Development of a control system for a rectification column with a neural network adjustment of the flag liquid flow and upper temperature

E A Muravyova
Ufa State Petroleum Technological University, Branch of the University in the City of Sterlitamak, 453118, Russian

E-mail: muraveva_ea@mail.ru

Abstract. The gas and oil industries are high-tech industries that are based on modern advances in science and technology. This contributed to the development of the control system and the increase in the level of automation of the oil refining process. At a refinery, which is complex production, a process control system plays a key role. There is a need to provide continuous and error-free control, safe and stable operation of the system. One of the perspectives in control systems is neural networks. They can implement any desired process of a non-linear control algorithm with an incomplete, inaccurate description of the control object, and also provide easily implemented adaptation with unstable statistics. This article presents the development of a control system with a neural network adjustment of the reflux fluid flow rate and the top temperature of the column and a comparison with the number of deviations from the norm of the process parameters under the control of the neuroregulator and under the control of the PID controller. Block diagrams of a control system with a neural network controller and a PID controller are compiled. The expediency of using a neural network controller to control the object is substantiated. A mathematical model of the control object was developed taking into account its inherent internal relationships between the parameters of the technological mode and taking into account the influence of external disturbing factors. Processing of the research results was carried out using the software package “MatLab”.

1. Introduction

The temperature in the upper part of the columns ensures the production of a distillate, for example, gasoline of a certain fractional composition according to the temperature of its boiling end, respectively, by changing its temperature or flow rate, the temperature of the upper part of the column and, therefore, the quality of the distillate can also be controlled. To solve this problem, it is necessary to develop a parameter control system for production with an accurate fractional composition and to improve the quality of the distillate.

Standard PID controllers cannot always be used to solve this problem, since not all parameters are linear, and have a mutual influence on each other. In this regard, it is advisable to use other types of regulators.

Today, the most promising is the use of neural network regulators to control the flow rate and temperature of the distillation column. The creation of such a system will allow: to improve the adaptive capabilities of the regulator, to improve the quality of management and, therefore, the quality indicators of the technological process [1-3].
2. Description of the process
The task of automation of all types of oil treatment plants is to provide operational automated control of the quality of the oil produced, computer control and management of all stages of oil preparation, control and management of technological equipment and processes.

Figure 1 shows the automation circuit of a distillation column.

![Diagram of the automation of a distillation column](image)

**Figure 1.** Diagram of the automation of a distillation column.
1 – Diaphragm valve; 2,12 – Level sensors; 3 – Flow meter; 4 – Pressure meter; 5,7 – Temperature sensors; 8 – Evaporator; 9 – Capacitor; 10 – Capacity; 11 – Pump.

The base mix heated up to a feed temperature in the vapor, vapor-liquid or liquid phase, inflows the column as feed. The area in which the power is supplied is called evaporation (from the English evaporation - vaporization), as far as there is a process of evaporation–one-time separation of steam from the liquid.

To create an upward flow of vapors in the bottom (lower, splitter) part of the distillation column, part of the bottom liquid is sent to the interchanger, the formed vapors are fed back under the bottom plate of the column.

Vapors rise to the top of the column, cool, condensates in the condenser-refrigerator.

3. Development of a neural network
It is necessary to build a distillation column control system with neural network construction of parameters.

ANN development was carried out in the Matlab environment. When solving the problem, the Matlab Neural Network package and the Simulink graphic tool were used.

The process of constructing a neural network model can be divided into 4 main stages [4].

The first step is to construct an ANN.

The second stage is related to network training, which can be carried out because of a constructive or destructive approach.

In the third stage, a neural network model is created in the Simulink graphical environment.

At the fourth stage, the obtained ANN model is tested on an independent sample of examples [5].

To solve the problem with the help of a neural network, it is necessary to collect data for training (table 1). Input parameters: temperature of the cube of the column Tс, temperature of the top of the column Tt. Output parameters: transfer function channel flow rate of superheated steam W₁ for the PID controller and neuroregulator, transfer function channel flow rate of reflux fluid W₂ for the PID controller and neuroregulator, transfer function channel concentration of the feed column W₃ for PID controller and neuroregulator.
Table 1. The training dataset

| No | Input | Output |
|----|-------|--------|
|    | $T_c$, °C | $T_t$, °C | $W_1$, PID/Neuroregulator | $W_2$, PID/Neuroregulator | $W_3$, PID/Neuroregulator |
| 1  | 263   | 70     | 70,9/88,06 | 153,8/77,83 | 1,051/29,55 |
| 2  | 217   | 90     | 129,1/112,9 | 190,4/93,46 | 1,881/16,16 |
| 3  | 285   | 74     | 66,77/72,68 | 109,2/78,2 | 0,984/31,46 |
| ... | ...   | ... | ... | ... | ... |
| 998 | 275   | 76     | 59,44/64,59 | 100,3/80,1 | 0,897/29,55 |
| 999 | 281   | 73     | 75,7/85,57 | 147,5/77,69 | 1,101/12,16 |
| 1000 | 248   | 84     | 101,5/75,57 | 143,3/75,12 | 1,432/14,33 |

The transfer function is one of the methods of mathematical description of a dynamic system. It is used mainly in control theory, communications and digital signal processing [6]. It is a differential operator expressing the relationship between the input and output of a linear stationary system. Knowing the input signal of the system and the transfer function, you can restore the output signal.

In control theory, the transfer function of a continuous system is the ratio of the Laplace transform of the output signal to the Laplace transform of the input signal under zero initial conditions [7].

Since the transfer function of the system completely determines its dynamic properties, the initial task of calculating the automatic control system is reduced to determining its transfer function [8]. When calculating the settings of regulators, rather simple dynamic models of industrial control objects are widely used. The transfer function is a fractional rational function of a complex variable for different systems [9,10]. Measurements will be carried out using the three transfer functions $W_1$ – channel flow rate of superheated steam, $W_2$ – channel flow rate of reflux fluid, $W_3$ – channel concentration of the feed column (concentration of the reaction mixture in the feed column).

For calculation, we choose a dynamic transfer function. We begin the construction of the first block diagram using the transfer function $W_1$ for a distillation column and select parameters for it (superheated steam flow channel $W_1$ and column temperature $T_c$):

$$W_1 = \frac{5.12}{15.349s^3 + 10.812s^2 + 4.785s + 1}$$

The following models are used in the flowcharts: Random Reference (generating a signal with a uniform distribution); Neural Network Predictive Controller (neuroregulator); Plant (Column) – control object; Graph (graph); Clock (generates a signal whose value at each calculation step is equal to the current simulation time); PID Controller (represents the sum of the input signal, the integral of the input signal and the derivative of the input signal); Display (illustrates the application of this source and the measurement of its input signal); Sum (summing element); Integrator (displays the value of the integral of its input signal relative to time).

Let’s build a model in a Simulink graphical environment with a neural network controller (figure 2).

After creating a block diagram of the control environment of the Simulink environment, we use the Plant Identification tool to plot the values and calculate the deviations from the norm of the parameters.

From the analysis of the data obtained, it follows that the reaction of the system to step effects with a random amplitude is quite satisfactory, has an oscillatory character with a fairly fast attenuation; at an interval of 15 s, all impacts are effectively worked out.

Next, we move on to constructing a block diagram for the first transfer function, but instead of the neuroregulator we use the PID controller.
We change the transfer function to $W_2$ to measure deviations from the norm on the second and third transfer functions:

$$W_2 = \frac{1.663}{5.083s^3 + 4.343s^2 + 1.698s + 1}$$

We consider the flow channels of the reflux liquid $W_2$ and the temperature of the top of the column $T_t$.

For the transfer function $W_2$, we construct mathematical control models with a neuroregulator and a PID controller.

Using the Plant Identification tool, we train the model and display the graphs of the input value, the output value of the Plant Output control object and the NN Output neural network, as well as the errors of the second transfer function Error (figure 4), these parameters indicate the learning results for the column, it follows from the graphs that the system reaction on step effects with a random amplitude is quite satisfactory, has an oscillatory character with a fairly rapid attenuation; at an interval of 20 s, all impacts are effectively worked out.

Deviations from the norm of a control system with a neuroregulator are shown in figure 5, with a PID controller in figure 6.

On the graph (figure 5) we see that the deviations in the second transfer function ($W_2$, NN Controller) are included in the norm of parameters (Optimal parameters), since the average values of the minimum and maximum points are close to the norm of the parameters of the neuroregulator.

On the graphs (figure 6) we see that the deviations in the second transfer function ($W_2$, PID Controller) of the model with the PID controller are not included in the optimal parameters norm(Optimal parameters), since the deviation values have a big difference with the norm of the parameters.
The following transfer function \( W_3 \) with the parameters of the channels of concentration of the power supply column \( W_3 \) and the temperature of the top of the column \( T_t \):

\[
W_3 = \frac{0.765s^2 + 1.816s + 1.72}{5.083s^3 + 4.343s^2 + 1.898s + 1}
\]  

(3)

The deviations in the third transfer function (\( W_3 \), PID Controller) are included in the optimal parameters norm (Optimal parameters), since the graph also covers the average norm values of the PID controller parameters.

The deviations in the third transfer function (\( W_3 \), NN Controller) are included in the norm of parameters (Optimal parameters), since the average values of the minimum and maximum points are close to the norm of the parameters of the neuroregulator.

The numerical values (deviations from the norm) obtained during the study were summarized in table 2. The average value for each transfer function was also derived.

| No measurement | First transfer function, \( W_1 \) | Second transfer function, \( W_2 \) | Third transfer function, \( W_3 \) |
|----------------|-----------------------------------|-----------------------------------|-----------------------------------|
|                | PID Controller | NN Predictive Controller | PID Controller | NN Predictive Controller | PID Controller | NN Predictive Controller |
| 1              | 70.90           | 88.06               | 153.80          | 77.83          | 1,051          | 29.55                 |
| 2              | 129.00          | 112.90              | 190.40          | 93.46          | 1,881          | 16.16                 |
| 3              | 66.77           | 72.68               | 109.20          | 78.2           | 0.984          | 31.46                 |
| 4              | 80.52           | 93.89               | 168.80          | 83.87          | 1.199          | 17.13                 |
| 5              | 103.70          | 87.78               | 158.60          | 83.26          | 1.517          | 11.51                 |
| 6              | 104.70          | 108.80              | 153.90          | 93.30          | 1.542          | 18.48                 |
| 7              | 136.90          | 131.00              | 205.30          | 99.84          | 2.006          | 12.89                 |
| 8              | 60.96           | 84.45               | 168.90          | 74.23          | 0.916          | 27.56                 |
| 9              | 108.60          | 93.83               | 177.40          | 95.77          | 1.615          | 27.64                 |
| 10             | 92.20           | 100.70              | 188.00          | 74.54          | 1.369          | 19.11                 |
| Mean value     | 95.43           | 97.41               | 167.43          | 85.43          | 1.41           | 21.15                 |
4. Neural network testing
According to the first transfer function, the difference in deviations between the studied control system with the neural network controller and the PID controller is insignificant, but the PID controller shows a lower error value.

In the second case, the situation is radically different, the control system with a neuroregulator shows the result 2 times better than the PID controller, therefore it is rational to choose a neural network controller to control the reflux fluid flow channel and the top temperature of the column.

To control the feed concentration channel of the column, a PID controller is suitable, for which the deviation from the norm is only 1.41, while the deviation of the neuroregulator is 21.15.

5. Conclusion
During the study, the following main results were obtained: the feasibility of developing a distillation column control system with a neural network adjustment of parameters using mathematical modeling methods was substantiated, and the efficiency of the distillation column control system was evaluated. The study also compares deviations from the norms of the PID controller and the neural network controller. Conclusions are drawn from the numerical data.

After comparing the control system with the PID controller and the neural network controller in three cases, we can conclude that it is more rational to use a neural network to control the reflux fluid flow channels and the top temperature of the columns, and the PID controller to control the column supply concentration channel.

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