Research and Practice of Neural Network PID Process Control Algorithm Based on Offshore Oil and Gas Platform

Qing Yang¹, Zhiyao Liu¹,²*, Yu Zhang¹

¹School of Electrical Engineering and Information, Southwest Petroleum University, Chengdu 610500, China
²China National Offshore Oil (China) Co., Ltd., Shanghai Branch, Shanghai 200335, China
*E-mail: 673982453@qq.com

Abstract: Since the exploitation of offshore oil and gas, after decades of development, it has gradually played an important role in world economic development. The central control system of offshore platforms is the core equipment of offshore oil and gas fields. Offshore platform industrial process control requires PID control most of the time. However, in practical applications, the tuning of PID parameters has not been well resolved. This paper combines neural network and PID control to build a neural network PID controller. At the same time, using OPC communication technology, the intelligent control PID algorithm is perfectly combined with the central control system, and the optimized model and parameters are applied to the actual control object of the oil level control of the offshore oil production platform, and the control effect is obtained satisfactorily.

1. Introduction

In recent years, with the development of automation technology and the continuous updating of control systems, the instrumentation and control systems of offshore platforms have also been rapidly improved[1]. However, through research, these control systems have not fully utilized their advanced control functions on offshore platforms: engineers and technicians need to frequently set PID parameters, and even switch from automatic control to manual control. These have seriously affected the productivity of offshore platforms and have potential production safety hazards. Therefore, it is imperative to develop intelligent control solutions for offshore platforms.

At present, for the lack of classic PID control, the corresponding intelligent control PID is gradually developed gradually[2][3][4], such as expert control PID, fuzzy control PID, neural network PID, genetic algorithm PID. However, most of the advanced control only carry out theoretical simulation research, and there are very few real application processes[5].

Based on the understanding of the central control system of CNOOC (China National Offshore Oil Corporation) offshore oil platform (Honeywell EPKS), this paper studies an intelligent control platform based on neural network PID control algorithm combined with central control system. The algorithm uses OPC (OLE for Process Control) technology to realize real-time communication between intelligent control software and central control system without changing the original control system: Honeywell EPKS serves as OPC Server and intelligent control software serves as OPC client. Realization of neural network PID control background optimization through OPC data interaction channel. The optimized parameters are written into the configuration software of the central control

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.
Published under licence by IOP Publishing Ltd
system to achieve good control effect and realize intelligent control.

2. Overview of offshore platform process control system
The process flow of K-A offshore platform is shown in Figure 1.

![Process flow chart of an offshore platform.](image)

Figure 1. Process flow chart of an offshore platform.

Its brief summary is as follows: The oil and gas mixed liquid produced by this platform is combined and measured by the manifold and sink, and then mixed into the separator for preliminary three-phase separation of oil, gas and water.

Generally, the level control of the platform separator is particularly important. The primary goal is to ensure the stability of the liquid level and reduce the frequent fluctuation of the liquid level. At the same time, frequent fluctuations of the control variables are reduced. This can not only bring a smooth process, but also reduce the wear of the corresponding control valve due to frequent adjustments. Therefore, this paper designs an intelligent control algorithm for offshore oil platform based on neural network PID to improve the accuracy and corresponding speed of the control system (offshore platform neural network PID, the following is abbreviated as OPNNPID).

3. The principle of the algorithm
Most of the current industrial process control will use the classic PID control[6], for the classic PID controller, in order to obtain better control effect, the three parameters which are named the proportional coefficient (Kp), the integration time (Ti) and the differential time (Td) must be set first.

At present, there are many intelligent control PID algorithms, among which the neural network is one of the most widely used because of their good ability to approximate nonlinear mapping and self-learning[7]. This paper combines BP neural network with PID, and uses the self-learning ability of neural network to learn three adjustable parameters of PID online, and outputs the optimal parameters corresponding to a certain working condition. The OPNNPID control system is shown in Figure 2.
Figure 2. Offshore platform neural network PID (OPNNPID).

It consists of two parts: a conventional PID controller and a BP neural network:

i) The conventional PID controller performs closed-loop control on the controlled object and is responsible for controlling the forward conduction of the signal;

ii) The BP neural network self-learns and optimizes the three PID parameters in the background according to the error caused by the change, so that the corresponding target can achieve the optimization of a certain performance index.

Typical incremental PID control algorithm:

\[
u(k) = u(k - 1) + K_p(e(k) - e(k - 1)) + K_i e(k) + K_d(e(k) - 2e(k - 1) + e(k - 2))\] (1)

In the above formula, \(K_p, K_i, K_d\) are PID adjustment parameters, where \(e(k) = r(k) - y(k)\). The \(u(k), r(k)\) and \(y(k)\) are respectively the control quantity, expected and actual output of the system.

The BP neural network used in this paper is a classical neural network using the error back propagation training algorithm. The typical three-layer network structure is shown in Figure 3. It consists of three parts: input layer, hidden layer and output layer. The output layer neurons correspond to the three control parameters \(K_p, K_i, K_d\) of the PID controller. BP neural network has the ability of arbitrary non-linear expression, which can adjust PID parameters by self-learning and self-adjustment according to system performance requirements and operation process state, so as to achieve the optimal combination of PID parameters [8].

Figure 3. BP neural network structure diagram.

Three-layer BP neural network, the input of the network layer is:

\[O_j^{(1)} = x(j)\] (2)

The input and output of the hidden layer of the network are:

\[net_i^{(2)}(k) = \sum_{j=0}^{m} w_{ij}^{(2)} o_j^{(1)}\] (3)

\[O_i^{(2)}(k) = f \left( net_i^{(2)}(k) \right)\] (4)

Where, \(W_{ij}\) is the weighted coefficient of the hidden layer, and the upper corner marks (2), (3) and (4) respectively represent the input layer, hidden layer and output layer. The hidden layer is the inner
information processing layer of neural network, which is responsible for information exchange. The activation function of neurons in the hidden layer selects the sigmoid function with positive and negative symmetry:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$  \hfill (5)

The input and output of the network output layer are:

$$net_i^{(3)}(k) = \sum_{l=0}^{q} w_{il}^{(3)} o_i^{(2)}(k)$$  \hfill (6)

$$o_i^{(3)}(k) = g\left(net_i^{(3)}(k)\right)$$  \hfill (7)

$$\begin{align*}
o_1^{(3)}(k) &= kp \\
o_2^{(3)}(k) &= ki \\
o_3^{(3)}(k) &= kd
\end{align*}$$  \hfill (8)

The activation function of the output layer is non-negative sigmoid function:

$$g(x) = \frac{e^x}{e^x + e^{-x}}$$  \hfill (9)

The BP algorithm makes the performance index function $E(k)$ close to the minimum value by continuously modifying the weight and threshold.

$$E(k) = \frac{1}{2} (rin(k) - y_{out}(k))^2$$  \hfill (10)

In order to make the network converge quickly, this paper also adds an inertia term:

$$\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial E(k)}{\partial w_{li}^{(3)}} + \gamma \Delta w_{li}^{(3)}(k - 1)$$  \hfill (11)

$\eta$ is the learning rate, $\gamma$ is the inertia coefficient:

$$\frac{\partial E(k)}{\partial w_{li}^{(3)}} = \frac{\partial E(k)}{\partial y(k)} \cdot \frac{\partial y(k)}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial o_i^{(3)}(k)} \cdot \frac{\partial o_i^{(3)}(k)}{\partial net_i^{(3)}(k)} \cdot \frac{\partial net_i^{(3)}(k)}{\partial w_{li}^{(3)}}$$  \hfill (12)

The above equation requires the use of the variable $\partial y(k)/\partial u(k)$. Since $\partial y(k)/\partial u(k)$ is unknown, it is usually approximated by a symbolic function, or it can be identified by NNI. This paper uses the method of symbolic function approximation. In this way, the output layer weight calculation formula of BP neural network can be obtained as follows:

$$\Delta w_{li}^{(3)}(k) = \eta \delta_i^{(3)} o_i^{(2)}(k) + \gamma \Delta w_{li}^{(3)}(k - 1)$$  \hfill (13)

$$\delta_i^{(3)} = e(k) \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial o_i^{(3)}(k)} g'(net_i^{(3)}(k))$$  \hfill (14)

Similarly, the weight calculation formula of hidden layer can be obtained:

$$\Delta w_{ij}^{(2)}(k) = \eta \delta_i^{(2)} o_j^{(1)}(k) + \gamma \Delta w_{ij}^{(2)}(k - 1)$$  \hfill (15)
\[ \delta_i^{(2)} = f'(net_i^{(2)}(k)) \sum_{l=1}^{3} \delta_l^{(3)} w_{li}^{(3)}(k) \] (16)

4. OPC communication

As an industry standard, OPC has solved the communication problems between Windows-based applications and field process control[9]. This paper makes full use of OPC communication technology and combines it with platform’s Honeywell EPKS to realize intelligent control of complex processes[10]. The control system structure diagram is shown in Figure 4.

The specific process is as follows: When the system is in a stable state, keep the classic PID parameters unchanged. Once the system fluctuates or even oscillates, the background control algorithm is called and reads the historical data of the PCS through OPC communication, and then adaptively adjusts the parameters of the PID. After the optimal parameters are trained, they are written into the process control system through the OPC data interaction channel, thereby completing the corresponding control.

The Honeywell EPKS of the K-A platform studied in this paper also fully supports the protocol. The background intelligent control algorithm exchanges real-time data with EPKS through the OPC interface program.

5. Actual results and conclusions

The OPNNPID algorithm runs on a computer that performs OPC communication (DCOM configuration is required) with the Honeywell EPKS IPC on the offshore platform. Once the running PID parameters do not meet the current operating conditions, the operator can run the algorithm program, write the optimized parameters to the Honeywell EPKS program through the OPC interactive channel, and re-apply to the actual industrial control object. Figure 5 shows the actual historical curve of the separator liquid level control system (The yellow curve is the actual level value and the green curve is the output of the control valve). It can be seen from the figure that the working conditions of the offshore platform are complicated and there is no rule to follow. Classic PID control can’t adapt to this kind of the system, and it is difficult to achieve optimal control of the system which will also cause frequent adjustment and wear of the platform regulating valve.
Figure 5. Actual historical curve of the separator liquid level control system.

Figure 6 shows one day before and after system operation. It is possible to see that after the OPNNPID, it was able to decrease and respect the desired level variability (purple curve) and manipulate even less the controller output (green curve), which is a control valve.

Figure 6. Performance during one day of the OPNNPID operation.

As can be seen from the above figure: Compared with the traditional PID controller, the OPNNPID has fast regulation, strong anti-interference ability, good tracking performance, and
stable adjustment process, which is conducive to the stability of the control process and also reduces The loss caused by frequent valve action has good industrial application value. Through in-depth study of offshore platforms, the author finds that the stability of process control on offshore platforms can bring other benefits:

i) increasing the stability in the oil flow, which enhances the lifetime of the pump and minimizes vibrations and fatigue in the pipelines due to a more stable pressure. Reduce the start and stop operation of the pump, reduce the sudden increase and decrease of the load, and improve the stability of the platform power system:

   ii) A smooth process can reduce the number of shutdowns of the platform and increase production.

This paper is aimed at the oil and gas gathering and transportation system of offshore platform. Under the technology of OPC, this paper adopts PID control algorithm based on BP neural network to realize PID adaptive control of industrial process, which can reduce manual intervention and improve process control effect. It has good universality and promotion value. The next research is mainly to improve the algorithm to make it faster, more accurate and more stable.

Reference

[1] Campos, M., Teixeira, A., Von Meien, O., Neto, S., and Santos, W. (2013). Advanced Control Systems for Offshore Production Platforms. In: Offshore Technology Conference Brazil. Rio de Janeiro.

[2] KanagalakshmiS, ManamalliD, Mohamedrafiq, MohamedrafiqM. (2016) Implementation of Multimodel-Based PID and Intelligent Controller for Simulated and Real-Time Temperature Control of Injection Molding Machine. Chemical Engineering Communications, Vol.203, no.4:452-462.

[3] Fister Dušan, Fister Iztok, Šafarič, Riko. (2016) Parameter tuning of PID controller with reactive nature-inspired algorithms. Robotics and Autonomous Systems, Vol.84:64-75.

[4] Mohsen Farahani, Soheil Ganjefar, (2012) Intelligent control of static synchronous series compensator via an adaptive self-tuning PID controller for suppression of torsional oscillations. International Journal of Control, Automation and Systems, Vol.10, no.4:744-752.

[5] Kern, A., Andrew, B. (2016) Understand Advanced Process Control. Chemical Engineering Progress, Vol.112(6): 69-72

[6] Bennett, S. (2001) The past of PID controllers. Annual Reviews in Control, Vol.25:43-53.

[7] Jing, X., Cheng, L. (2013) An Optimal PID Control Algorithm for Training Feedforward Neural Networks. IEEE Transactions on Industrial Electronics, Vol. 60, no. 6:2273-2283.

[8] Liu, Z. D., Wang, J. M., Yang, G. (2018) Research on Grinding Circuit Control System Based on Improved BP-PID Control. Mining Research and Development, 38(07): 99-103.

[9] Şahin, C., Bolat, E. D. (2009) Development of remote control and monitoring of Web-based distributed OPC system. Computer Standards and Interfaces, vol. 31 no. 5: 984-993.

[10] Mahmoud, M. S., Sabih, M., Elshafei, M. (2015) Using OPC technology to support the study of advanced process control. ISA transactions, vol. 55 :155-167.