algorithm are expressed with qubit. A basic qubit is: |ψ〉 = α|0〉 + β |1〉 , of which α and β can be any plural, but must meet the normalization condition |α|2+|β|2=1, [α, β] T stands for the qubit. X=(x1 x2...xn) stands for the real-valued vector input; y stands for the output index.

$$|\psi\rangle = \left(|\psi_1\rangle, |\psi_2\rangle \cdots |\psi_n\rangle\right)^T = \left[\begin{pmatrix}\cos\theta_1 \\ \sin\theta_1\end{pmatrix}, \begin{pmatrix}\cos\theta_2 \\ \sin\theta_2\end{pmatrix} \cdots \begin{pmatrix}\cos\theta_n \\ \sin\theta_n\end{pmatrix}\right]^T \tag{1}$$

Tands for the weight vector. Activity value of the network is |φ〉 = [cosy, siny] T.QNN Model can be constructed with the above quantum neuron model.

### *2.2. QNN Model*
QNN based water locking damage forecast model is a neural network topology [7-8] (FIG. 1) consisting of n input layers, p hidden layers, m output layers and connection between neurons of each layer.

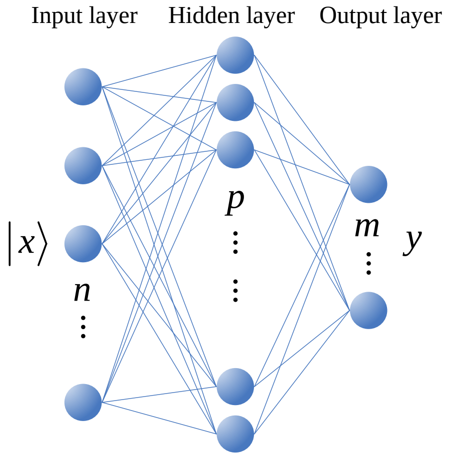


**Fig**. 1 QNN Topology

The relationship between input and output of QNN is

$$y_k = f\left(\sum_{j=1}^{P} h_j |\psi_{jk}\rangle \cdot |\phi_k\rangle - \mu_k\right) = f\left\{\sum_{j=1}^{P}\left[\sum_{i=1}^{n} x\cos(\theta_{ij} - \gamma_j) - \mu_j\right]\cos(\theta_{jk} - \gamma_k) - \mu_k\right\} \tag{2}$$

of which i = 1, 2, …, n; j = 1, 2, …, p; k = 1, 2, …m; yk stands for the network output index; xi stands for the network input vector; ψij and ψjk stand for the weight value of hidden layer and the weight value of output layer respectively; φj and φk stand for the activity value of hidden layer and the activity value of output layer respectively; μj and μk stand for the threshold of hidden layer and the threshold value of output layer respectively.

The influence factors of the water locking damage are screened through the laboratory experiment, gas log permeability Ka of the core, initial water saturation Swi, porosity φ and oil-water interfacial tension σ[9-10] are selected as the network input, and the permeability damage rate R is selected as the network output.

## 3. Training of QNN Forecast Model

### 3.1. Composition of Training Set

Reliable and representative training set should be selected during training, besides, data in the training set should be normalized to accelerate the convergence rate. Table 1 shows water locking effect training set established based on the field data.

**Table 1.** Test Set of QNN Forecast Model of Water Locking Damage

| Core No | $K_a$ /$10^{-3}\mu m^2$ | $S_{wi}$ /% | φ /% | σ /(m/N/m) | $R$ /% |
|---|---|---|---|---|---|
| Tower 30-2 | 19.30 | 53.40 | 19.38 | 0.864 | 34.20 |
| Tower 30-8 | 36.60 | 33.46 | 15.80 | 0.653 | 25.10 |
| Tower 33-4 | 9.15 | 57.72 | 22.70 | 0.360 | 8.05 |
| Tower 38-2 | 10.30 | 43.25 | 18.76 | 0.655 | 16.58 |
| Tower 39-7 | 36.42 | 33.66 | 15.82 | 0.654 | 25.00 |

The normalized data are trained with QNN algorithm previously established to correct the quantum weight value, quantum activity value, threshold value, etc. at each layer.

### 3.2. Training of Network Algorithm

In the training cycle of forecast network, the training algorithm should update and correct the quantum weight value, quantum activity value and threshold value [11] at each layer.

The network error function is $E = \frac{1}{2}(t_m - o_m)^2$, then:

$$\Delta\theta_{ij}\left(t+1\right) = \eta f_{(xj)}(1 - f_{(xi)}) + \kappa\Delta\theta_{ij}(t) \tag{3}$$

$$\Delta\theta(t+1) = \eta(t_m - o_m)o_m(1 - o_m) + \kappa\Delta\theta_{jk}(t) \tag{4}$$

$$\Delta\mu_j(t+1) = \eta f_{(xi)}(1 - f_{(x_i)}) + \kappa\Delta\mu_j(t) \tag{5}$$

$$\Delta\mu_k(t+1) = \eta(t_m - o_m)o_m(1 - o_m) + \kappa\Delta\theta_k(t) \tag{6}$$

In the formula: η stands for the learning rate; κ stands for the factor of momentum, 0<κ<1; tm stands for the ideal output; Om stands for actual output.

After the output of the network reaches the desired accuracy, the training is over. When the connection weight and quantum interval in network are fixed, the corresponding relation between the influence factor and damage degree of water locking effect has been established.

## 4. Application Example

Based on the determination of QNN forecast model, the software that may forecast the water locking damage of low permeable reservoir rapidly is developed and made, and the network forecast model trained is applied to forecast 6 cores of Longxi Area of Daqing Oilfield to gain the forecast value of water locking permeability damage rate. The measured water locking permeability damage rate is gained through the laboratory experiment. In addition, a contrast experiment is made for QNN model and traditional water locking forecast method- grey correlation analysis (Table 2).

Grey correlation analysis requires an analysis on evaluation matrix, and is quite complicated in operation, while QNN based software is featured by simple operation, short operation time, high forecast accuracy and practical level. According to the comparison between the result forecast and the result measured, the average error of QNN forecast is 4.88%, which is far lower than the average error of grey correlation analysis (7.37%), and can meet the forecast demand of drilling engineering, thereby providing reliable data for oil-gas reservoir protection.

**Table 2.** Comparison between the Measured Value and Forecast Value of Water Locking Effect

| Core No | $K_a$ /$10^{-3}$μm$^2$ | $S_{wi}$ /% | φ /% | σ /(m/N/m) | Measured R/% | Forecast by grey theory | | Forecast by QNN | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | R/% | Error/% | R/% | Error/% |
| Tower 30-2 | 19.30 | 53.40 | 19.38 | 0.864 | 34.20 | 36.12 | 5.61 | 33.07 | 3.30 |
| Tower 30-8 | 36.60 | 33.46 | 15.80 | 0.653 | 25.10 | 26.67 | 6.25 | 26.54 | 5.74 |
| Tower 33-4 | 9.15 | 57.72 | 22.70 | 0.360 | 8.05 | 8.76 | 8.82 | 7.65 | 4.97 |
| Tower 38-2 | 10.30 | 43.25 | 18.76 | 0.655 | 16.58 | 18.01 | 8.62 | 15.97 | 3.68 |
| Tower 39-7 | 36.42 | 33.66 | 15.82 | 0.654 | 25.00 | 23.58 | 5.68 | 23.88 | 4.48 |
| Tower 42-5 | 37.20 | 51.81 | 23.70 | 0.360 | 13.61 | 12.35 | 9.26 | 12.64 | 7.13 |
| | | | Mean error/% | | 7.37 | 4.88 | | | |

## 5. Conclusion

(1) Gas log permeability of the core, initial water saturation, porosity and oil-water interfacial tension are main influence factors of water locking effect of low-permeable reservoir and can be selected as the network input, and the permeability damage rate R can be selected as the network output.

(2) Based on the determination of influence factors of water locking damage, QNN forecast model can accurately solve the problems of high nonlinearity and strong randomness of water locking effect, and is a good algorithm to facilitate the computer to realize fast forecast.

(3) QNN model to forecast the water locking damage of low permeable reservoir overcomes the local extreme of canonical algorithm and problems of grey correlation analysis that it is easily influenced by human factors, requires evaluation matrix analysis, has a high accuracy, and plays a guiding role in intelligent development of the reservoir protection.

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