Neural Network Predictive Control Method of Sand Mixing Device

Meiqiu Li, Yuanhua Zhou*, Ye Tian, Bangxiong Wu

ABSTRACT

In the process of oil extraction, fracturing technology has been widely used as a viable means to increase oil and gas permeability, and sand mixing device is one of the important devices in fracturing process. Based on the working process of the second-stage sand agitator tank, this study establishes the kinetic equations of the mixing process of the second-stage sand mixing device, proposes a network predictive control algorithm based on BP neural network, analyzes its dynamic matrix predictive control structure and apply it to predictive control of the agitator tank of blender. The simulation experiment proves that the neural network control algorithm can effectively improve the control quality of the mixing device of the blender and improve the sand mixing effects.

Key Words: Sand Mixing, BP, Neural Network, Predictive Control, Fracturing

DOI Number: 10.14704/nq.2018.16.6.1611 **NeuroQuantology 2018; 16(6):674-678**

Introduction

With the increasing difficulty of oil field exploitation in China, fracturing technology has been widely used (Deng and Chen, 2011). Fracturing is mainly to inject fracturing fluid mixture from sand mixing equipment into formation fractures through fracturing pump to improve permeability of oil and gas, which makes sand mixing equipment the key to success or failure of the whole fracturing process (Hu and Lan, 2008; Xie and Chao, 2007). In fracturing operation, the final purpose of sand mixing device is to improve the sand mixing effect, so that water, sand and cement can be evenly mixed (Huang *et al.*, 2012; *Zhou et al.*, 2011), which means, the solid and liquid two-phase systems are dispersed heterogeneously to make them in suspension. Such mixing effect of this kind of stirring device can be expressed by the level of the concentration. When the amount of material added is the same, the axial concentration of the particles increases as the rotational speed of the mixing device increases. This is because the high output speed of the motor of the mixing device provides a high stirring power for the equipment, thus the mixture material can be stirred more fully and uniformly, under the action of the high stirring power, and the amount of material deposited on the bottom of the tank is reduced (Liu *et al.*, 2012; Wang *et al.*, 2008; Eisinger, 2002; Tamburini *et al.*, 2009). When the pulp concentration is low, it indicates that it is necessary to increase the stirring strength of the pulp. If the stirring speed is too high, vortices will be formed and the materials will fail to mix, causing mechanical stability at the same time. Therefore, the supply speed of water, sand and cement must be controlled reasonably (Zhou *et al.*, 2014; Xiao *et al.*, 2014; Wan *et al.*, 2014).

Sand Mixing System Control Model

The agitator tank used in fracturing blender applies vertical mixing, and the mixing device is installed in the center of the tank. In order to ensure the uniformity of mixing, a two-stage mixing structure is adopted, and the sand mixing

Corresponding author: Zhou Yuanhua
Address: School of Mechanical Engineering, Yangtze University, Jingzhou 434023, China
e-mail ✉ 747028409@qq.com
Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.
Received: 4 March 2018; **Accepted:** 25 April 2018

system control model is shown in Figure1. The cement fracturing sand mud enters through the inlet of the first-stage agitator tank. In Figure 1, ω_1 is the cement input flow rate, and ω_2 is the fracturing sand input flow rate. After the mixing time t of the first-stage mixing, the mixture is discharged through the first-stage outlet, with an output flow rate of ω_0, which becomes the input speed of the mixture at the second stage agitator tank. In the second-stage mixing process, fresh water is added at a flow rate of ω_3, which is input to the fracturing pump through the second-stage agitator tank outlet after the mixing. The fracturing pump input is ω_4. In the figure, c_1, c_2, c_3, and c_4 are the concentrations of mixed media at various stages.

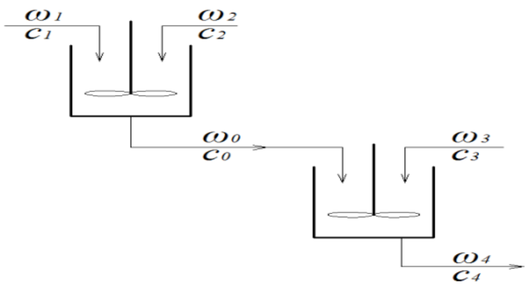


Figure 1. Medium flow model of sand mixing system

For the first-stage mixing device, let the liquid height be h_1, then the kinetic equation can be expressed as:

$$\begin{cases} \frac{dh_1(t)}{dt} = \omega_1(t) + \omega_2(t) - 0.2\sqrt{h_1(t)} \\ \frac{dc_0(t)}{dt} = (c_1 - c_0(t))\frac{\omega_1(t)}{h_1(t)} + (c_2 - c_0(t))\frac{\omega_2(t)}{h_1(t)} - \frac{k_1 c_0(t)}{(1+k_2 c_0(t))^2} \end{cases} \quad (1)$$

Similarly, for the second-stage mixing device, let the liquid height be h_2, and the kinetic equation can be expressed as:

$$\begin{cases} \frac{dh_2(t)}{dt} = \omega_0(t) + \omega_3(t) - 0.2\sqrt{h_2(t)} \\ \frac{dc_4(t)}{dt} = (c_0 - c_4(t))\frac{\omega_0(t)}{h_2(t)} + (c_3 - c_4(t))\frac{\omega_3(t)}{h_2(t)} - \frac{k_3 c_4(t)}{(1+k_4 c_4(t))^2} \end{cases} \quad (2)$$

In the above formulas, k_1, k_2, k_3, and k_4 are undetermined coefficients.

Neural Network Predictive Control Algorithm

Predictive control has a low demand for mathematic model and can directly deal with the processes with pure lag, with good tracking performance and high anti-interference ability, strong robustness of model errors and other advantages. The use of predictive control during the control of the mixing device is more in line with the actual requirements of the industrial process. Based on the BP neural network prediction, this study carries out the dynamic prediction of the fracturing sand mixing device, which improves the effects of the mixing device.

Basic structure of neural network predictive control

The basic principle of neural network predictive control is to construct the predictive model of the object using neural network according to the input and output of the object, with predictive control algorithm as the optimization means to realize the control of the system. The neural network predictor establishes the prediction model of the nonlinear controlled object and can be modified on-line. The flow is shown in Figure 2, where $r(t)$ is the reference input, $u(t)$ is the control input, $y(t)$ is the system output, and $y_m(t)$ is the prediction output.

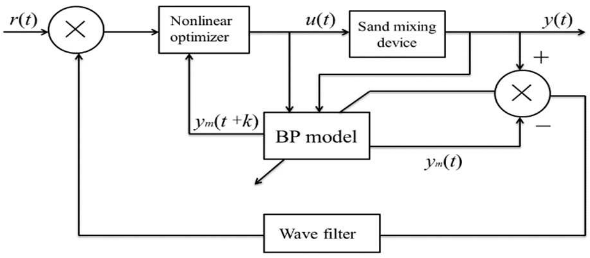


Figure 2. Neural network predictive control system

Predictive control algorithm based on BP neural network

(1) BP neural network

As shown in Figure. 3, a typical three-layer BP neural network structure mainly includes input layer, hiding layer and output layer.

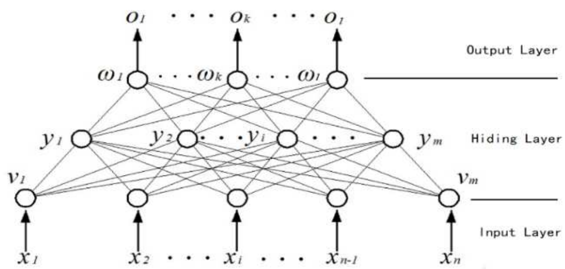


Figure 3. Three-layer BP neural network model

Input vector:

$$X = (x_1, x_2, \ldots x_i \ldots, x_n)^T \quad (3)$$

675

If x0=-1 is added, a threshold can be introduced for the hidden layer neuron, and the output vector of the output layer is:

$$O=\left(o_1,o_2,\dots o_k\dots,o_l\right)^T \tag{4}$$

The desired output vector is:

$$d=\left(d_1,d_2,\dots d_k\dots,d_l\right)^T \tag{5}$$

The weight matrix between the input layer and the hidden layer is denoted by *v*:

$$v=\left(v_1,v_2,\dots v_i\dots,v_m\right)^T \tag{6}$$

Where, the column vector v_i is the weight vector corresponding to the *i*-th neuron of the hidden layer, and the weight matrix from the hidden layer to the output layer is denoted by ω:

$$\omega=\left(\omega_1,\omega_2,\dots\omega_k\dots,\omega_l\right)^T \tag{7}$$

Where the column vector ω_k is the weight vector corresponding to the *k*-th neuron of the output layer. The relationship between the layers of signals are: For the output layer, there is:

$$O_k=g\left(net_k\right)\quad net_k=\sum_{j=0}^{m}\omega_{jk}y_j\quad k=1,2,\dots,l \tag{8}$$

For the hidden layer, there is:

$$y_j=g\left(net_j\right)\quad net_j=\sum_{i=0}^{n}v_{ij}x_i\quad j=1,2,\dots,m \tag{9}$$

The transfer function *g* (*x*) is generally taken as a unipolar Sigmoid function:

$$g\left(x\right)=\frac{1}{1+e^{-x}} \tag{10}$$

(2) Predictive control algorithm based on BP neural network

The predictive control algorithm based on BP neural network is as follows: The first step: offline modelling. BP neural network predictive controller uses past input and output samples and current samples to identify the system model offline. Once the BP neural network identification model reaches the training requirement, the system uses the trained BP neural network identification model to predict the system output.

The second step: prediction. With the neural network prediction model, at time *k+P-1* (P is the maximum prediction range), the model predictive control system (MPC) calculates the system input *U(k+P-1|k)*, including the current input *U(k|k)* and the future input *U(P-1|k)*.

The third step: optimizing the calculation. The prediction error and the cumulative error are calculated. The performance optimization indexes are established as follows:

$$\min J=\sum_{j=1}^{P}\gamma_j[y_r(k+j)-y_m(k+j)]^2 + \sum_{j=1}^{M}\lambda_j[u(k+j-1)-u(k+j-2)]^2 \tag{11}$$

Where, γ and λ are the weight coefficients, P is the maximum prediction range, and M is the maximum control range. Usually, M≤P. The optimization constraints are as follows:

$$\begin{cases}0\le y[k]\le v_{g\max}\\ 0\le i_q[k]\le i_{q\max}\end{cases} \tag{12}$$

Where, v_{gmax} is the maximum mixing speed of the mixer and i_{qmax} is the maximum output concentration of the mixer.

The fourth step is to use the first control quantity U(k) and then return to the second step.

Simulation Experiment

Establishment of simulation model

In the process of sand mixing simulation, it is necessary to ensure that there is no great deviation in the results, and that the simulation time will not be too long, so as to properly simplify the simulation model.

$$k_1=k_2=k_3=k_4=1 \tag{13}$$

Under the environment of Matlab /Simulink, the NN Predictive Controller neural network predictive control module is used for the simulation experiment, when the medium concentration c1=c2=1.0, without considering the influence of the liquid level in the agitator tank. The predictive time-domain length is set as 7, the control time-domain length as 2, the control quantity weighting coefficient as 0.05, the linear search parameter as 0.001, and the concrete mixing parameters are combined for simulation. First, a 2-10-1 BP network model is established and model training is performed. The training data is shown in Figures 4 and 5.

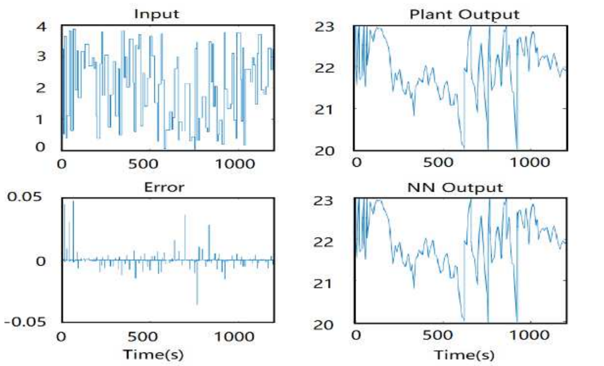


Figure 4. Training data under random jump signals

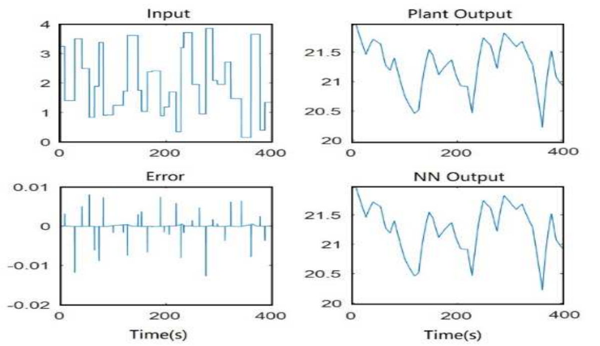


Figure 5. Selected neural network legal training data

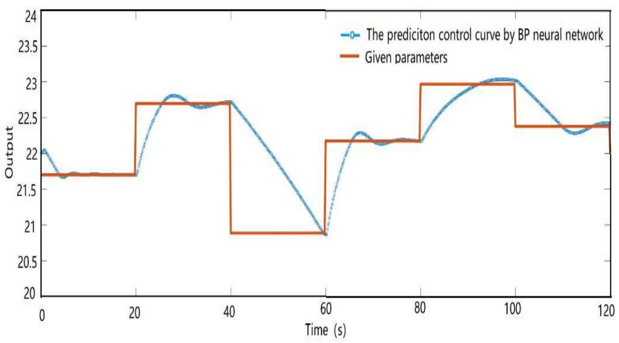


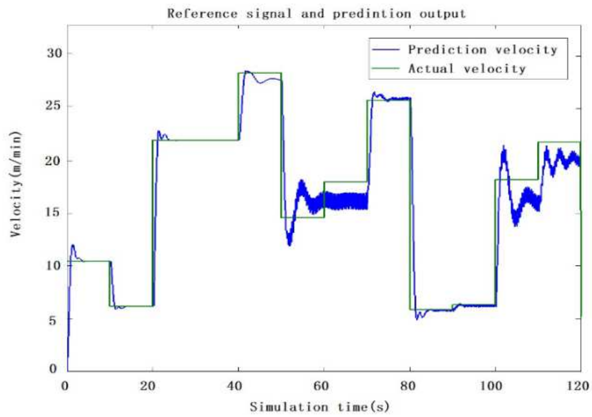
Figure 6. Predictive control results of neural networks under jump response

Control simulation

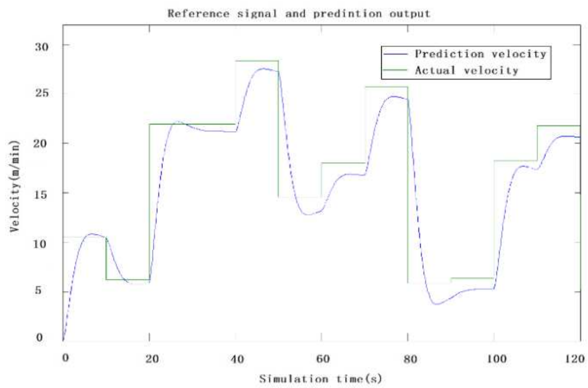
After the network training is completed, training is performed using legal data, the obtained model is saved and closed-loop control simulation is performed. With consideration of random input, the curve in a control process is shown in Figure 6. By comparing the reference signal with the control output signal, it can be seen that the neural network predictive controller can complete the control of the sand mixing device.

Comparative analysis

Simulations are performed under both neural network predictive control and PID control. The simulation results are shown in Figure 7.



(a) Neural network predictive control results



(b) Traditional PID control results

Figure 7. Neural network predictive control and traditional PID control results

It can be seen from Figure 7 that when the system is started at a certain stable speed, the traditional PID control does not have a large overshoot amount, but it takes a long time to achieve stabilization, and speed cannot be adjusted quickly. The neural network predictive control react fast, thus can meet the control requirements.

Conclusions

This study analyzes the control process of the sand mixing device in the drilling fracturing process, establishes the fluid kinetic model of the second-stage stirring device, and constructs a prediction model of the mixing device using the BP neural network prediction method, which is predicted through simulation experiment. From the simulation results, it can be seen that the neural network predictive control algorithm not only retains the advantages of traditional predictive control, but also overcomes such disadvantages of complex objects in traditional predictive control as difficult modeling and real-time application, thus it can effectively predict the operating parameters under the jump response of the two-stage sand mixing device. Therefore, the established BP neural network prediction model and its control algorithm can meet the requirements of engineering application and effectively improve the control quality.

Acknowledgements

The projects supported National Key R & D project (2016YFC0303703) are gratefully acknowledged. The authors would like to thank all members for their support and all members of the project team.

References

Deng BQ, Chen H. Research on the development trend of sand mixer. Standard and quality of China's petroleum and chemical industry 2011; 31(7): 193.

Eisinger FL. Acoustic fatigue of impellers of rotating machincry. Journal of Press Vessel Technology 2002; 124(2): 154-60.

Hu BZ, Lan ZX. Hydraulic fracturing engineering in Daqing Oilfield. Petroleum Industry Press 2008.

Huang TC, Wang DG, Zhou SZ. Modal Research of Fluid-solid Coupling for the Blender Truck Mixing Impeller. Journal of Southwest Petroleum University (Science & Technology Edition 2012; 34(1): 165-70.

Liu ZH, Zhen QQ, Wang YD. Laminar mixing enhanced by flexible impeller in high-viscosity fluid stirred tank. China Sciencepaper 2012; 7(3): 185-89.

Tamburini A, Cipollina A, Micale G, Ciofalo M, Brucato A. Dense solid-liquid off-bottom suspension dynamics: Simulation and experiment. Chemical Engineering Research Design 2009; 87(4): 587-97.

Wan ZZ, Huan J, Yin T. Numerical Simulation of the Flow Field and Power of the Blender Mixing Tank. China Petroleum Machinery 2014; 42(2): 80-83.

Wang JJ, Gu XP, Feng LF. Experimental study and CFD simulation of fluid mixing process in a horizontal stirred vessel. Sciencepaper Online 2008; 3(12): 911-14.

Xiao YT, Shi WK, Liu J. Numerical simulation of mixing process in stirred tank of blender truck. Journal of Chang'an University (Natural Science Edition) 2014; 34(2): 120-26.

Xie YJ, Chao LM. Research on new type of non pressure well operation equipment. Petroleum Machinery 2007; 35(9): 161-64.

Zhou SZ, Chen X, Wu HC. Flow field analysis method for mixing tank of sand mixer. China Petroleum Machinery 2011; 39(S1); 23-24.

Zhou SZ, Yuan XM, Huang TC. Similarity design and numerical simulation of test model of mixing tank in fracturing blender truck. China Sciencepaper 2014; 9(5): 616-19.