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OPTIMIZATION OF FRACTIONAL DISTILLATION COLUMN IN CRUDE OIL REFINERY USING ARTIFICIAL NEURAL NETWORK

ISMAGULOVA D.M.

JSC "Wood KSS", 060011, Atyrau, Kazakhstan

Abstract. *The paper outlines the methods, which improve the controlling process of separating methanol from water in the distillation column to produce crude oil products. Nowadays, many industries use PID controllers to control process variables like temperature, flow, pressure, level, which helps maintain good performances. However, PID controllers can have slightly bad performances in complicated control systems, such as in Multiple Input and Multiple Output (MIMO) systems; due to this, optimization methods of improving PID are considered. A tremendous amount of work has been done refining, studyingandimproving the PID controlling techniquesand methods. However, PID still faces challenges in a variety of common control problems. This article represents NeuralNetworkAlgoritmbased PID controller, whichisusedtocontrolthe separating process of methanol from water in the distillation column, due to Neuralnetwork's good generalization results. The Wood and Berry mathematical Model was chosen as the main control object.*

Keywords: *distillation column, Neural network, PID controllers, Artificial intelligence, MIMO system.*

ЖАСАНДЫ НЕЙРОНДЫҚ ЖЕЛІСІН ҚОЛДАНА ОТЫРЫП, ШИКІ МҰНАЙ ӨҢДЕУ ЗАУЫТЫНДА ФРАКЦИЯЛЫҚ АЙДАУ БАҒАНЫН ОҢТАЙЛАНДЫРУ

ИСМАГУЛОВА Д.М.

«Wood KSS» АҚ, 060011, Атырау қ., Қазақстан

Аңдатпа. *Мақалада метанолды судан дистилляциялау бағанында шикі мұнай өнімдерін алу үшін бөлуді бақылау процесін жақсартатын әдістер көрсетілген. Қазіргі уақытта көптеген өнеркәсіптер PID контроллерлерін температура, ағын, қысым, деңгей сияқты айнымалыларды басқару үшін пайдаланады, бұл жақсы көрсеткіштерді сақтауға көмектеседі. Алайда PID контроллерлері күрделі басқару жүйелерінде, мысалы, бірнеше енгізу және бірнеше шығару (MIMO) жүйелерінде сәл нашар көрсеткіштерге ие болуы мүмкін, сондықтан PID-ді жақсартудың оңтайландыру әдісі қарастырылады. PID техникасын зерттеуге, жетілдіруге, басқарудың жетілдірілген әдістерін жасауға көптеген жылдар жұмсалды. Дегенмен әлі де PID контроллері жауап бере алмайтын бірқатар жалпы басқару қиындықтары бар. Бұл жұмыста, нейрондық желісінің жақсы жалпылау нәтижелеріне байланысты, жасанды нейрондық желісіне негізделген PID контроллері метанолды дистилляциялық бағандағы судан бөлу процесін бақылау үшін қолданылады. Басқарудың негізгі объектісі ретінде Вуд және Берриматематикалық моделі таңдалды.*

Түйінді сөздер: *дистилляция бағаны, нейрондық желі, PID контроллері, жасанды интеллект, MIMO жүйесі.*

ОПТИМИЗАЦИЯ РЕКТИФИКАЦИОННОЙ КОЛОННЫ НА НЕФТЕПЕРЕРАБАТЫВАЮЩЕМ ЗАВОДЕ С ИСПОЛЬЗОВАНИЕМ ИСКУССТВЕННОЙ НЕЙРОННОЙ СЕТИ

ИСМАГУЛОВА Д.М.

АО «Wood KSS», 060011, г. Атырау, Казахстан

Аннотация. *В статье изложены методы, позволяющие улучшить управление процессом отделения метанола от воды в ректификационной колонне с целью получения сырых нефтепродуктов. В текущее время почти во всех отраслях индустрии используются ПИД-регуляторы для управления такими переменными процессами, как температура, расход, давление, уровень, что действительно помогает поддерживать хорошие характеристики. Однако ПИД-контроллеры могут иметь несколько плохую производительность в сложных системах управления, например в системах с многоканальным входом и многоканальным выходом (MIMO), из-за чего рассматривается метод оптимизации для улучшения ПИД. Было потрачено много лет на изучение, уточнение и совершенствование техники ПИД-регулирования, а также на разработку улучшенных методов управления. Тем не менее все еще существует ряд общих проблем управления, при которых ПИД-регулятор сталкивается с трудностями. В этой работе ПИД-регулятор на основе нейронной сети используется для управления процессом отделения метанола от воды в дистилляционной колонне благодаря хорошим результатам нейронной сети. Математическая модель Вуда и Берри была выбрана в качестве основного объекта управления.*

Ключевые слова: *ректификационная колонна, нейронная сеть, ПИД-регуляторы, искусственный интеллект, система MIMO.*

Introduction

The crude oil refining industry has a huge effect oneveryone’s life. Numerous products can be produced using raw petroleum since it is a soup of various sorts of hydrocarbon molecules, each of which has its own set of unique chemical and physical properties. Furthermore, these attributes make every particular hydrocarbon in crude oil either a good fuel, a useful fluid or solid. This work will consider methods for controlling the fractional distillation column for producing crude oil products. The objective of the work is to control the process of separating methanol from water in the distillation column using a Neural Network based PID controller in the atmospheric distillation column to send it to the storage tank properly. Artificial neural networks have been used in a variety of applications by several manufacturers for fault detection, control management and pattern recognition. The most significant advantage of ANN is learning from historical data and being utilized for many industrial applications. Furthermore, compared to conventional PID control algorithms, neural-based PID improves the system's real-time characteristics and complexity. [1] In turn, Mostafa MJAHED [2] shows good performance and benefits from decreased values of rising time, overshootingand settling times and lesser oscillatory response using the Genetic Algorithm. Compared to traditional tuning methods, Genetic Algorithms outperformed them in terms of steady-state response and output performances. Compared to the research above, in [3] the presented neural PID model, the PID coefficients are considered Gaussian potential function networks (GPFN) weights. Furthermore, they are fine-tuned using an online learning algorithm. So, the presented model outperforms the basic PID controller with fixed gains in terms of capability and flexibility. The PID neural network performs admirably in terms of position control and behavior [4]. Genetic algorithm with particle swarm optimization results demonstrates that the settling time, overshoot percentage, rise time are better than conventional PID controllers [5]. Ibtissem Chiha, Noureddine Liouane, and Pierre Borne propose Multiobjective ant colony optimization to tune PID controllers. The results show that the proposed tuning technique outperforms the genetic algorithms and traditional approach and control system performance [6]. Another concept of artificial neural networks (ANN) was proposed to establish new setpoints after system disturbances and proved to have a much better speed and feasible solution [7].

The presented new model improves the performance of the traditional controller; this new control approach is conceptually simple and can be easily implemented in oil and other industries. Furthermore, additional energy costs and costs associated with product specifications can be avoided. In work [8], Muravyova and Mustaev, 2017 solved a problem associated with the large error in the amount of cement at the outlet relative to a given capacity, as well as to increase the speed of the control system and increase its fault tolerance by using an artificial neural network in the Matlab environment. M.M. Gouda, S. Danaher, C. P. in the research [9] designed a more robust and efficient fuzzy logic controller. Itdecreases the sensitiveness of the systemand improvesfast changes of theparameters, and has lower energy consumption. The research paper [10] represents that the performance of PID with the Ziegler - Nichols method is better than the conventional Ziegler-Nichols technique. Experiments show minimum overshoot, settling time for rate demand utilities of DC motor. Different types of artificial intelligence were compared; among them, Neural Network was chosen as the main controller for our distillation column.

Problem statement

Many industries use Proportional-Integral-Derivative (PID) controllers to maintain and regulate process variables. In in industrial process loops, PID is the most common feedback control systems. They are simple to comprehend and put into practice. Many scientists have spent time studying, refining, and improving the PID controlling methods, as well as designing workarounds for the flaws they've discovered.

However, there are a variety of common control issues that PID can't solve, some of which can be solved with appropriate augmentations. Due to the aggressiveness of control processes, a conventional PID controller would have issues regulating them. Also, advanced control is necessary for MIMO systems, where the controller must coordinate the initiatives of several actuators to manipulateseveral control variables simultaneously.

For example, the distillation column, as it is a MIMO system, requires advanced control. Moreover, they can face quite bad performances like overshooting, steady-state error, response time increase, etc. Those problems can lead to hazardous situations and loss of money. Due to this, new methods of process control are being developed. In this research, a new method of improving PID control is presented.

Relevance of the project

Proportional-integral-derivative (PID) controllers are commonly used to regulate the process variables of many different types of dynamic systems. Due to itssimple structure and ability to provide an excellent closed-loop response characteristic, these controllers are significant in control process. Nonetheless, selecting a suitable PID controller might be challenging. Various methods for tuning controllers have been developed in response to this issue. The Ziegler-Nichols method is the most frequently used tuning technique, but sometimes it can be difficult to establish optimal controller coefficients. As a result, many artificial intelligence algorithms, such as neural network (ANN), fuzzy logic, swarm, ant colony optimizations and others, have been created to tune PID parameters.

The main drawbacks of the PID controller include the complexity of controlling the three parameters and the fact that it does not work well for systems with time-varying, nonlinear systems, linear systems with a time delay and complex systems. AI-based controllers have more benefits than traditional PID controllers, such as independence, better reliability, lower load, smarter control loops, higher speedand adaptability in the enterprise, regardless of human intervention.

Atmospheric Distillation Column

An atmospheric distillation column with a tray contacting device is mainly used to separate the crude oil components into its fractions: valuable products like gasoline, LPG, kerosene, Diesel fuel, naphtha, and heavy gas oil. Tray or plates enable good separation of the fractions of crude oil. The working principle of ADU is fractional distillation or distillation on boiling ranges. An atmospheric distillation column is demonstrated in figure 1.

Trays located inside the ADU collect various fractions as they cool to their boiling value and vaporize. Forthe oil to be vaporized at the bottom of the column, the reboiler heats the crude oil to 350 ° C. Using a condenser, each fraction of crude oil is cooled and condensed at various temperature values at the top of the column.

As each fraction of condensation, the liquid is collected in the trays of the column. Higher boiling fractions condense on the column's lower trays, and lowersteaming point fractions condense on the higher trays. A reflux drum is used to keep the condensed vapor, resulting in which reflux can be sent back from the top of the distillation column. One input stream and two product streams make up the distillation column.

Mathematical model

There was chosen a mathematical model of distillation column created by Wood and Berry. They established a mathematical model of an 8-tray binary fractional distillation column with a complete condenser and a basket-style reboiler for disunion of methanol from water.

The model has been frequently utilized in recent decades in severalresearchesto evaluate the efficacy of various control methods since it has been proven useful. Equations (1) and (2) were used to express it when it was discovered experimentally:

$$\begin{bmatrix} x_D(s) \\ x_B(s) \end{bmatrix} = G(s)\begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} x_D(s) \\ x_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8}{16.7s+1}e^{-s} & \frac{-18.9}{21s+1}e^{-3s} \\ \frac{6.6}{10.9s+1}e^{-7s} & \frac{-19.4}{14.4s+1}e^{-3s} \end{bmatrix}\begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \quad (2)$$

Here, outputs (controlled variables) are:

$x_D(s)$ – methanol proportion in the distillate,

$x_B(s)$ – the amount of methanol of lowerproducts;

Inputs (manipulated variables) are:

$R(s)$ – reflux flow speed,

$S(s)$ – flow speed of steam in the reboiler. The P&ID diagram of the distillation column for this process is illustrated in Fig. 1. P&ID diagram was developed in the online "Visual Paradigm" tool.

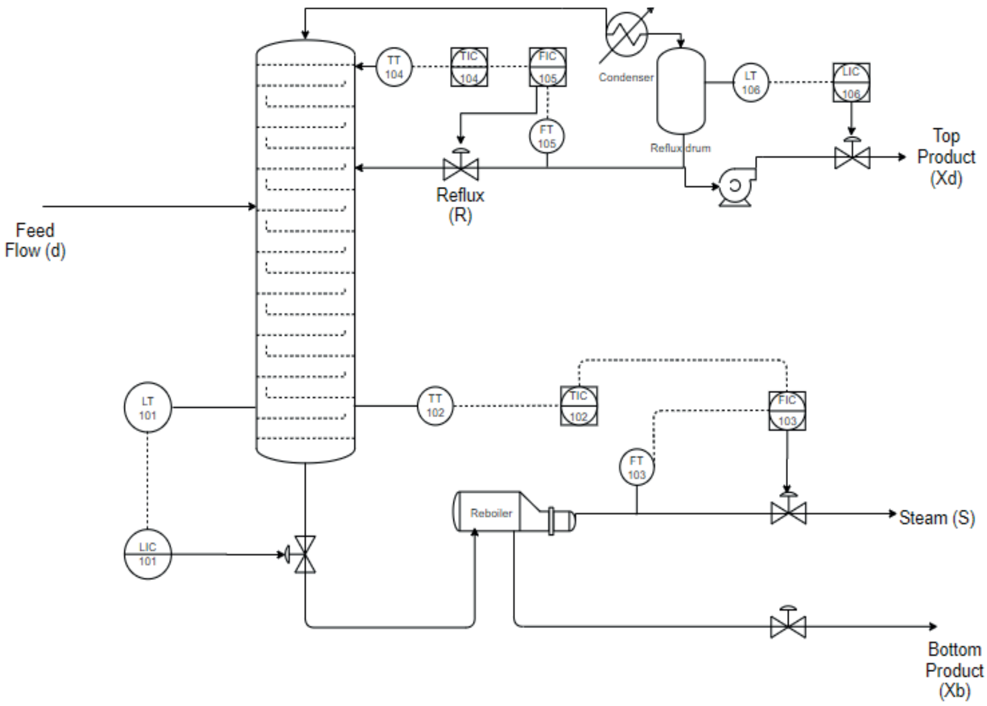

Figure 1 – P&ID diagram of fractional distillation column

The control structure of the distillation column

The steam and reflux flow rates regulate the top and bottom product concentrations, while the feed flow rate acts as a disturbance. A distillation column must have at least four feedback control loops to monitor and control distillate concentration, bottom concentration, reboiler level, and reflux rate level. As a result, it's classified as a MIMO control system. This paper proposes a controller for controlling distillate and bottom concentrations. MIMO control can be accomplished by using two controllers, one for each component (two outputs). Figure 2 shows a block scheme of a PID controller-based MIMO system for a distillation column.

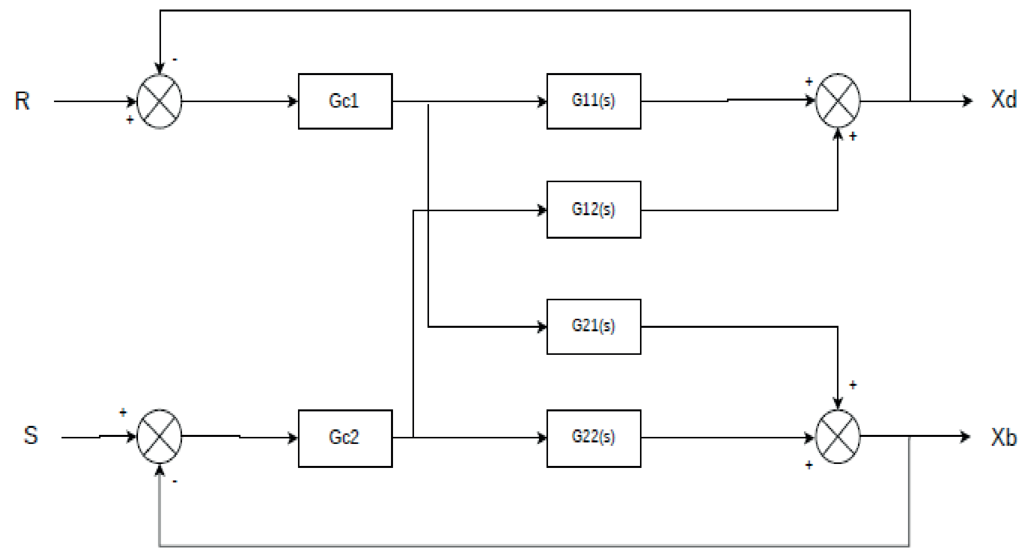

Figure 2– PID controller-based MIMO controller

Here:

$G_{c1}(s), G_{c2}\ (s)$ – PID Controllers,

$G_{11}(s)G_{12}(s)G_{21}\ (s)G_{22}\ (s)$ – transfer functions of control objects.

Due to multiple variables, the control structure of the MIMO system reqresdecoupler elements. The block diagram of the control system with decoupler is illustrated in Fig. 3. Decouplers helps to remove process interactions to turn the MIMO system into interacting, allowing for smooth tuning of control loops.

Equation (3) shows decoupler elements $D_{12}(s)$ an $D_{21}(s)$:

$$D_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)} \tag{3}$$

$$D_{21}(s) = -\frac{G_{21}(s)}{G_{22}(s)}$$

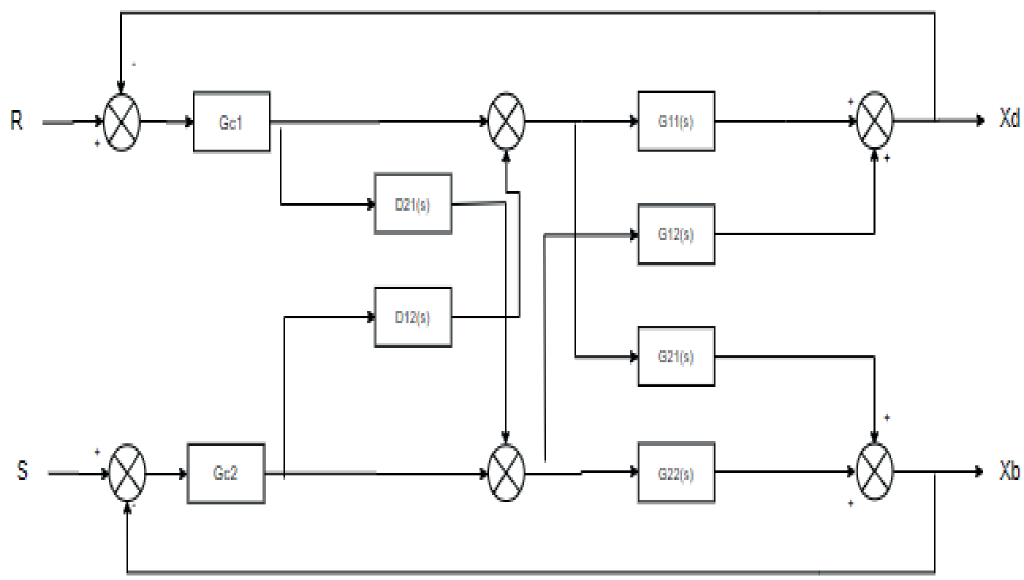

Figure 3– MIMO with simplified decoupling method

The diagonal elements Q(s) of the product G(s)D(s) as a diagonal matrix are the independent SISO systems that should be found.

Simplified decoupling is presented in Equations 4 and 5:

$$D(s) = \begin{bmatrix} 1 & D_{12}(s) \\ D_{21}(s) & 1 \end{bmatrix} = \begin{bmatrix} 1 & -\frac{G_{12}(s)}{G_{11}(s)} \\ -\frac{G_{21}(s)}{G_{22}(s)} & 1 \end{bmatrix} \quad (4)$$

$$Q=\begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix} \begin{bmatrix} 1 & D_{12}(s) \\ D_{21}(s) & 1 \end{bmatrix} = \begin{bmatrix} G_{11} - \frac{G_{12}G_{21}}{G_{22}} & 0 \\ 0 & G_{22} - \frac{G_{12}G_{21}}{G_{11}} \end{bmatrix} \quad (5)$$

The controller design is shown in Equation 6:

$$K(s) = \begin{bmatrix} K_1(s) & 0 \\ 0 & K_2(s) \end{bmatrix} = \begin{bmatrix} K_{p1} + \frac{K_{i1}}{s} + K_{d1}s & 0 \\ 0 & K_{p2} + \frac{K_{i2}}{s} + K_{d2}s \end{bmatrix} \quad (6)$$

In such a way, the block diagram ofthe MIMO system shown in figure 3 can be simplified to two independent SISO systemsillustrated in figure 4.

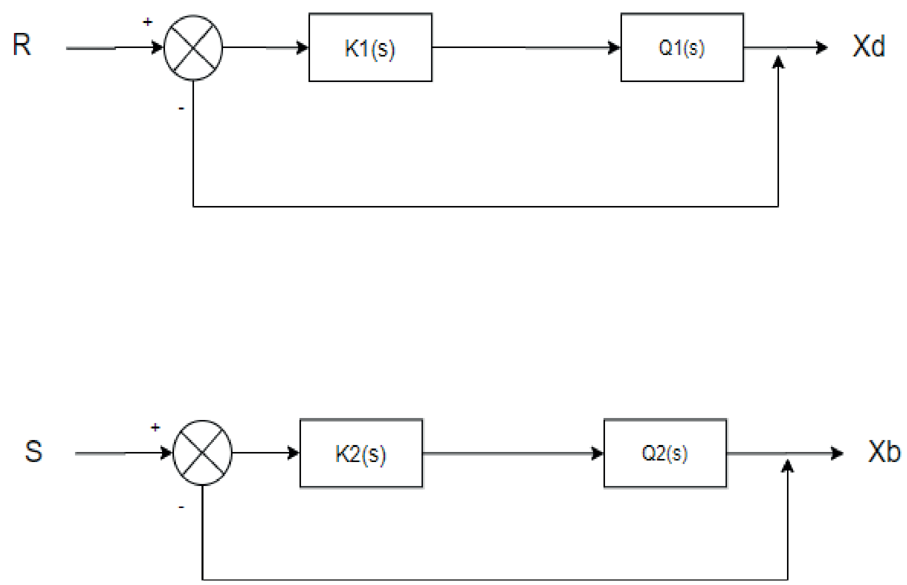

Figure 4 – Independent SISO systems

So, the obtained Diagonal matrix (Q_1 and Q_2) of the system are shown in Equations 7, 8:

$$Q_1 = \frac{1.896 * 10^4 * s^3 + 4042 * s^2 + 291.5 * s + 6.37}{2.676 * 10^4 * s^5 + 3.591 * 10^4 * s^4 + 1.026 * 10^4 * s^3 + 1157 * s^2 + 56.6 * s + 1} \quad (7)$$

$$Q_2 = \frac{-3.294 * 10^4 s^3 - 6758 s^2 - 461.2 s - 9.655}{8.9 * 10^4 s^5 + 5.814 * 10^4 s^4 + 1.281 * 10^4 s^3 + 1271 s^2 + 58.3 s + 1} \quad (8)$$

Stability verification

The step response is the system's response to a unit step input; it helps analyze the system's stability and find characteristics such as overshoot, the steady-state error, and other dynamic characteristics of the system.

The step response for the first closed-loop system is illustrated in fig. 5 below.

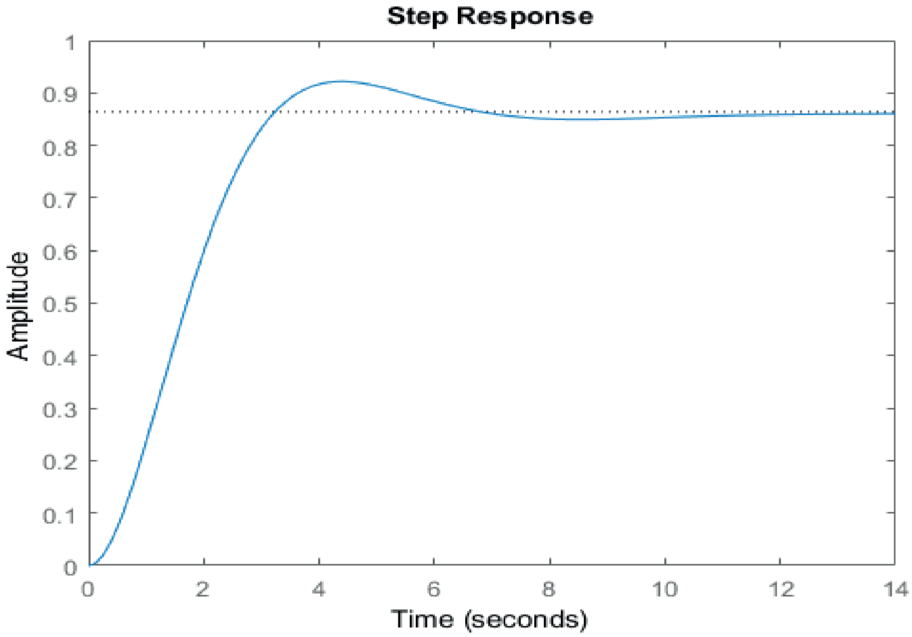

Figure 5 – The step response of the 1st system

Figure 5 illustrates thatthe system is underdamped and has overshoots and oscillations. Using the *step info( )*command, it was found that the overshoot of the system was equal to M_p=6.64%, settling time t_s is 6.0801 seconds and rise time t_r is 2.1397 seconds. The steady-state error e_{ss}Was equal to 0.139. So, using PID controllers with an Artificial Neural Network algorithm, it is expected that the error will be eliminated, and the output response will be improved.

The step response for the second closed-loop system is illustrated in Figure 6 below.

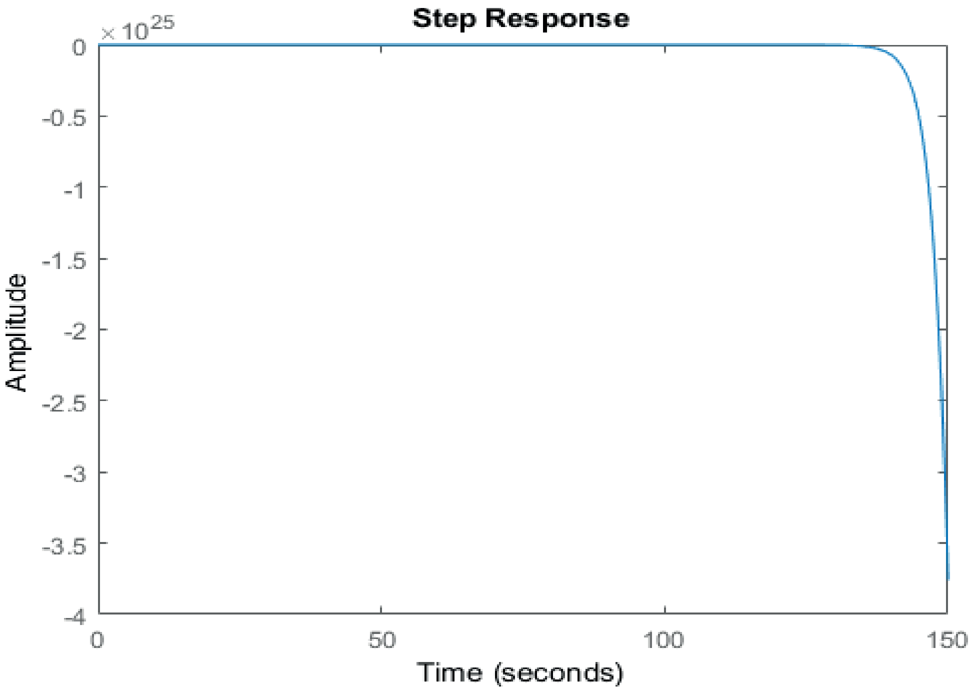

Figure 6 – The step response of the 2nd system

Figure 6 illustrates that the system is not stable. The results show that the system doesn't have any overshoots (%M_p), settling time (t_s), rise time (t_r) or any other characteristics. The steady-state error e_{ss}Was equal to 8.7242e^24. So, using PID controllers with an Artificial Intelligence algorithm, it is expected that the output response will be improved.

Artificial Neural Network

The purpose of an artificial neural network(ANN) is to use the target data to construct a system that accurately corresponds the input values to the output. The obtained model is used to get the intended output when the desiredoutputis unrevealed. Neuralnetwork-based PID controllers aims to eliminate computing complexity and improve real-time performance comparing to a traditional PID controller. A control structure of ANN-basedPID controller is represented in fig. 7.

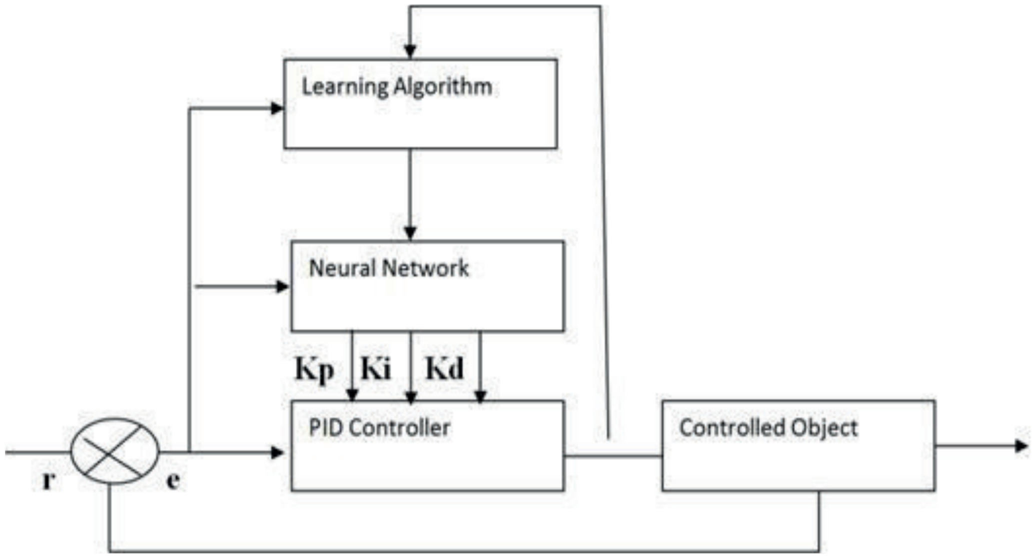

Figure 7 – Structure of PID controller based on neural network

Fig. 7 shows that the controller is made up of two parts: traditional PID control and a neural network. Here the conventional PID affects the control object directly. The PID controller's parameters are tuned using a neural network, which compares the target values with the input values to achieve performance optimization. Output neurons must match the parameters of PID.

Training neural network

To train a neural network, I used PID parameters obtained using a Genetic Algorithm and used them as target values. To get target values, a scheme was constructed where the output response of the closed-loopwas exported to the Workspace using simout1. For the input valuesof the NN, there were extracted output response values of the closed-loop without any PID controller.

There were used *“nnstart”* neural network fitting app for this article. A sigmoid like transfer function of a two-layer feedforward network is used for a hidden layer of our network in Matlab software. The output layer is based on the linear transfer function (TF). Thenetwork will be trained with the Levenberg-Marquardt backpropagation algorithm. The structure of the neural network, which has input, hidden, and output layers,as shown in figure 8.

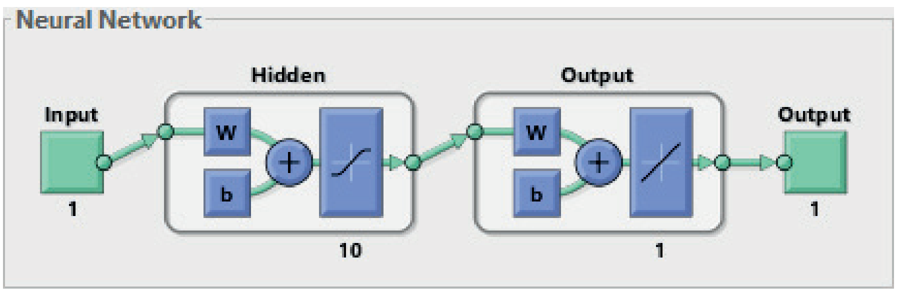

Figure 8 – Neural network structure

10 neurons were selected for a hidden layer of neural network architecture and one neuron both for input, output layers as in the picture above.

The training results of ANN for the first (on the left side) and second (on the right side) closed-loop systems is illustrated in figure 9.

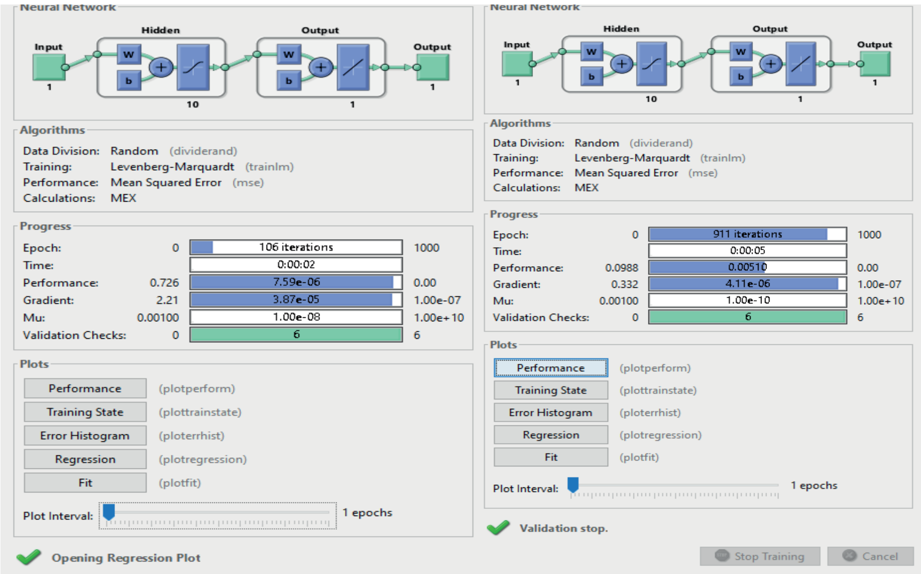

Figure 9 – Neural network training results (First loop)

Overall, the training performance for the first system was slightly good compared to the second loop. The first loop was trained at 106 Epochs and the second at 911 Epochs, which is very long.

Finally, to check the output response of two independent closed-loopsystems, a block diagram of the PID controller feedback system was constructed with an Artificial Neural Network, shown in figure 10.

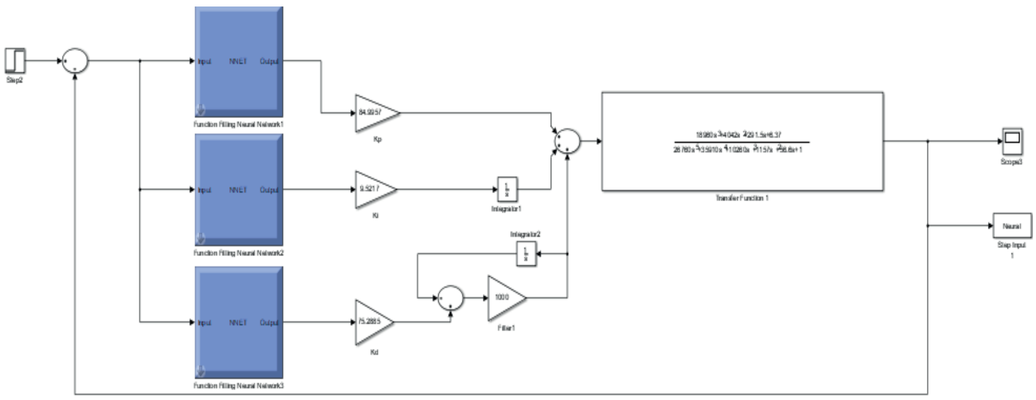

Figure 10 – Neural network-based PID controller

The results of the first feedback system are illustrated in figure 11.

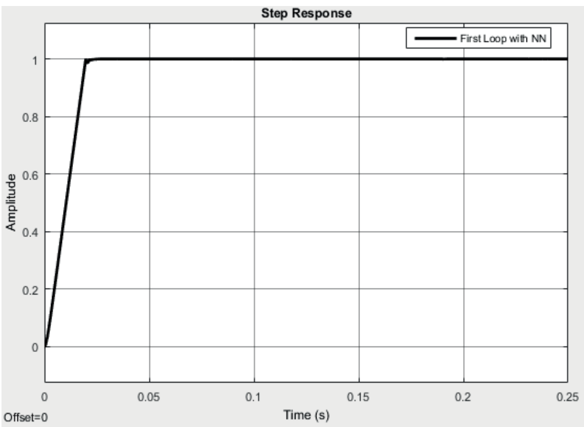

Figure 11 – Step response of 1st loop with NN based PID

Figure 11 shows that the output response of the first loop using NN based PID controller was improved. It was found that the overshoot of the system was equal to M_p=0.0397%, settling time t_s is 0.0194 seconds and rise time t_r is 0.0150 seconds. So, by using PID controllers with the Artificial Neural Network algorithm, there was obtained better results.

The step response for the second closed-loop system with NN PID is illustrated in Figure 12.

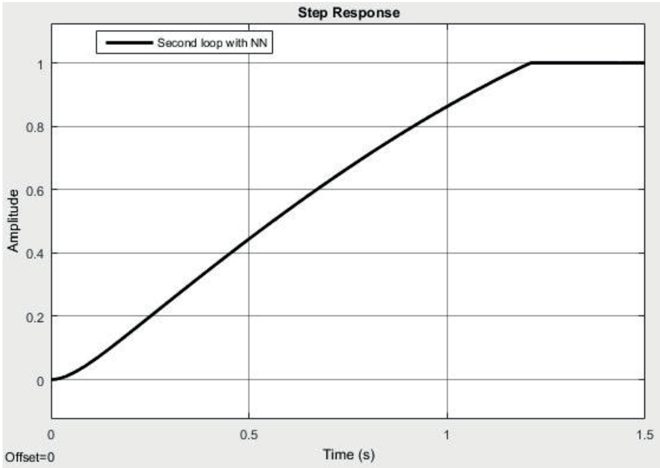

Figure 12 – The step response of the 2nd system

The results show that the system hasan overshoot equal to M_p=0.0397%, settling time t_s=1.1777, rise time t_r – 0.9038. So, NN based PID controller helped to make the system stable and improve overall performance.

Conclusion

In this article, the techniques of improving traditional PID controllers in crude oil refineries are considered. To sum up, there was studied the usage of artificial intelligence in different fields. As seen from the research done, the artificial intelligence-based PID controllers are one of the optimal algorithms that can be used for controlling the object and whole system. The artificial neural network helps to predict future plant behaviors.

Neural networks are widely applied to solve technical problems. Based on my research, it was discovered that the majority of researchers use ANN for modeling and designing linear and nonlinear systems for industrial control systems.

Moreover, training a Neural network-basedPID controller feedback system to control the process of separating methanol from water in a distillation column in a crude oil refinery showed good performances compared to the system without the AI network. It was proven that by using a neural network, the system response improved overshoots eliminated, rise time and settling times decreased. Applying the NN based PID controllers and replacing the conventional PID controllers reduced the error between desired values and system output.

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Information about author

Ismagulova Dana Maksutkyzy
Master, Associate Automation and Control Engineer, JSC "Wood KSS",
st. Kanysh Satbaev, 46, 060011, Atyrau, Kazakhstan;
ORCID ID: 0000-0002-3423-9701;
E-mail: danaismagulova7@gmail.com.

Автор туралы мәлімет

Исмагулова Дана Мақсұтқызы
Магистр, автоматтандыру және басқарма кіші инженері, «Wood KSS» АҚ,
Қаныш Сәтбаев көшесі, 46, 060011, Атырау қ., Қазақстан;
ORCID ID: 0000-0002-3423-9701;
E-mail: danaismagulova7@gmail.com.

Сведения об авторе

Исмагулова Дана Максуткызы
Магистр, младший инженер по автоматизации и управлению, АО «Wood KSS»,
ул. Каныша Сатпаева, 46, 060011, г. Атырау, Казахстан;
ORCID ID: 0000-0002-3423-9701;
E-mail: danaismagulova7@gmail.com.