Mathematical Modeling and Advanced Control of the Distillation Column: A Review

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Abstract

The oil industry has a direct impact on the economic feasibility of other sectors and is considered to be the most important energy source used to turn the wheels of other industries. Therefore, it was necessary to pay attention and continuously develop this industry, to find the best modern techniques for designing, pre-commissioning and controlling process, to improve efficiency, preserve energy and achieve the highest production of costly components with the highest purity of the product. This study aims to provide a literary analysis of the stages of development and progress of the dynamics and control of the petroleum industry, in particular the distillation column, because it is multivariable with high interaction between control cycles, nonlinear behaviour and large gains. Control processes have undergone many developments and modernizations to achieve the best results. Various control methods have been used, ranging from simple proportional-integral-derivative controller (PID) to advanced control strategies such as model predictive control (MPC), multivariate model predictive control (MMPC), fuzzy logic control (FLC), quadratic dynamic matrix control (QDMC), artificial neural network control (ANN) and other advanced control techniques. The authors concluded from the review that the advanced control strategies superior than the conventional methods.

Keywords: Modeling and advanced control, Distillation column, Model Predictive Control, Fuzzy logic control, Artificial Neural Network.

النمذجة الرياضية والتحكم المتقدم في عمليات التصفية: مراجعة

ليث صادق محمود ، خالد مخلف موسى ، سلام كاظم الدواري

الخلاصة:

ان صناعة النفط لها تأثير مباشر على الجدوى الاقتصادية للقطاعات الأخرى، وتعتبر أهم مصدر للطاقة يستخدم لتحريك عجلات الصناعات الأخرى، لذلك كان من الضروري الاهتمام بهذه الصناعة وتطويرها بشكل مستمر ، لإيجاد أفضل التقنيات الحديثة لتصميم وتشغيل والتحكم فيها، لتحسين الكفاءة والحفاظ على الطاقة وتحقيق أعلى إنتاج للمكونات الثمينه بأعلى نقاء للمنتج. تهدف هذه الدراسة إلى تقديم تحليل أدبي لمراحل تطور وتقدم ديناميكيات التحكم في صناعة البترول، وخاصة عمود التقطير ، لأنه متعدد المتغيرات مع تفاعل عالٍ بين دورات التحكم والسلوك غير الخطي والمكاسب الكبيرة. لقد خضعت عمليات التحكم للعديد من التطورات والتحديثات لتحقيق أفضل النتائج. تم استخدام طرق تحكم مختلفة، تتراوح من وحدة التحكم التفاضلية التكاملية المتناسبة البسيطة (PID) إلى استراتيجيات التحكم المتقدمة مثل التحكم التنبئي بالنموذج (MPC)، والتحكم التنبئي بالنموذج المتعدد المتغيرات (MMPC)، والتحكم المنطقي الضبابي (FLC)، والتحكم في المصفوفة الديناميكية التربيعية (QDMC)، والتحكم في الشبكة العصبية الاصطناعية (ANN) وغيرها من تقنيات التحكم المتقدمة. استنتج المؤلفون من هذه المراجعة أن استراتيجيات السيطره المتقدمة متفوقة على الطرق التقليدية.

1. Introduction

The development of industries at the present time has led to the consumption of large amounts of energy. This has led to a significant increase in energy consumption, especially that produced from oil and gas, so there must be development and monitoring processes for optimal energy consumption [1], [2].

Crude oil generally consists of thousands of hydrocarbon and non-hydrocarbon compounds that vary from low molecular weight to compounds with very high molecular weight, with different proportions of paraffinic, naphthenic, and aromatic compounds. The properties of crude oil depend on the oil well and the location at which the oil to be extracted, which makes the stability of the operation of crude oil units and achieving the specifications of the products difficult [3].

One of the most crucial procedures in the chemical process industries is the crude distillation unit (CDU). The percentage of separation using a distillation column in the chemical industry worldwide is estimated at 95% [4], [5] and [6]. The crude oil initially must pass through the crude distillation unit (CDU) before going into the upgrading and developing units. In that unit, the crude oil submits to physical fractionation to get many hydrocarbon components like light and heavy naphtha, kerosene, light gas oil, heavy gas oil and atmospheric residue [7]. After passing through several processing stages to turn these products into more valuable products. The products go to the blending or pooling stage, where components are combined to create the final products. Each cut must have some important quality requirements like the aromatic and total sulfur content, viscosity index (VI), red vapor pressure, octane number, cetane number, etc. [8], [9].

The distillation column consists of a vertical column with trays used to increase the contact area to improve component separations, a reboiler to supply heat for the necessary vaporization from the bottom of the column, a condenser to cool and condense the vapor from the top and a reflux drum to collect the condensed vapor so that reflux liquid can be recycled back from the column. A collection equipment used for mass transfer or heat transfer [10], [4], [11] and [12]. The process of distillation of crude oil is considered as a complex and integrated process, which represents a major challenge in its work. Therefore, control and simulation processes have become important to study the behavior of this type of important process due to the presence of complex dynamic interactions between the inputs and outputs of the process [5], [13]

The system used in the process of controlling the distillation tower is known as the multiple input and output (MIMO) systems. These systems are considered more complex and difficult than systems with a single input and output (SISO) due to interactions that occur among the variable inputs and variable outputs [14]. Different approaches are taken to study the control of the distillation columns. The impact of interactions between the control loops, the effect of disturbances, the rejection of disturbances, the process performance, and the decupling [15], [16], [17] and [18].

A simulation and experimental study of the control dynamics of a binary distillation column with a side stream was carried out. Three compositions were studied: an upper composition, a lower composition and a side composition. It was noted that the change in the flow rate of the side stream was ineffective in adjusting this stream by changing the location of the withdrawal tray for the side stream. It gives great control over the composition of the side stream flow rate. In addition, closed-loop control of the upper, side and lower compositions has been achieved in simulation and experimental studies [19].

The control of a multivariable distillation column containing an upper product, lower product, and side product was studied. Multivariable controllers with multiple time delays were used, combined with traditional single-loop PI controllers. It was observed that the performance of this method is better than the traditional single-loop PI controller, especially in the process of rejecting disturbance [20], [21].

Alatiqi and Luyben 1986 compared a ternary mixture distillation process containing a small percentage of the intermediate distillate (less than 20%) by using a multivariable, complex and interacting side stream column/stripper distillation configuration (SSS) Fig.1 was explored via digital simulation, it was compared quantitatively with the conventional sequential (light-out-first) two column configurations (LOF) Fig.2. They found possible to control a complex (SSS) configuration using four conventional SISO controllers, and the dynamic response using the complex SSS system is better than the traditional (LOF) system. The SSS configuration was controlled using four conventional PI controllers. The SSS system's load response was on equal with, if not better to, that of the traditional (LOF) system [22].

The transfer function matrix for (SSS) [22] is

$$\begin{bmatrix} X_{D1} \\ X_{B3} \\ X_{S2} \\ \Delta T \end{bmatrix} = \begin{bmatrix} \frac{4.09\,e^{-1.3s}}{(33s+1)(8.3s+1)} & \frac{-6.36\,e^{-1.2s}}{(31.6s+1)(20s+1)} & \frac{-0.25\,e^{-1.4s}}{21s+1} & \frac{-0.49\,e^{-6s}}{(22s+1)^2} \\ \frac{-4.17\,e^{-4s}}{45s+1} & \frac{6.93\,e^{-1.02s}}{44.6s+1} & \frac{-0.05\,e^{-6s}}{(34.5s+1)^2} & \frac{1.53\,e^{-3.8s}}{48s+1} \\ \frac{1.73\,e^{-18s}}{(13s+1)^2} & \frac{5.11\,e^{-12s}}{(13.3s+1)^2} & \frac{4.61\,e^{-1.01s}}{18.5s+1} & \frac{-5.49\,e^{-1.5s}}{15s+1} \\ \frac{-11.18\,e^{-2.6s}}{(43s+1)(6.5s+1)} & \frac{14.04(10s+1)\,e^{-0.02s}}{(45s+1)(17.4s^2+3s+1)} & \frac{0.1\,e^{-0.05s}}{(31.6s+1)(5s+1)} & \frac{4.49\,e^{-0.6s}}{(48s+1)(6.3s+1)} \end{bmatrix} \begin{bmatrix} R \\ Q_B \\ Q_{BS} \\ Ls \end{bmatrix} \quad \ldots(1)$$

And for (LOF) [22] is:

$$\begin{array}{c} X_{D1} \\ X_{D2} \\ X_{B2} \end{array} = \begin{bmatrix} \frac{2.7\,e^{-105s}}{42s+1} & 0 & 0 \\ \frac{9.0\,e^{-23s}}{(33s+1)^2} & \frac{2.05\,e^{-3s}}{(38s+1)(25s+1)} & \frac{-0.79\,e^{-1.1s}}{(36s^2+8.4s+1)} \\ \frac{-1.2\,e^{-3.8s}}{(19s+1)^2} & \frac{-0.03\,e^{-4s}}{(9.5s+1)^2} & \frac{0.33\,e^{-s}}{(3.8s+1)^2} \end{bmatrix} \begin{array}{c} R_1 \\ RR_2 \\ Q_{B2} \end{array} \qquad \ldots(2)$$

These columns are complex, multi-variable, interactive, and non-linear, so a new successfully control scheme was developed by Han and Park (1993), to solve problems of a non-linear and multi-variable nature using a nonlinear wave model as a generic model control. Dynamic simulation experiments to control these two systems show that the proposed control scheme can successfully improve the distillation components [23], [24].

Relative gain array (RGA) and multivariate Nyquist-Bode schemes were used to adjust the preferred structures according to the specified load rejection criterion and the specified robustness for developed multivariable systems using (SISO) type controllers, which includes designing control loops using dynamic and steady state models of the transfer function type. The best frequency response scheme is chosen as a result of the resulting disturbances in the load system [25], [26] and [27].

The transfer function matrix for Alatiqi (RR) scheme [25] is

$$\begin{bmatrix} X_{D1} \\ X_{B3} \\ X_{S2} \\ \Delta T \end{bmatrix} = \begin{bmatrix} \frac{2.22\,e^{-2.22s}}{(36s+1)(25s+1)} & \frac{-2.94(7.9s+1)e^{-1.05s}}{(23.7s+1)^2(25s^2+2s+1)} & \frac{0.17\,e^{-1.2s}}{(31.6s+1)(7s+1)} & \frac{-0.64\,e^{-20s}}{(29s+1)^2} \\ \frac{-2.33\,e^{-6s}}{(35s+1)^2} & \frac{3.46\,e^{-1.01s}}{32s+1} & \frac{-0.51\,e^{-8.5s}}{(32s+1)^2} & \frac{1.68\,e^{-3s}}{(28s+1)^2} \\ \frac{1.12\,e^{-23s}}{(17s+1)^2} & \frac{3.54\,e^{-14s}}{(12s+1)^2} & \frac{4.41\,e^{-1.01s}}{16.2s+1} & \frac{-5.38\,e^{-1.5s}}{17s+1} \\ \frac{-5.73\,e^{-2.5s}}{(8s+1)(50s+1)} & \frac{4.32(25s+1)e^{-0.2s}}{(50s+1)(20.2s^2+2.6s+1)} & \frac{1.25\,e^{-2.85s}}{(43.6s+1)(9s+1)} & \frac{4.78\,e^{-0.15s}}{(48s+1)(5s+1)} \end{bmatrix} \begin{bmatrix} RR \\ Q_B \\ Q_{BS} \\ Ls \end{bmatrix} \qquad \ldots(3)$$

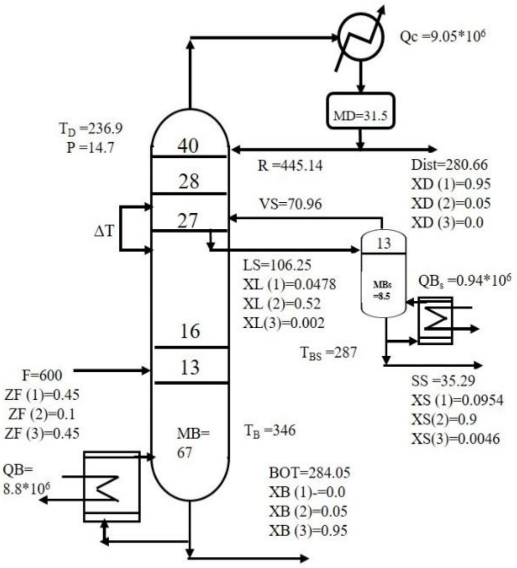


Figure (1): The basic design for SSS system.

A performance comparison was made for the modern control techniques used to control distillation towers, including conventional control (PI) techniques, nonlinear Process Model Based Control (PMBC) and Artificial Neural Networks (ANN). The results were presented for two cases of disturbance rejection and set point changes for a C_3 splitter column. It was noted that the (PI) control was similar to the performance of the (PMBC) control with an exception in the feed composition, and also the (PMBC) control is equivalent to the (ANN) control [28].

A smart and advanced sensor was proposed to predict the quality of crude oil distillation tower products. This approach relies on a new real-time modeling technology, namely, the use of eXtended Evolving Fuzzy Takagi-Sugeno Models (exTS) for real-time monitoring and prediction of certain refinery distillation process parameters, which has proven its efficiency in predicting real-time analysis of crude oil distillation quality parameters and its high robustness in using a small number of fuzzy rules to interpret the complex dynamics of product specifications [29].

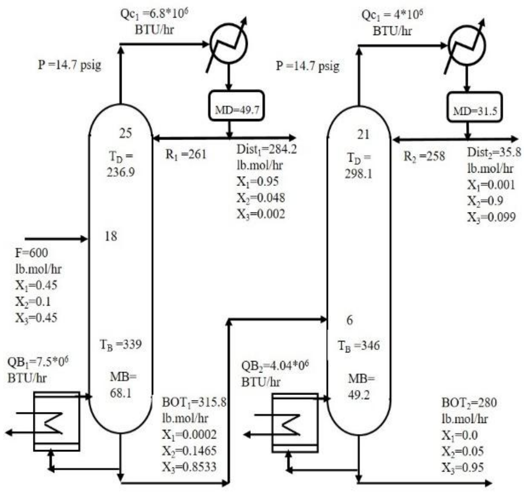


Figure (2): Basic design for LOF system.

The controlling the distillation column is one of the important matters to reduce energy consumption and increase the efficiency of the separation process, so, a methodology called adaptive predictive expert (ADEX) control was proposed and the results were compared with traditional controller (PID) used in oil refineries. This is done through careful control of the main towers variables, increasing their stability and eliminating the interaction between variables to reduce the problem of resonance that occurs in distillation towers when using a controller (PID) Fig.3 [30].

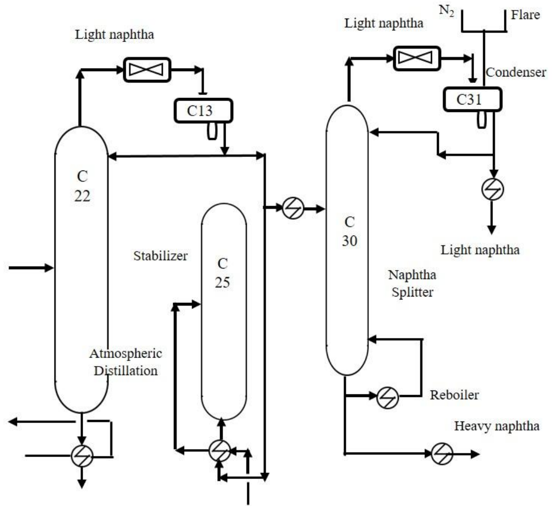


Figure (3): Process description of the naphtha splitter.

A predictive control strategy was proposed to solve the problem of non-linear control of the multivariable estimation column (4*4). A model predictive control (MPC) was used to give better results than traditional control. This strategy was applied to the (Alatiqi and Luyben 4x4 process) and (Doukas and Luyben 4x4 process) and gave good results and different from other traditional methods [31], [32].

Based on the energy balance structure (L-V), a computational model is presented to model the distillation and control tower. The reflux rate (L) and the boiling rate (V) were used as inputs to control the purity of the upper distillate(X_D) and the impurities present in the lower product (X_B) as outputs of the process Fig.4. Modeling and machining were completed in three stages: the basic nonlinear model of the plant, the full-order model, and the reduced-order linear model. The reduced-order linear model used a reference model for a model-reference adaptive control (MRAC). The process outputs to track reference control points to ensure the purity and quality of the product and the presence of disturbances occurring in the process feed [33].

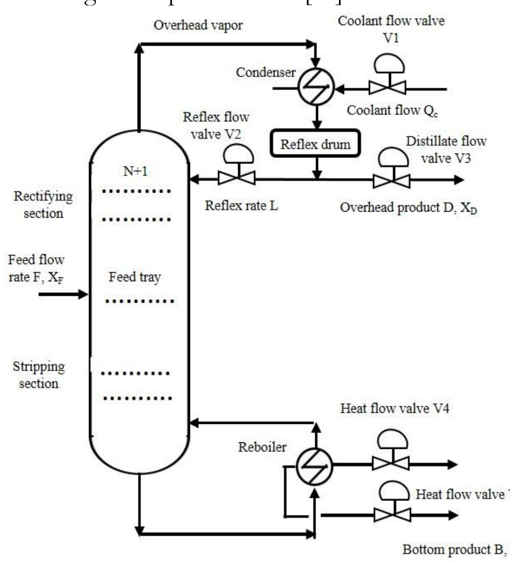


Figure (4): Distillation flow sheet.

An improvement in the performance of the model predictive control (PMC) using a quadratic program (QP) was studied. The purpose is to control and economically improve the system. It was applied to a distillation system and showed effective results. What distinguishes the proposed approach is that the predictive control problem can be solved using the available (QP) tools [34], [35].

The control system based on the non-linear model (NMPC) used to control distillation columns is considered one of the best options used for control. The system (NMPC) was developed using a non-linear autoregressive model with external inputs (NARX) and the Unscented Kalman Filter (UKF) was used to estimate the state variables in (NMPC). The sequential quadratic programming method (SQP) was used to solve the non-linear programming problem (NLP). The results showed that the performance of (NARX NMPC) in closed loop control was good in tracking the set point and rejecting disturbances [36].

Khalid M. Mousa, Samer A. Kasim (2010) used two control systems, decoupling and fuzzy logic control, after the failure of conventional control. The control of the side stream distillation column was studied, and the controlled variables were the composition of the distillate (X_D) and the composition of the side stream (X_S). The manipulated variables were the side stream flow rate (L_S) and the reflux flow rate (R) (the system was modeled by (Alatiqi and Layben). The fuzzy logic control showed a noticeable improvement in the system's response and control, where the decoupling of variables made the system more stable [37].

Sivakmar and others (2010), supposed a solution to the problem of multivariable nonlinearity in the distillation column was proposed by using a fuzzy model predictive control strategy (FMOC) that is used to predict the outputs to control the process, where using a binary distillation column (Wood and Berry) and comparing the results between proposed strategy (FMPC) and conventional control (PID) and show that (FMPC) gives Better performance than (PID) [38].

A distillation process of a binary mixture of methanol and water was studied in a batch distillation column, where a predictive control model (MPC) was designed based on theoretical analysis of dynamic mass balance, liquid and vapor phase balance, and using a state space model. The control strategy of (MPC) is considered very feasible and effective in controlling the batch distillation column. This process gave smooth and accurate results that are much better than the common and traditional control process (PI) [39]. A model predictive controller (MPC) algorithm has been used to improve the performance of distillation column of a crude oil unit [40]. To succeed in applying (MPC) requires not only effective deployment, but also maintaining effectiveness through a support strategy for (MPC) systems through diagnosing performance, monitoring performance, and automatic tuning [41].

The performance of four different state space models for the reactive distillation process to produce ethyl acetate in a typical predictive control system was studied. This was done with the help of (System Identification Toolbox) in the MATLAB program. It was found that the best closed-loop dynamic responses and the fastest time with the least number of oscillations were using the control unit predictive space model (n4sid) with outstanding performance [42].

The laboratory separation column was used to separate methanol from water. The process of controlling the distillation column was done using the concepts of model predictive control and implementing the control unit directly on the laboratory device. The MATLAB Simulink environment was used in implementing the designed control unit (MPC), and to estimate the condition and the operation of disturbances on the distillation column. The simulated scenarios were implemented and verified experimentally on the laboratory device. The results showed that the (MPC) is capable of tracking the required temperature at the head of the distillation tower while rejecting process disturbances [38], [43], [44], [34] and [45].

The supervisory control and data acquisition (SCADA) with a programmable logic control (PLC) was used instead of the traditional distributed control system (DCS) used in oil refineries. The high speed of data transfer in the main control loop using the Multipoint Interface/Decentralized Peripherals (MPI/DP) connection (185) kbps instead of the Ethernet connection (10/100) kbps, increased the data transfer speed through the system and led to avoiding wastage of material resources and the safety of workers [46].

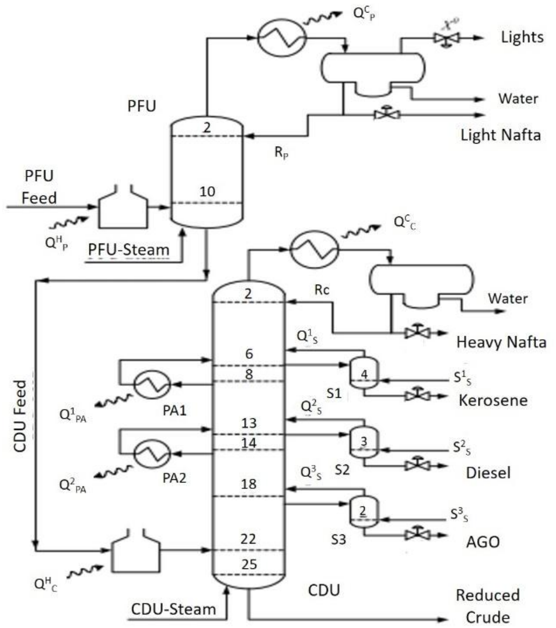
An adaptive predictive (AP) control strategy is designed for the multiple-input and multi-output (MIMO) process Fig.5. The strategy uses control units (AP) to confront the non-linear and time-varying dynamics of the process, as it was defined using classical analysis tools such as the Relative Gain Array (RGA). A simulation of the atmospheric distillation process was performed. The control strategy (AP) was simulated using the control strategy (ADEX) and MATLAB programs, the process was simulated using the Aspen Dynamic model. The proportional gain matrix coupling technique was used to determine the adaptive predictive control strategy. The simulation results were also compared with the PID control strategy, showing an improvement in operating stability [47], [48].

Figure (5): Crude oil distillation plant.

Abdul Wahid and Richi Adi 2016 used a Model Predictive Control (MPC) to develop a multi input multi output (MIMO) due to the interaction of the control loops with each other. The program (UNISIM R390.1) was used to obtain a dynamic model for controlling the distillation column (The transfer function matrix as shown in (4) where X_{ID}, X_{IB}, F_R and F_{UB} are composition of distillate, bottom products, reflux flow rate and boil-up flow rate respectively). The control was implemented by adjusting the information of the control unit (MPC) [1].

$$\begin{bmatrix} X_{ID} \\ X_{IB} \end{bmatrix} = \begin{bmatrix} \frac{0.3405\, e^{-6s}}{36s+1} & \frac{-0.1081\, e^{-5s}}{51s+1} \\ \frac{-0.122\, e^{-13.5s}}{34.52+1} & \frac{0.1555}{13s+1} \end{bmatrix} \begin{bmatrix} F_R \\ F_{BU} \end{bmatrix} \quad \ldots(4)$$

A multivariable model predictive control (MMPC) was proposed to improve the performance of the vacuum distillation unit (VDU) due to the interaction between variables. The results were compared with the conventional control (PI) and the individual model predictive control (MPC). Set point (SP) and disturbance changes are used to test the control performance. It was noted that the control unit (MMPC) is better than other controllers (PI) and (MPC), with a high percentage improvement in performance [10].



Simulation and design of multivariable control systems for the distillation tower by applying multiple forms of control systems for a mixture consisting of benzene toluene using the MATLAB-Simulink program was studied. Four control systems were applied based on the variables of temperature and liquid level at the top and bottom of the tower. A multivariate proportional-integral-derivative (PID) type controller was also used. The Integral absolute error (IAE) criterion was used. The controller performance and the efficiency of these controllers was compared by using several influential functions. The results also showed that the tower was more stable, had a lower value for the Integral absolute error (IAE) criterion, and reached the desired value faster, in the form of a control system for the condenser temperature and liquid level at the bottom and top of the tower [49], [50].

The effect of advanced control systems on ethanol production was studied. An integrated computing platform MATLAB with Aspen HYSYS was developed to simulate the industrial process. Two types of control systems were used: an infinite-horizon model predictive control (IHMPC) and a Filtered Smith Predictor (FSP) controller to ensure the quality of ethanol production under any change in production conditions or feeding disturbances. These systems were evaluated using performance indexes and computational processing time. It was noted that both IHMPC and MIMO FSP controllers succeeded. They gave satisfactory results for rejecting disturbance, tracking the product, and maintaining process stability [51].

The study introduces a new approach to model predictive control (MPC) in the process industry, utilizing an artificial neural network (ANN) model instead of a linearized model. The ANN model was trained and tested on a depropanizer model, resulting in improved performance compared to conventional control methods like PID feedback control. This methodology can be applied to various control systems in the industry, enhancing operational efficiency [52].

In the process of producing dimethyl ether, the researchers showed that the use of model predictive control (MPC) in the production of dimethyl ether is better than traditional control units (PID, PI), because these units (SISO MPC) have high costs that make the production of dimethyl ether uneconomical. Four manipulated variables (condenser duty (MV_1), cooler duty (MV_2), flow rate methanol (MV_3) and Flow rate wastewater (MV_4)) and four controlled variables (condenser vessel temperature (CV_1), output cooler temperature (CV_2), condenser liquid level (CV_3) and Column liquid level (CV_4)) make up the Multivariable Model Predictive Control (MMPC 4x4) controller system that was suggested to reduce the number of controllers and overcome the interaction between the variables that affect the control performance. A matrix (4*4) (Equation 5) was obtained containing 16 first-order plus dead time (FOPDT) model. The values of integral square error (ISE) and integral absolute error (IAE) were used as contrast tools, and it was found that the multivariable model predictive control (MMPC) is better than individual model predictive control (MPC) or traditional control (PID) [53], [54] and [55].

The transfer function matrix [55] is

$$\begin{bmatrix} CV_1(s) \\ CV_2(s) \\ CV_3(s) \\ CV_4(s) \end{bmatrix} = \begin{bmatrix} \frac{-0.2\,e^{-0.68s}}{0.15s+1} & \frac{0.008\,e^{-6.29s}}{2.4s+1} & \frac{-0.001\,e^{-1.17s}}{0.752+1} & \frac{-0.0732\,e^{-0.35s}}{0.15s+1} \\ \frac{-0.012\,e^{-7.41s}}{1.12s+1} & \frac{-0.502\,e^{-0.01s}}{0.33s+1} & \frac{0.003\,e^{-0.05s}}{0.66s+1} & \frac{-0.049\,e^{-1.21s}}{1.32s+1} \\ \frac{0.584\,e^{-0.05s}}{0.03s+1} & \frac{-0.004\,e^{-0.46s}}{0.75s+1} & \frac{(-0.3E-3)\,e^{-0.35s}}{0.75s+1} & \frac{-0.007\,e^{-0.42s}}{1.635s+1} \\ \frac{(0.6E-3\,e^{-0.57s})}{1.32s+1} & \frac{(-0.2E-3)\,e^{-10.01s}}{0.27s+1} & \frac{(-6.7E-5)\,e^{-0.15s}}{0.27s+1} & \frac{-0.32\,e^{-0.02s}}{0.76s+1} \end{bmatrix} \begin{bmatrix} MV_1(s) \\ MV_2(s) \\ MV_3(s) \\ MV_4(s) \end{bmatrix} \quad \ldots(5)$$

A soft sensing model based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Rough Set Theory (RST) were used to replacing physical sensors to improve the control system and maintain the purity of the products. Soft sensors are developed based on historical data on industrial operations from supervisory control and data acquisition (SCADA) associated with the distributed control system (DCS) or programmable logic control system (PLC) system. Moreover, the cascade controller based on the Neural Fuzzy Inference System (ANFIS) outperforms other conventional controllers (PID, FLC, FLC-GA, PID-FIS) in terms of over/under, rise time and stabilization [56], [57] and [58]. Unmeasurable disturbances and in order to maintain the process in a stable manner, soft sensors (SS) based on nerves were used for better performance. These devices are characterized by their speed and low time delay [59]. Artificial neural network (ANN) was used and its ability to predict responses with rejection of disturbances was exploited. Several control strategies were used and connected to the (Simulink and Aspen Dynamics) program, where this method provided a short response time and good performance in rejecting disturbances and the ability to adapt to changes in the control environment [60], [61], [62] and [63].

2. Mathematical dynamic model

Most distillation processes are multicomponent, but sometimes, to simplify the process, some of these columns can be approximated to binary or quasi-binary mixtures. The purpose of this is to study the simplified case of them so that we can clarify the basic structure of the equations. The model is simplified under assumptions, no chemical reaction occurs inside the distillation column, feed at boiling point (saturated liquid), column is perfectly insolated, vapor holdup in each tray is neglected, liquid and vapor are in equilibrium on each tray, constant pressure (totally condensate), ideal trays, reboiler and condenser dynamics are neglected, liquid holdup varies from tray to tray and the relative volatility remain constant through the column and represented by this equation

$$y_n = \frac{\alpha x_n}{1+(\alpha-1)x_n} \quad \ldots(6)$$

According to these assumptions, the dynamic of the distillation column can be represented by the following mass and heat balance equations [64], [65]

Mass accumulation = mass flow rate in – mass flow rate out …(7)

Heat accumulation = Heat flow rate in – Heat flow rate out …(8)

Condenser and reflex drum

$$\frac{dM_{RD}}{dt} = V_1 - (R + D) \quad \ldots(9)$$

$$\frac{dM_{RD}x_{RD}}{dt} = V_1 y_1 - (R + D)x_{RD} \quad \ldots(10)$$

$$C_{RD}\frac{dM_{RD}T_{RD}}{dt} = H_1^V V_1 - H_{RD}^L (R + D) - Q_c \quad \ldots(11)$$

For first tray (n=1)

$$\frac{dM_1}{dt} = R + V_2 - V_1 - L_1 \quad \ldots(12)$$

$$\frac{dM_1 x_1}{dt} = R x_{RD} + V_2 y_2 - V_1 y_1 - L_1 x_1 \quad \ldots(13)$$

$$C_1\frac{dM_1 T_1}{dt} = H_{RD}^L R + H_2^V V_2 - H_1^V V_1 - H_1^L L_1 \quad \ldots(14)$$

For any tray (n) except first tray and feed tray

$$\frac{dM_n}{dt} = L_{n-1} + V_{n+1} - V_n - L_n \quad \ldots(15)$$

$$\frac{dM_n x_n}{dt} = L_{n-1}x_{n-1} + V_{n+1}y_{n+1} - V_n y_n - L_n x_n \quad \ldots(16)$$

$$C_n \frac{dM_n T_n}{dt} = H^L_{n-1}L_{n-1} + H^V_{n+1}V_{n+1} - H^V_n V_n - H^L_n L_n \quad \ldots(17)$$

For feed tray (nF)

$$\frac{dM_{nF}}{dt} = L_{nF-1} + V_{nF+1} + F - V_{nF} - L_{nF} \quad \ldots(18)$$

$$\frac{dM_{nF}X_{nF}}{dt} = Fx_F + L_{nF-1}x_{nF-1} + V_{nF+1}y_{nF+1} - V_{nF}y_{nF} - L_{nF}x_{nF} \quad \ldots(19)$$

$$C_{nF}\frac{dM_{nF}T_{nF}}{dt} = H^L_{nF-1}L_{nF-1} + H^V_{nF+1}V_{nF+1} + H_F F - H^V_{nF}V_{nF} - H^L_{nF}L_{nF} \quad \ldots(20)$$

Foe last tray (n=N)

$$\frac{dM_N}{dt} = L_{N-1} + V_B - V_N - L_N \quad \ldots(21)$$

$$\frac{dM_N X_N}{dt} = L_{N-1}x_{N-1} + V_B y_B - V_N y_N - L_N x_N \quad \ldots(22)$$

$$C_N \frac{dM_N T_N}{dt} = H^L_{N-1}L_{N-1} + H^V_B V_B - H^V_N V_N - H^L_N L_N \quad \ldots(23)$$

For reboiler and the bottom of column

$$\frac{dM_B}{dt} = L_N - V_B - B \quad \ldots(24)$$

$$\frac{dM_B X_B}{dt} = L_N x_N - V_B y_B - Bx_B \quad \ldots(25)$$

$$C_B \frac{dM_B T_B}{dt} = H^L_N L_N + Q_R - H^V_B V_B - H^L_B B \quad \ldots(26)$$

3. Conventional Controllers

There are many types of controllers used for process control especially in refinery process such as proportional controllers (P), integral controllers (I) and derivative controllers (D) or combination of these controllers. By PID control, the physical parameters including temperature, pressure, flow rate, and level can all be managed. The PID is only an equation that the controller uses to evaluate the variables that it is trying to govern. For example, a feedback signal is sent to the controller when a process variable's (PV) temperature is monitored. The controller then compares the feedback signal to the set point (SP) to generate an error value. To analyze the value, one or more of the three proportional, integral, and derivative techniques are applied. In order to fix the error (E), the controller then issues the required commands or modifies the control variable (CV). An iterative process is formed by these steps [64], [66], [67] and [68]. Table 1 summarize the advantages and disadvantages of each controller.

Table (1): Advantages and disadvantages of the controllers

Controller	Advantages	Disadvantages
Proportional (P)	-Fast response -Minimize fluctuation	-Large offset and doesn't bring the system to the desired set point
Integral (I)	-No offset, return the system to its set point	-Slow response
Derivative (D)	-Reducing error change and reducing oscillations	-Having offset -Amplifies the noise signals
Proportional-Integral (IP)	-Improve damping -No offset	-Reduce stability -Slow response
Proportional-Derivative (PD)	-Increased stability -Decreased settling and rising time	-Steady-state error is not zero -Highly affected by external noise
Proportional-Integral-Derivative (PID)	-Steady-state error is zero -Moderate peak overshoot stability	-Highly cost -Complexity in tuning and design

Controller tuning is the process of determining the controller parameters that produce the desired output. The PID parameters can be determined either by a mathematical model of the system if it's available, or, by the information is determined experimentally.

There are many methods for tuning controllers including, the trial and error method, it relies on the principle of guessing and checking, this is done by adjusting the gain of the control unit (K_c) while keeping the integral derivative action at a minimum until the required outputs are obtained [64], [69]. Process Reaction Curve is used for an already existing system, where a stable system is disturbed by either changing the set point or the system variables, and a curve is obtained. These kinds of curves are produced in open-loop systems, which allow the disturbance to be recorded because there is no system control. Multiple parameters can be measured, such as transportation lag or dead time, and the final steady state value [64]. The Ziegler-Nichols (ZN) controller settings are a simple way to adjust PID controllers, as they provide reasonable performance for some loops. The ZN settings are considered a starting point from which the settings of other controllers are performed [67], [68] and [70]. Cohen-Coon Method is an open-loop method and is often used as an alternative to the Ziegler-Nichols (ZN) method, where it corrects the slow steady-state response of the Ziegler-Nichols (ZN) method when there is a delay in the process (a large dead time). It is used for first-order models with a high time delay [64], [68]. Tyreus-Luyben method its considered similar to the Ziegler-Nichols (ZN) method, but it provides safer setting and is suitable for controlling some chemical processes because the Ziegler-Nichols (ZN) method has a small damping coefficient with a small time constant, while the Tyreus-Luyben method gives a large damping coefficient with a large time constant [69].

4. Advanced Control

There are many advanced process control strategies used in the refinery process such as Model Predictive Control, Adaptive Control, Feedback and feedforward, Fuzzy Logic Control (FLC) and Neural Network.

Model predictive control (MPC) is considered the most advanced form of advanced process control. It is considered a way to deal with control problems such as multivariate, time delay, nonlinearity and open-loop instability. Model predictive control (MPC) aims to lower the performance standard going forward. The factory model is utilized to predict future behavior, and mathematical expressions are also employed to forecast system behavior and enhance the procedure within a given time frame Fig.6.

The most common MPC techniques are Dynamic Matrix Control (DMC) and Modular Algorithmic Control (MAC), as they have been used in a large number of industrial processes and are highly efficient in dealing with constraints. There are several types, linear model predictive control (LMPC). It aims to improve performance by predicting future signals and optimizing control variable values. Nonlinear MPC (NMPC) it is employed when the linear model is insufficient to accurately represent the process.

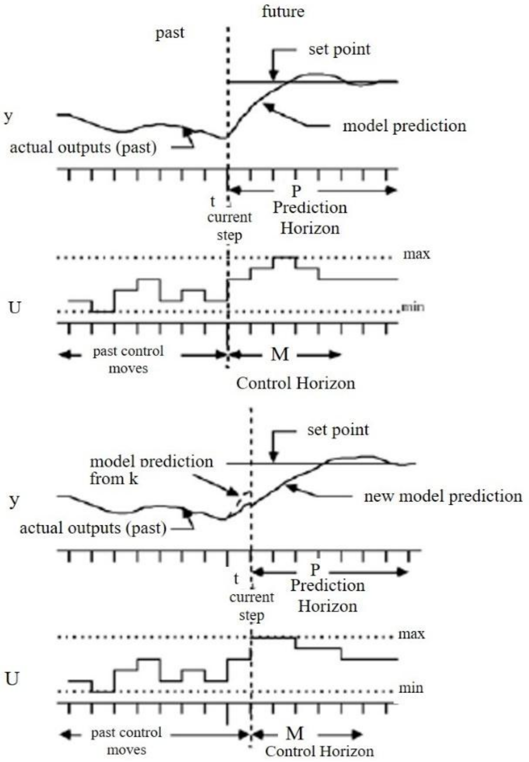


Figure (6): Basic concept of MPC.

Quadratic Dynamic Matrix Control (QDMC) algorithm is considered the second generation of model predictive control, as it consists of a set of algorithms that provide a way to implement input and output restrictions [64] [71], [72], [73], [74] and [75].

Adaptive control is a strategy that relies on constantly changing parameters. The parameters of the process model are set using online process identification and then the control action is derived and executed accordingly. Therefore, this type is used in systems that exhibit non-linear behavior or where the process structure is unknown [76].

Feedback and feedforward, Feedback includes receiving information about an action or behavior that occurred at a previous time and making a future change to address this event or behavior. Therefore, it focuses on what happened in the past and is useful in learning from mistakes and addressing weak points. Feed-forward includes instructions, suggestions, and visions to improve performance during the continuation of the event or behavior, and its work focuses on and expands future capabilities and solutions. Therefore, these insights are taken advantage of to achieve better performance in the future [77], [78].

Fuzzy Logic Control (FLC) is considered one of the most effective control designs based on intelligence that is used for multivariable and non-linear industrial processes. It is used to overcome the difficulty faced by the designer in the process of modeling and simulating complex processes Fig.7. However, despite obtaining a relatively accurate model of a dynamic system, sometimes it is complex and difficult to implement in design and control processes, especially with traditional control methods [79], [80], [77], [81] and [82].

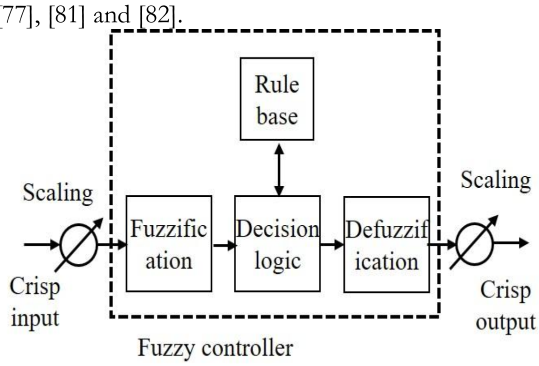


Figure (7): Structure of a Mamdani type of fuzzy logic controller.

Classical logic differs from fuzzy logic in that the former relies on an inaccurate way of thinking to perform a basic task, as it relies on the ability to deduce an approximate solution to a specific problem based on inaccurate information. The concept of fuzzy logic (FL) was introduced in the name of fuzzy set theory as a programming language and is considered a basic branch of artificial intelligence. It constitutes a new era of control systems called fuzzy logic control (FLC), which has proven to be an effective way to control non-linear and complex systems [83], [84] and [85]. Zadeh is considered the founding father of this field, as he implicitly advanced the concept of approximate human reasoning to make effective decisions. He is primarily concerned with dealing with ambiguous qualitative quantities. The fuzzy logic controller (FLC) works based on converting an experience-based linguistic control strategy into an automatic control strategy utilizing fuzzy logic. To accomplish this, we must supplement the standard input-output data set with a front-end "fuzzifier" and a rear-end "defuzzifier." [86] [87] and [88]. It has been used in many applications, including robotics [89], [90], [91], [92], [93] and [94], many of chemical industries [95], [96], disk drives [97], fuzzy logic chips [91], [98],[99] and [100], electronic devices [92], [101] and[102], automated control [98], [103], model and helicopter landing systems [90], [92], [98] and [101], sensors [104], pattern recognition [103], [104], [105], [106] and [107] etc.

Neural Network, in the forties of the twentieth century, researchers began to develop models of neurons cells that mimic the function of the human brain. Biological and psychological concepts were merged to create the first artificial neural network (ANN) [108]. They were first employed as electronic circuits, but later on, they were modified to become a more adaptable method of computer simulation. The process of studying and developing the neural network continued because, of its ability to simulate the human brain, in addition to its ability to respond and learn. It has been used in many fields, such as prediction, control systems, pattern recognition and others. Learning and adaptation are the main focus of neural network research, which gives accuracy and robustness to the neural network (NN). The artificial neural network (ANN), which learns from a succession of sets of input data and output data that are supplied to it, assigns a set of input patterns to a set of output patterns in the modeling and prediction process. The network, through what it has learned, approximates and predicts outputs [62], [81], [109], [110], [111], [112], [113] and [114].

It's worthy to state that the process of controlling one variable is relatively easy. However, when a second pair of variables appear, the process becomes more complicated because an interference process occurs between the control loops. This happens because the inputs that are controlled affect more than the outputs that are controlled. Therefore, not only must a choice be made between the pairs used for control, but there may be interference, and in this case, the control becomes more difficult. To facilitate the control process, the process of decoupling variables is used using a computer system, where one control unit is set to adjust many control valves through a decoupling system Fig.8 [66], [78].

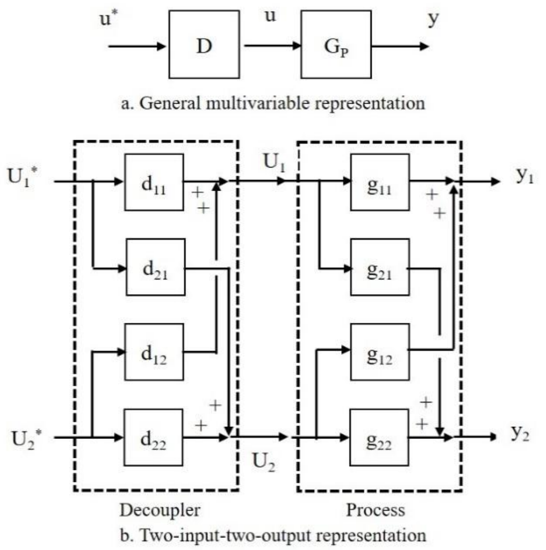


Figure (8). Decoupling control strategy.

5. Conclusions

This research discusses the methods and types of control in the distillation tower. The process of controlling the distillation tower is considered one of the most difficult and complex processes due to the non-linearity of the process, the interference between control loops, and the large number of input and output variables. Several types of controllers have been studied, starting from simple traditional units (proportional, integral, derivative controllers (PID)) to more complex units such as model predictive controllers (MPC) of various types, fuzzy logic control (FLC), artificial neural networks (ANN), etc. Proportional, integral, and derivative controllers (PID) were more widely used in many control processes due to their simplicity and ease of principles, but these units were not effective in controlling systems due to multivariable with high interaction between control cycles, nonlinear behaviour and large gains, so advanced adaptive and predictive control systems were used because they relied on model predictive control and stochastic optimization algorithms.

Nomenclature

B	Flow rate bottom product (kg/hr)
C	Heat capacity (kJ/kg °C)
D	Flow rate distillate product (kg/hr)
F	Feed flow rate (kg/hr)
H_F	Feed enthalpy (kJ/hr)
H^l	Enthalpy of liquid phase (kJ/hr)
H^v	Enthalpy of vapor phase (kJ/hr)
L	Liquid flow rate (kg/hr)
M	Liquid holdup (kg)
Q_c	Heat amount reduced by condenser (kJ/hr)
Q_R	Heat amount supply by reboiler (kJ/hr)
R	Reflux flowrate (kg/hr)
T	Temperature (°C)
V	Vapor flow rate (kg/hr)
x	Liquid concentration
x_F	Feed concentration
y	Vapor concentration
α	Relative volatility
<u>Subscription</u>	
1	Tray number one
2	Tray number two
B	Bottom of the column
RD	Reflex drum

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