Neural network controller identification for refining process

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Abstract. The article discusses the task of identifying a neural network controller for the installation of rectification of oil refining production. A rectification process research model is used to evaluate the effectiveness of the controller. The control parameters of the rectification process that are used to identify the controller and evaluate its effectiveness are determined. In a numerical study, the possibility of using a neural network controller to control the rectification process is shown. As a basic option for a comparative study, we used a PID-regulator, which is the standard version in production today. The advantage of a neural network controller in controlling processes in the context of the implementation of various target trajectories is shown. The proposed model of a neural network controller can be adapted and used for computer control of the rectification process.

1. Introduction

Worldwide, oil refining is one of the most dangerous types of production, which is accompanied by incidents that threaten safety, including explosions, fires, and heavy machinery accidents. The consequences of these accidents can be cases of injuries and death of maintenance personnel at facilities, the likelihood of a man-made environmental catastrophe, large economic losses to the enterprise itself, and to the city, region or country economy. Therefore, ensuring safe and trouble-free operation of equipment is the primary task of enterprise management.

In order to avoid emergency conditions of oil refining equipment, special attention should be paid to forecasting its operation, as well as the speed of selecting the optimal parameters by the control system when any parameters go beyond the set limits, or to achieving the specified parameters in the shortest possible time. This requires a control system, which provides automatic control of the process parameters in the control object in order to achieve maximum control accuracy, reduce the time of transients and minimize errors [1], [2], [3].

One of the main processes of primary refining is rectification. Rectification is a complex process, which takes place under conditions of initial information uncertainty depending on many factors. Therefore, to control this process, it is advisable to use artificial intelligence methods based on fuzzy control and artificial neural networks (ANN). Another means widely used for the rectification control include proportional-integral-differentiating (PID) regulators and their modifications (PD-regulator, PI-regulator), a linear quadratic regulator (LQR), and a linear quadratic Gaussian control (LQG control).
In the reviewed works, automatic control systems are designed to improve the quality of the effluent fractions. PID controllers, LQR and LQG controllers and fuzzy controllers were used for this purpose [4], [5], [6], [7], [8], [9].

2. Description of subject methods

Artificial neural network is a model based on the functioning of biological neural networks of living organisms [10]. Neural networks consist of simple artificial neurons, which perform simple signaling operations, however, connecting neurons into a neural network makes it possible to perform fairly complex tasks. Equipment troubleshooting, dynamic process management, equipment operation forecast, and process control monitoring are the functions that can be performed by neural networks [11], [12], [13], [14], [15]. Neural networks are widely used in the management of industrial facilities where conventional control systems are not efficient and accurate enough. They are capable of learning and summarizing accumulated knowledge in the course of their work, able to adapt to changing properties of the control object and the external environment. When a network is trained with a limited set of data, it is able to summarize the information received and to process the data that was not used for training.

To date, many types of neural networks have been developed and used, which differ in learning algorithms, architectural features and the task pane. In industry, the use of neural control is an important field of activity. Neural control of dynamic objects is achieved through the use of automatic control methods and artificial intelligence methods. Neural control will help in managing such a complex process as rectification to achieve higher accuracy and object control rate. Various methods of neural control have been recently developed, which include: imitative, inverse, predictive, multi-modular, hybrid and auxiliary control [16], [17], [18], [19]. Predictive neural control is used as a basis for the rectification process control, in particular, a neural predictive controller, because this type of neural control is often used to control dynamic objects [21].

To study the performance of control algorithms for a rectification column, it is necessary to obtain a dynamic mathematical model of the process. This requires determination of the input and output parameters interconnection in the rectification column. In [22] an analytical dynamic mathematical model of a rectification unit was found using the material balance equations of the rectification process for the entire column. The main interconnections of input and output parameters in a rectification unit are shown in figure 1. The main channels of regulatory actions are indicated by solid lines. They help stabilize the adjustable values using the control system. Dotted lines denote impacts that are internal or external disturbances in relation to the regulatory actions.

Column parameters are: \( G_{sw} \) - consumption of superheated steam in the column boiler, \( G_r \) - reflux consumption in the column, \( G_{ref} \) - refrigerant consumption in the reflux condenser, \( G_{bl} \) - bottom liquid consumption from the column (finished product), \( G_{feed} \) - reaction mixture on the feed tray, \( G_{cow} \) - reflux withdrawal consumption (finished product), \( C_{feed} \) - column feed concentration, \( C_{dist} \) - concentration of distillate, \( C_{bl} \) - concentration of the bottom liquid, \( C_r \) - concentration of reflux, \( T_b \) - temperature of the column bottom, \( T_t \) - temperature of the column top, \( T_{rl} \) - temperature of reflux liquid, \( P_t \) - pressure of the column top, \( H_b \) - pressure of the column bottom, \( H_b \) - liquid level in the column bottom.

Most of the control systems are designed to control column top parameters. This paper addresses the communication channel \( W_{22}(p) \) — \( G_r \) (reflux consumption in the column) — \( T_t \) (temperature of the column top), response function of the communication channel is:

\[
W_{22}(p) = \frac{1.663}{5.083p^3 + 4.343p^2 + 1.698p + 1}
\]  

To build a mathematical model of the column top temperature dependence on the reflux consumption, which simulates the processes occurring in a real object, the MatLab Simulink application software package was used.
Figure 1. General and simplified scheme of interconnections between input and output parameter.

3. Experimental study

Let's look at the rectification process control using the predictive controller. The temperature of the column top was assumed as a control parameter.

The NN Predictive Controller is provided as a control system, based on neural network regulation with the ability to predict the process behavior in the future. The controller provides calculation of the control signal to optimize the control object behavior at a given time interval and consists of a neural network model and an optimization block. The optimization block calculates the values of $u'$, which minimize the control quality criterion, and the corresponding signal controls the process. The model of the temperature control system at the top of the column is presented in figure 2.

For a comparative analysis, we consider the classical parameter control using the PID controller. All parameters of the control object and the perturbing action remain unchanged, the control model is presented in figure 3.
Random signal “Random reference”, step signal “Step”, and random signal with normal distribution “Random Number” were assumed as signal sources. As a result, a regulation error was calculated when different signal sources were used (table 1).

| Controller / Signal source | Column top temperature regulation error, °C |
|----------------------------|--------------------------------------------|
|                            | Random reference | Step | Random Number |
| PID-regulator              | 2,48            | 1,64 | 0,96          |
| NN controller              | 0,98            | 1,31 | 0,63          |

Analysis of the research results showed that the use of a controller based on neural network regulation with the ability to predict the process behaviour has reduced the transient process time, increased the accuracy of rectification process control and reduced the regulation error compared to the PID based controller.

4. Conclusion
The article deals with the problem of complexity of the rectification process control system, simulates a mathematical model of the column top temperature dependence on the reflux flow rate, simulates a predictive control system and a PID control system.

A comparative analysis of PID regulation and neuroregulation has been carried out, during which it was found out that the control accuracy in the predictive control system has increased in comparison with PID regulation.

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