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Intelligent Control on Industrial Vinyl Chloride Monomer Column: A System Identification and Artificial Intelligence Based Control Approach

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Abstract

In the production of vinyl chloride monomer (VCM), the separation of VCM vapors from ethylene dichloride (EDC) in the distillation column is complicated due to uncertain dynamic behavior and nonlinearity of the process and results in poor controlling of the column which may overlook product quality. In this regard, the column is simulated with integrated tuned-controllers using Aspen Plus dynamics. For system identification of the VCM column, the nonlinear autoregressive model with exogenous inputs (NLARX) gives a higher Fit% for the real-time data in comparison with the first order plus time delay (FOPTD) model. The study shows the application of artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) based control strategies, alongside a traditional proportional-integral-derivative (PID) controller for the control of the top composition and bottom composition of the VCM column. The results indicate that for top composition, the ANFIS-based controller having an integral time absolute error (ITAE) value of 0.132 outperforms ANN-based controller with an ITAE value of 0.78 in terms of set point tracking, and a similar behavior is found for bottom composition. In terms of disturbance rejection, the ANFIS having an ITAE value of 0.036 outperforms ANN having an ITAE value of 1.03 for top composition and shows the same behavior for bottom composition while the PID control exhibits significantly lower performance in both set point tracking and disturbance rejection.

Keywords

VCM distillation column, ANN, ANFIS, FOPTD models, NLARX, intelligent control techniques

1 Introduction

1.1 Vinyl chloride monomer (VCM) column

VCM is a key chemical monomer in the production of polyvinyl chloride (PVC), a versatile polymer with widespread applications in the construction, automotive, packaging, and healthcare industries [1]. Given the importance of VCM in the manufacturing supply chain and its significant impact on various industrial sectors, continuous research and development efforts are directed towards enhancing the efficiency, reliability, and sustainability of VCM production processes. The VCM distillation column is located at a VCM processing plant in which vinyl chloride is separated from ethylene dichloride (EDC) as shown in Fig. 1. VCM is produced by the pyrolysis of EDC along with by-product hydrogen chloride. Unconverted EDC goes into the HCl column for removal of HCl from mixture followed by a VCM column [2].

Controlling the purity of VCM at both the top and bottom products of the column in VCM production processes is crucial for ensuring product quality, process efficiency, and regulatory compliance. Maintaining a high purity level at the top of the column is necessary for producing PVC with consistent quality and performance characteristics, while precise control at the bottom removes impurities to protect downstream units and result in a safe working environment. Innovative approaches, including the application of intelligent control systems, are increasingly being researched to address the challenges associated with industrial distillation columns along with their production and market demand [2, 3]. Using artificial intelligence (AI) based approaches, the VCM column also needs to be controlled to meet the required demands and specifications while being operated under large operating ranges.

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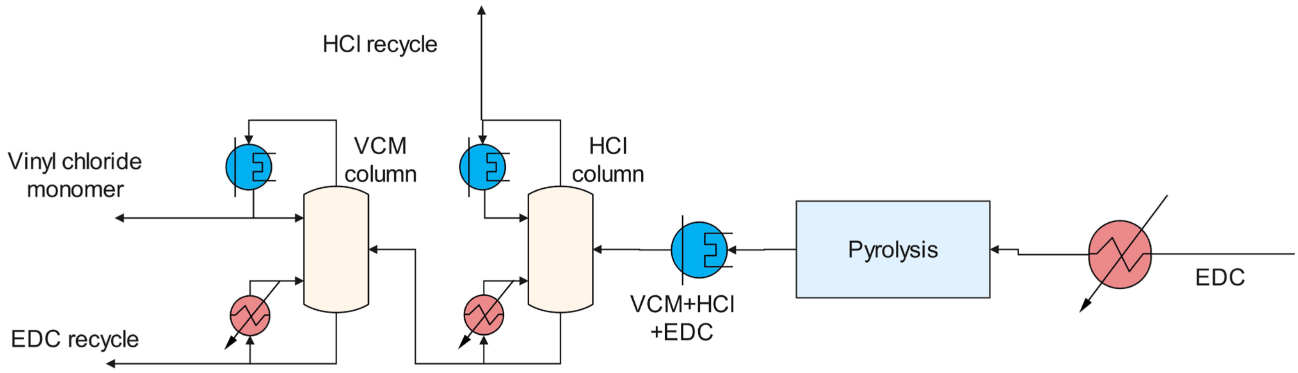

Fig. 1 Process flow diagram (PFD) of VCM process

1.2 System Identification of Distillation Column

In order to set up a control structure, it is essential to identify the system based on dynamics. System identification uses input and output data to generate a mathematical model of a system [4]. The steps of system identification include measurement of input/output signals, selection of a candidate model structure, estimation of adjustable parameters, and validation of the estimated model [5, 6]. One of the challenges in system identification for complex systems is the problem of the researcher introducing biases into the model, which can affect the accuracy of the recognized model [7]. Another challenge involves avoiding specifying the model structure too restrictively or too generally, as this can lead to biased or high-variance models [8]. To overcome these issues, Recent research has highlighted the efficiency of nonlinear models over linear models for dynamic systems due to enhanced flexibility, accuracy, and robustness in representing dynamic systems [9, 10].

For the optimization of the distillation column, mathematical models obtained from system identification are used for a better understanding of the behavior of the column and for developing control structures [11, 12]. For the model identification of distillation columns, a novel approach combining hybrid particle swarm optimization and artificial neural networks (ANNs) is developed, showcasing the better performance of the controller for nonlinear and dynamic columns [13]. An AI-based predictive control algorithm is developed for distillation column systems to accurately predict system behavior and also design a corresponding control scheme to deal with the system effectively [14]. Further, the continuous rise in global energy demand necessitates proficient energy production and utilization, making it essential to carry out the process efficiently while handling the complexities of distillation columns for high-end-product quality [15].

The literature review presents the usage of nonlinear models in controlling of dynamic and intricate systems [16, 17]. For system identification of an industrial debutanizer column, Fatima et al. [18] developed first order plus time delay (FOPTD) models and nonlinear autoregressive with exogenous inputs (NLARX) models using the system identification toolbox in MATLAB and compared both models on the basis of Fit%. NLARX model shows a higher fit % with the real data. Likely, the application of NLARX for system identification can be seen in [19, 20]. Further, the application of other mathematical models such as Wiener model [21, 22], FOPTD model [23] and Hammerstein model [24, 25] on distillation column for system identification have been reported. Among all these, NLARX is the most admired one due to its extension of linear autoregressive exogenous (ARX) models to capture complex nonlinear behaviors in data. Conclusively, the linear or nonlinear models help in understanding the insights of the process and developing advanced process control (APC) of the system.

1.3 AI-based control approaches for distillation column

AI-based control schemes have been addressed in the literature. ANN [26–28], generic model control (GMC) [29], support vector machine (SVM) [30], fuzzy logic control (FLC) [31–33] and other hybrid-based control methods [34] have been reported. ANN and FLC approaches are the most widely used algorithms in chemical processes along with hybrid control techniques.

The application of the above-mentioned AI-based control schemes on distillation columns is found in the literature review. Díaz [35] compared traditional proportional integral (PI) controllers with various strategies, including Expert, Fuzzy, and Neural-Network control on a simulated distillation column. The Neural-Network control with the NARMA-L2 controller is found to be the most effective, providing good disturbance rejection and fast set-point tracking. Fatima et al. [36] applied ANN and adaptive neuro-fuzzy inference system (ANFIS) based control strategies to control the top and bottom composition of a debutanizer column and found the performance of the ANFIS-based controller better in set point tracking of top and bottom streams and disturbance rejection. In Mishra et al. [32], a fractional-order fuzzy proportional-integral-derivative (FOFPID) controller acted as an intelligent control system to address the complex dynamics of a distillation column, providing a practical solution for managing the complexities of the distillation process. Shin et al. [26] applied neural network model predictive control on a distillation column with an optimizer for optimum solution and for prediction of future responses. The proposed methodology showed high controllability in multivariable system. Kwon et al. [37] developed ANN-based prediction model for optimization of distillation column by reducing the energy requirement. The procedure was followed by data collection, characteristic data collection to reduce minimum learning time and normalization to improve prediction performance. A nonlinear hybrid model predictive controller was presented by Elsheikh et al. [38] to control the composition of a mother liquor distillation column with a variable feed flow. A data-based component is added to a phenomenological model to reduce the plant-model mismatch.

Hadian et al. [39] proposed distillation column predictive controller using an event-based neural network which is a multiple-input-multiple-output (MIMO) nonlinear time-delayed system, using cuckoo optimization algorithm (COA). A novel observer-based direct adaptive Neuro-sliding mode control strategy was proposed by Cheng [40] for a nonlinear MIMO system in which the only known variable is the system output. A radial basis function (RBF) NN is constructed to take into consideration the unknown control laws, model dynamics, and state variables. To forecast and operate a continuous ethanol-water nonlinear pilot distillation column, Serra [29] described applying feedforward ANN with genetic algorithms (GA). When compared to four decoupled proportional-integral-derivative (PID) controllers, the suggested approach was determined to be better. Chavan et al. [41] applied FLC coupled with conventional PID using MATLAB on a non-linear MIMO distillation column. The algorithm delivered a smooth control when outputs were compared in the simulation environment.

Maldonado et al. [42] applied two different control strategies based on PID and fuzzy logic on a non-linear distillation binary column. It was found that the transfer function coupled and decoupled of the system to solve the problem of monitoring and controlling of distillation column. Ochoa-Estopier et al. [43] discussed the application of machine learning for prediction of flooding in distillation column using data driven approach. The approach relies on real time data which is used for training of random forest algorithm-based model for prediction of pre-operation stage before flooding. Neves et al. [44] applied ANN based control system on extractive distillation process enabling simultaneous consideration of changes in feed and ethanol specifications. The proposed control system determines specific set points to adjust specifications and rejects disturbances, outperforming conventional control methods based on errors. Overall, the integration of an ANN-based control system incorporates in enhanced adaptability, efficiency, and accuracy in extractive distillation operations.

1.4 Methodology for the VCM column

The literature review on distillation column control shows a major dependence on either ANN or FLC approaches [3]. The literature shows the limitations of single methodology to be insufficient to properly address the challenges inherent in distillation column [45]. It is more convenient to use unified framework combining both ANN and FLC based methodologies to develop ANFIS, which merges the interpretability and linguistic reasoning of fuzzy logic with the learning capabilities of neural networks [46]. By combining these approaches within the ANFIS framework, improved control performance, robustness, and compliance in distillation column operations can be achieved [47, 48].

This paper presents the following methodology to develop AI-based control structures. Initially, the dynamic simulation of VCM distillation column is created through Aspen Plus and is followed by setting and tuning up the controllers. Aspen Plus is chosen due to being industry-standard renowned accurate tool in process modeling and simulation. It provides precise thermodynamic property predictions, extensive libraries of chemical components, and a robust dynamic simulation environment, making it ideal for capturing the real-time dynamics of complex industrial processes like distillation [49]. The transfer function model FOPTD and NLARX model of the system is developed using system identification toolbox in MATLAB. These models help in building up the control structures. MATLAB's integrated environment for designing and testing AI-based control algorithms ensures optimal performance and seamless execution [50]. Innovative control strategies including ANFIS and ANN are designed and implemented on the industrial VCM column for control of top and bottom composition; the comparative evaluation of performances of AI-based control and traditional PID based control is carried out based on step change and disturbance rejection using real-time data.

2 Simulation-based Control of VCM Column

The distillation column consists of a tall vertical structure with 40 trays. The feed *F* coming from the bottom of the HCl column enters at stage 23 (feed tray), and is heated, causing VCM to be vaporized. As the vapor rises through the column, it meets the valve trays. These components provide a large surface area for condensation and vapor-liquid equilibrium to occur. At the top of the column, the vapor is condensed back into a liquid through the condenser, and the purified vinyl chloride is collected as fraction x_D, and some of the portion is returned as a reflux to the column as *L*. Meanwhile, the heavier component, i.e. EDC that did not vaporize as readily remains in the bottom of the column, is recycled to the light column for re-purification as fraction x_B, while some portion of the EDC goes back to the rectifying section of the column as *V*. The column is controlled by overhead (O/H) and bottom control loops. The level control of the reflux drum in the overhead control loop is achieved through the regulation of the distillate flow rate. Meanwhile, the reflux ratio is fine-tuned to maintain control over the distillate composition. The reboiler vapor rate maintained by the temperature is controlled by the steam flowrate in the reboiler as shown in Fig. 2. Normally, the extreme end temperatures are used as the variables for control of the column [51]. However, in the current study, the top composition and bottom composition of vinyl chloride are the controlled variables, and reflux flowrate and reboiler flowrate are the manipulated variables. The unit operation block data of the VCM column is presented in Table 1.

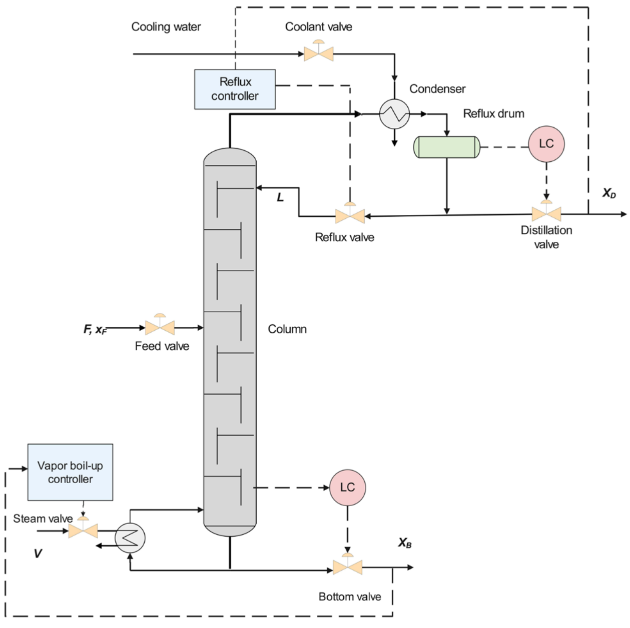

Fig. 2 Schematic Diagram of a binary Distillation Column

Aspen Plus® software [52] is used in this study to build a steady-state simulation of the VCM column. Reliability in design of column is largely dependent on the choice of thermodynamic model and the precision of parameter values [53]. Hence, the nonrandom two-liquid (NRTL) model equation of state has been selected as the property package (base method) in the steady-state simulation of VCM column as it involves both liquid-liquid equilibrium (LLE) and vapor-liquid equilibrium (VLE) [54]. This is followed by Aspen Dynamics® simulation, which is developed utilizing licensed Aspen Tech® software and industrial data. Parameters from Table 1 are used for dynamic evaluation of the process. After exporting the dynamic simulation, controllers are set up as shown in Fig. 3. The dynamic simulation is being run and checked for set-point tracking as shown in Fig. 4 and closed loop auto-tune variation (ATV) test for the temperature controller in order to tuning of controller as shown in Fig 5. For tuning up the controllers, Tyreus-Luyben PI method was chosen over Ziegler-Nichols proportional integral (PI) control method due to its improved robustness and stability [55]. The input/output data in the form of manipulated variables and controlled variables, i.e. top composition and bottom composition is obtained from the simulation as shown in Fig. 6. After being normalized, the data is split into two subsets: 40% of the data sets are tested (validation) and 60% of the data sets are used for training.

3 System Identification of VCM Column

To address the nonlinear and complex behavior of distillation columns, a best-fitted mathematical model is required

Table 1 Parameters of the VCM column

Parameter	Value
VCM tower height	26.67 m
Tower diameter	1.69 m
Tray count	40
Tray type	Valve
Condenser pressure	583.85 kPa
Condenser design	Partial
Feed temperature	105 °C
Feed mass flowrate	65612 kg/h
Pressure of feed	1185.8 kPa
O/H liquid mass flowrate	22504 kg/h
O/H vapor mass flowrate	47510 kg/h

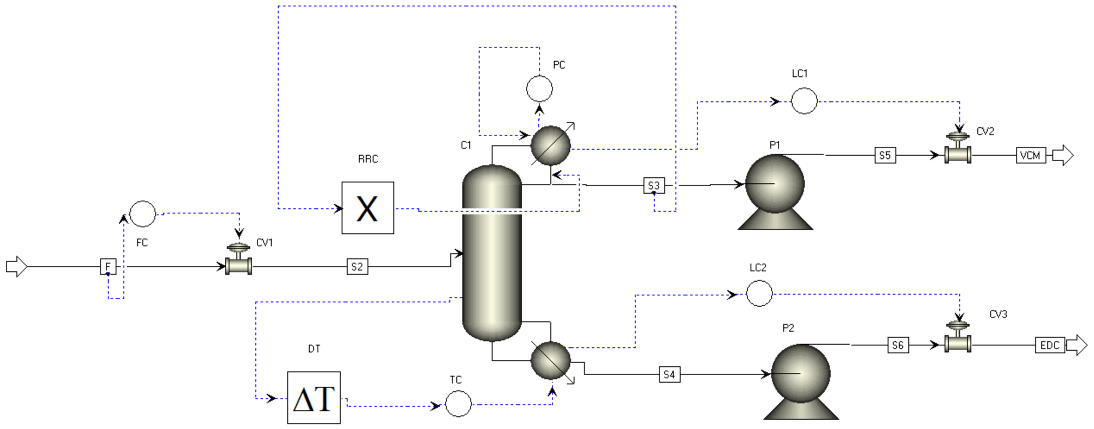

Fig. 3 Dynamics flow diagram of VCM column on Aspen Plus along with controllers

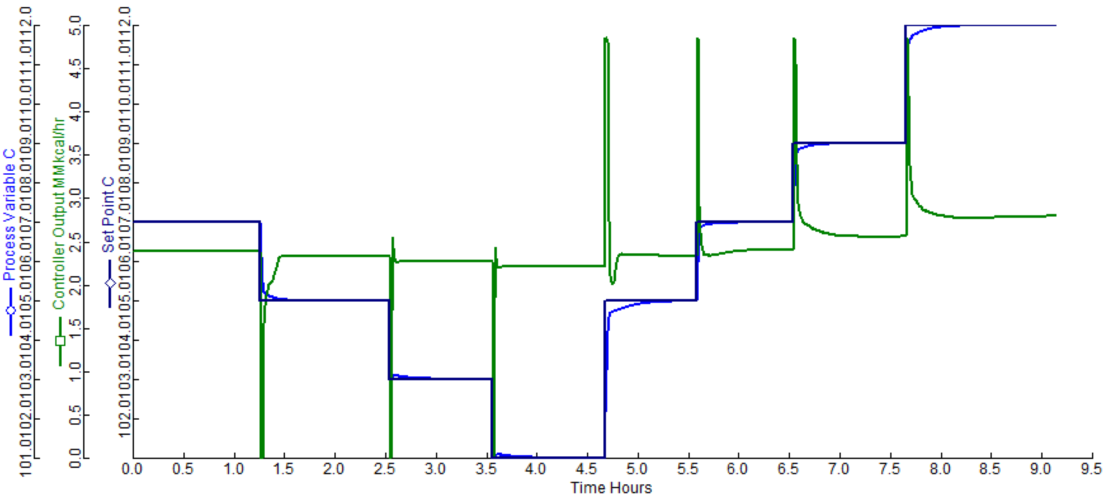

Fig. 4 Temperature controller performance based on step test on reboiler of VCM column

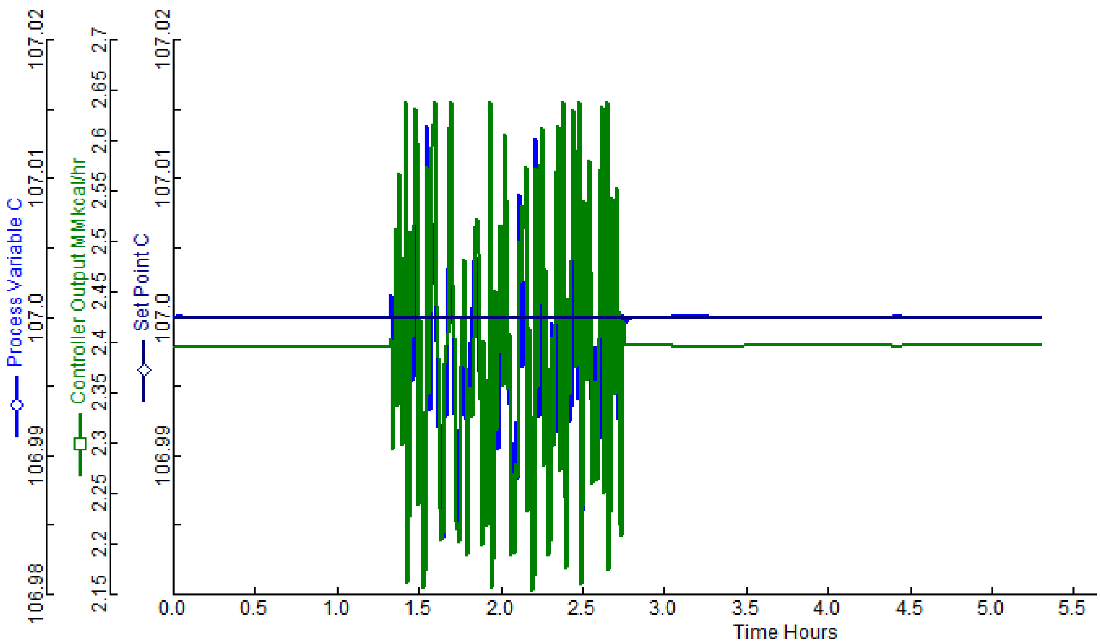

Fig. 5 Closed-loop auto-tune variation (ATV) test of temperature controller

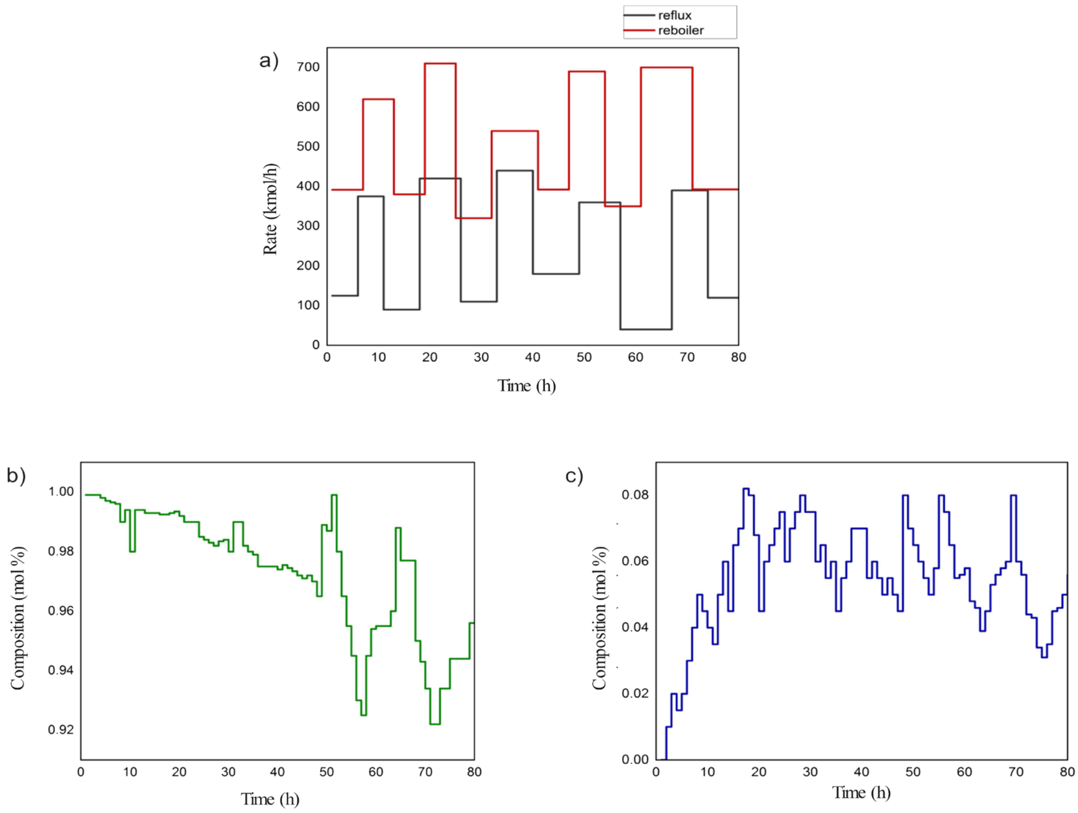

Fig. 6 (a) Reflux rate and reboiler rate as manipulated variables, (b) top composition as controlled variable and (c) bottom composition as controlled variable

for the system [56]. In this study, for model identification of industrial VCM column, the FOPTD transfer function model and NLARX model are used and compared. Two 2 × 1 multiple-input-single-output (MISO) systems are created using the system identification toolbox in MATLAB. In the first MISO Model 1, reflux flowrate (R) and reboiler flowrate (Q) serve as input variable and top product composition (x_D) as output variable, while in the second MISO Model 2, the input variables are R and Q and the output variable is bottom product composition (x_B) with a sampling rate of 60 s.

A sample of 2500 input-output data sets is inserted in the system identification toolbox. To develop a linear FOPTD model, the algorithm uses the "prediction focus" option to minimize the final prediction error (FPE) and mean square error (MSE), and refine until the best model is achieved. The parameters of the identified linear FOPTD transfer function model along with fit% of the model with data are shown in Table 2.

The above two MISO models are used for identification of nonlinearities in VCM column using NLARX model as well. Developing NLARX models can be challenging, particularly when it comes to creating and selecting appropriate input and output regressors. Increasing the number of delays adds complexity to the model, so it's important to keep the structure as simple as possible while maintaining accuracy [21]. NLARX uses input and output regressors to predict the dynamic of the system as shown in Fig. 7. Sigmoid function is used as dynamic nonlinearity estimator. For the two nonlinear MISO models in this case, the parameters were set as

Table 2 Specification of linear FOPTD models for top composition (x_D) and bottom composition (x_B)

Parameter	Model 1 (x_D)	Model 2 (x_B)
Model gains		
K_{11}	−0.00134	2.64478
K_{12}	0.56784	0.02389
Time constants		
τ_{11}	145.48	343.23
τ_{12}	89.0087	22.8909
Time delays		
$t_{D,11}$	25.89	30
$t_{D,12}$	22.90	0
Errors and Fit%		
FPE	0.0166	6.7E-5
MSE	0.0164	6.62E-5
Fit%	73.36	57.09

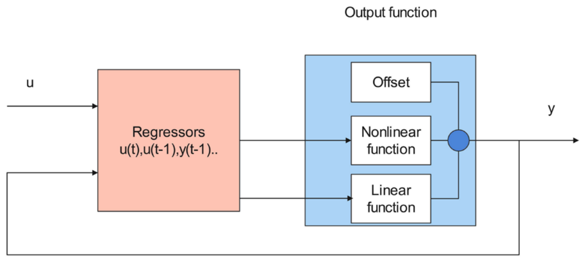

Fig. 7 Structure of NLARX model

$n_a = 3$, $n_b = [4\ 4]$, and $n_k = [1\ 1]$. The best set of regressors was identified by determining which combination provided the highest fit percentage (Fit%) between the system's actual output and the model's estimated output [18].The specification of the models along with the values of FPE, MSE and fit% of model with the actual data is given in Table 3.

By comparing values of FPE, MSE, and Fit% of Model 1 and Model 2 between FOPTD and NLARX, it is found that the NLARX model is best fitted to the actual data and closely represents the actual dynamic of the process for both models.

4 Implementation of AI-Based Control Models

4.1 Development of ANN Models

ANN being a powerful tool, is capable of handling complex and nonlinear dynamics with accuracy along with excellence in nonlinear control, adaptive control, and predictive control [40, 44, 57, 58]. ANN uses historical data for system model development, ensuring real-time control adjustments [59]. As shown in Fig. 8, the ANN structure contains three layers; the input layer, the single hidden layer, and the outer layer. The input layer receives the features or data points (x_1, x_2, …, x_n) along with bias terms (θ_1) that enhance the model's flexibility. Each input is associated with weights (w_{ij}) that determine the strength of its connection to neurons in the next layer. The hidden layer, which may contain multiple layers, processes these inputs by computing the weighted sum of inputs, adding a bias, and passing the result through an activation function (f) such as ReLU, sigmoid, or tanh. This activation function introduces non-linearity, enabling the model to learn complex patterns. The output layer generates the final output values (y_1, y_2, …, y_i) based on the processed information from the hidden layer [60]. ANNs can handle complex patterns and relationships in data, while NLARX models are dedicated to capturing nonlinear dynamics in connection with external inputs [61]. Using a hybrid structure combining both ANN and NLARX gives the advantages of both methods, i.e., better model dynamic systems and predictive analysis of time series data.

Table 3 Specifications of NLARX models for top composition (x_D) and bottom composition (x_B)

	Model 1 (x_D)	Model 2 (x_B)
Nonlinear function	Sigmoid	Sigmoid
Number of units	10	10
n_a	4	4
n_b	[4 4]	[4 4]
n_k	[1 1]	[1 1]
FPE	0.0003976	9.7E-8
MSE	0.0003887	9.6E-8
Fit%	95.9	98.36

The current study shows the application of an ANN-based model for prediction of top and product compositions using the series-parallel structure of the NLARX network. The hidden layer, whose size is determined through an optimized hit-and-trial process, uses a tangent sigmoid (tansig) transfer function, while the output layer uses a linear (purelin) transfer function. The choice of the training algorithm and the number of neurons in ANN structure is critical to its performance and applicability. The Levenberg-Marquardt (LM) algorithm was selected for training the network due to its efficiency and fast convergence for medium-sized datasets [60, 62, 63]. LM combines the advantages of gradient descent and Gauss-Newton methods, making it particularly effective for complex, nonlinear systems such as distillation column processes [63, 64]. The number of neurons in the hidden layer was determined based on the complexity of the problem, with 14 neurons for the top composition and 10 for the bottom composition. This configuration was selected through empirical testing and cross-validation to balance the model's capacity to capture intricate relationships in the data while avoiding overfitting.

It is chosen for its balance between robustness and fast convergence, complemented by the application of early stopping criteria. Table 4 shows the parameters of the developed ANN model.

4.2 Development of ANFIS model

ANFIS is a combination of an ANN and a Takagi-Sugeno-Kang (TSK) fuzzy inference system [65]. TSK is chosen for ANFIS over Mamdani's fuzzy inference due to being computationally efficient and more compact [35]. This hybrid robust structure holds the strengths of both ANN and fuzzy logic, that can effectively combines these methodologies [66].

Fig. 9 illustrates the structure of an ANFIS, consisting of five distinct layers, each performing a specific function in the process of fuzzy inference. In the first layer (fuzzification layer), input variables X and Y are passed through membership functions (A_1, A_2, B_1, B_2) to convert crisp inputs into

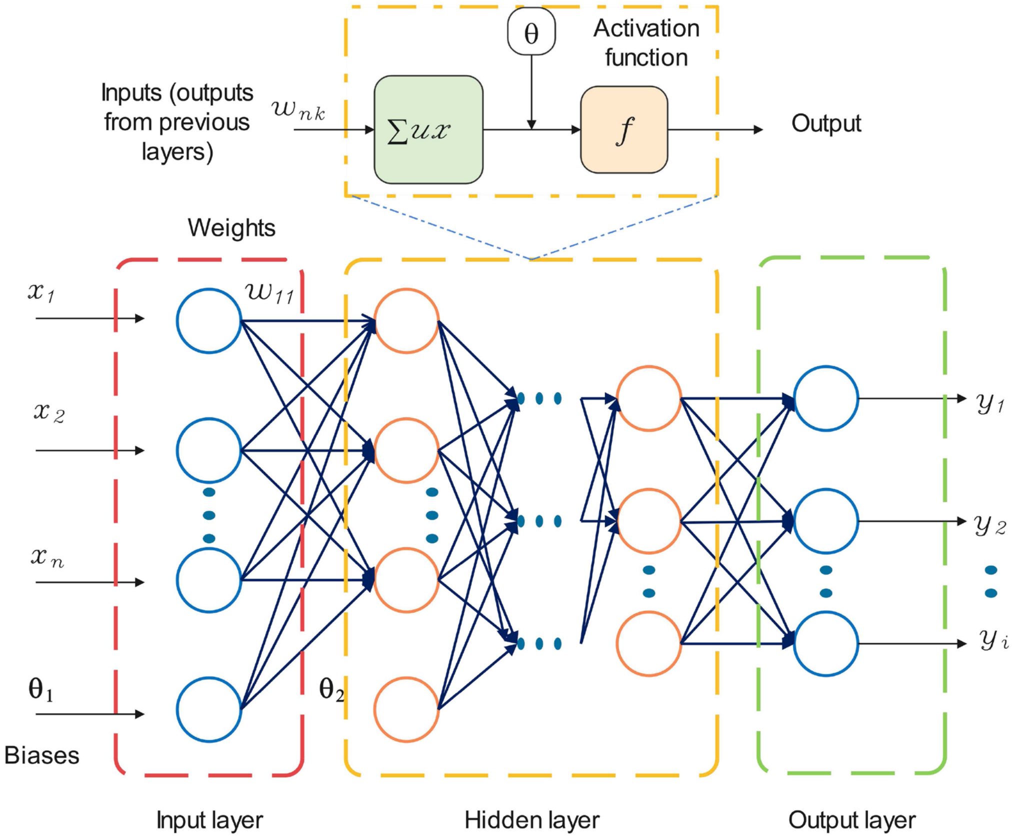

Fig. 8 Model Structure of ANN network

Table 4 Parameters of ANN structure for top composition and bottom composition

Parameter	Description
Network type	NARX-NN
No. of layers	3
Number of neurons in hidden layer	14(top), 10 (bottom)
Epochs	500
Training algorithm	Levenberg-Marquardt
Performance function	RMSE
Hidden layer transfer function	Transig
Output layer transfer function	Purelin

fuzzy sets. These membership functions determine the degree of belonging of the inputs to specific fuzzy sets. The second layer (rule layer) applies fuzzy logic rules using the outputs from the first layer. Each node represents a rule, and the firing strength of each rule is computed as the product (Π) of the corresponding membership degrees. The third layer (normalization layer) normalizes the firing strengths by dividing each rule's strength by the sum of all rule strengths, ensuring the outputs are proportional. In the fourth layer (defuzzification layer), the outputs from the normalized layer are used to calculate rule contributions. Each rule contributes a weighted output based on its firing strength and associated parameters. Lastly, the fifth layer (summation layer) aggregates the outputs from all rules by summing them up to produce a single crisp output (*f*) [67]. This structure allows ANFIS to learn and adjust both the membership functions and rule parameters during training, making it a powerful tool for modeling nonlinear systems. ANFIS, being a universal approximator, offers significant help in modeling complex systems. In essence, it automates the tuning of membership functions (MFs) of Sugeno fuzzy model using the training input-output dataset, and associated parameters within a fuzzy inference system (FIS) [68].

For the current study, the ANFIS structure is developed using a hit-and-trial method for finding the optimal type and number of MFs. In particular, Gaussian MFs are used for the input variables due to their smooth and continuous nature, providing better approximation capabilities [69]. To simplify the input space by partition, subtractive clustering is chosen over grid partitioning due to its efficient and scalable approach, especially with higher-dimensional data, by generating fewer rules and avoiding the exponential growth of rules that grid partitioning entails [70]. A hybrid algorithm, merging least squares estimation with backpropagation, is utilized for optimization, ensuring effective tuning of both the premise and consequent parameters. The model is trained, and its performance is subsequently tested to validate its predictive

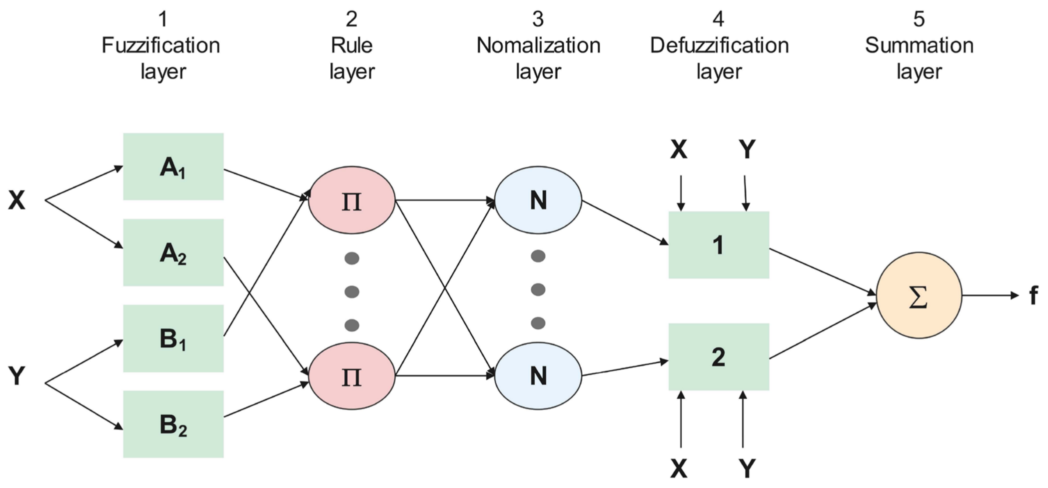

Fig. 9 Model structure of ANFIS network

accuracy and generalization capability. The parameters of the ANFIS structure are listed in Table 5.

4.3 Comparison of the ANN and ANFIS Models

To forecast the accuracy of the prediction, ANN and ANFIS are compared using the root mean square error (RMSE) criteria. The error levels for the models created using the ANFIS technique are comparatively lower than those for the ANN, as the table illustrates. Overall, the ANFIS demonstrated improved prediction performance with reduced RMSE values as shown in Table 6.

5 PID Control on VCM column

Industrial control applications frequently use PID: a feedback loop control scheme. A PID controller computes the variation between the desired set-point and measured process variable using derivative, integral, and proportional actions. Based on this calculation, it produces an amended control signal, $u(t)$. PID control design has been thoroughly studied in the literature and has found beneficial applications in several fields. Its primary benefit and drawback are regarded as being related to its simplicity, which limits the breadth of operations it can effectively control [69].

In this study, two separate PID controllers are set up for the top composition and bottom composition of an industry-based vinyl chloride column. Both of the PID controllers were tuned by MATLAB/Simulink software. The values of the optimal gains of the PID controllers i.e., (K_p, K_i, K_d) are listed in Table 7.

Table 5 Parameters of ANFIS structure for top composition and bottom composition

Parameter	Description
No. of input MF for top composition	8
No. of input MF for bottom composition	6
Input MF type	Gaussian
Output MF type	Linear
Epochs	30
Clustering method	Subtractive clustering
Optimization method	Hybrid algorithm

Table 6 Evaluation of top and bottom composition models on the basis of RMSE

	Testing	Training
ANN-top	2.23E-2	4.30E-2
ANN-bot	4.33E-2	3.78E-2
ANFIS-top	1.08E-2	3.76E-2
ANFIS-bot	3.97E-2	2.48E-2

6 Results and discussion

The top composition and bottom compositions of the VCM distillation unit are controlled by three different control strategies: PID, ANN, and ANFIS. The performance of each controller is assessed through set-point tracking and disturbance rejection tests.

6.1 Evaluation of the ANN and ANFIS-based Models on the basis of set point tracking

The controllers' capability of tracking the new set point is observed and compared by introducing a step change in the set point. The performances are compared based on integral square error (ISE) and integral time absolute error (ITAE).

Table 7 Parameters of PID controller for top and bottom composition

Parameter	K_p	K_i	K_d
Top composition	20.56	0.01	25.2
Bottom composition	22.2	0.53	18.92

ISE refers to steady-state errors while ITAE reflects the controller's ability to regulate its dynamic response properties.

Fig. 10(a) illustrates how well the three controllers, i.e., PID, ANN, and ANFIS performed in following the top composition's new set point when it was adjusted from 0.94 to 0.99. However, the results clearly show that in set point tracking, PID controllers exhibit significant oscillations, prolonged settling times, and a slow response. Since, ANN-based and ANFIS-based controllers hold reduced rising time with zero offsets, they outperform PID controllers with faster settling times.

Similarly, in Fig. 10(b), when the set point of the bottom composition is changed from 0.02 to 0.01, the PID controller shows a similar behavior with oscillations and overshoots. Both ANN and ANFIS show smooth tracking of set points with faster responses. However, a slight undershoot is seen in ANN response before meeting the targeted set point. No offset is observed in ANFIS response as it directly meets the set point.

The performance indices are shown in Table 8. The error values, ISE and ITAE, provide critical insights into the performance of different controllers in tracking set points and rejecting disturbances. ISE quantifies the sum of squared deviations between the actual and desired outputs over time, with lower values indicating greater control precision and minimized oscillations. The ANFIS-based controller demonstrates superior performance with the smallest ISE values for both top composition (0.020) and bottom composition (0.013), highlighting its ability to achieve precise control. Similarly, ITAE, which measures the time-weighted absolute error, emphasizes long-term stability and rapid error correction [71]. The ANFIS controller achieves significantly lower ITAE values for both top composition (0.132) and bottom composition (0.56), reflecting its ability to stabilize quickly and effectively manage transient responses. Compared to the ANN-based controller, which performs moderately well based on the values of ISE and ITAE in terms of tracking the set point in comparison with PID in both top composition and bottom composition. However, ANFIS shows the best results with less value of ISE and ITAE.

Table 8 Performance comparison of controllers based on ISE and ITAE on set point basis

	ANFIS	ANN	PID
	Top composition		
ISE	0.020	0.06	0.22
ITAE	0.132	0.78	2.43
	Bottom composition		
ISE	0.013	0.045	0.098
ITAE	0.56	0.96	5.67

6.2 Evaluation of the ANN and ANFIS based Models on basis of disturbance rejection

To assess the system's robustness, stability, and performance under external influences, a disturbance is introduced assumed as an external disturbance caused by some unknown sources, to deviate the controlled variables from their respective set points. Evaluation of controllers is based on their capability to regain the set point while handling the disturbances.

In Fig. 11(a), for top composition, there is an abrupt and prolonged disturbance of 0.006 mol fraction, results in deviation of set point from 0.990 to 0.996 at $t = 10$ min. The figure shows the initial response and stabilization of the top composition to the set point over time. The ANFIS line reaches the set point quickly with minimal overshoot, ANN follows with a slightly slower response, and PID shows the largest overshoot before stabilizing. Similarly, in Fig. 11(b), a disturbance of 0.006 mol is introduced at $t = 10$ min which shifts the set point from 0.010 to 0.004.

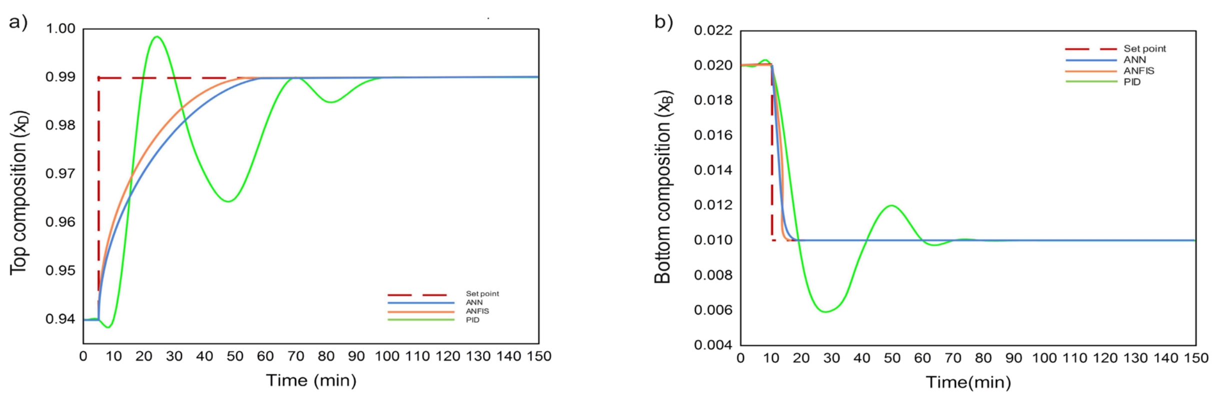

Fig. 10 Performance of controllers (ANN, ANFIS & PID) on basis of set point tracking for (a) top composition and (b) bottom composition

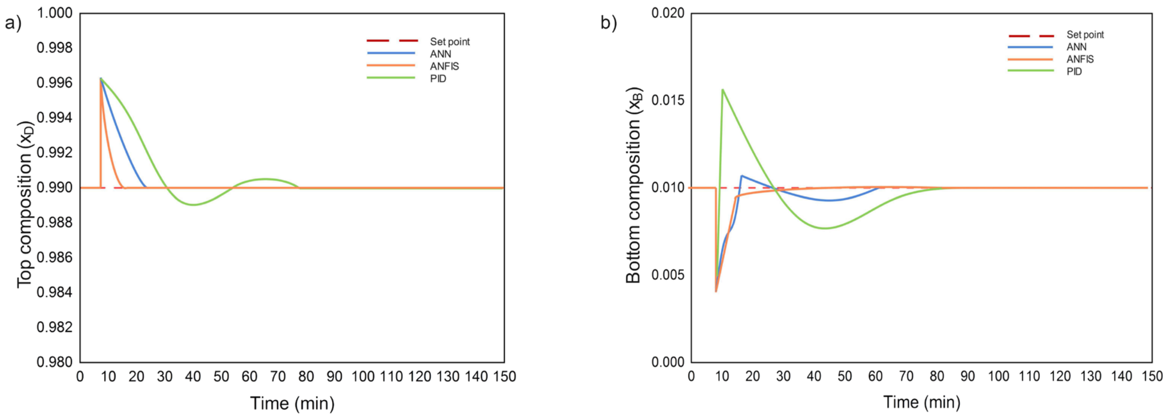

Fig. 11 Performance of controllers (ANN, ANFIS & PID) on basis of step disturbance for (a) top composition and (b) bottom composition

Similar behavior with initial deviations and eventual stabilization is observed in the case of ANN and ANFIS which appear to reach and maintain the set point faster rejecting the disturbance. While the PID controllers experience significant overshoot and extended settling time.

For step disturbance rejection test, Table 9 shows the performance indices of controllers based on the values of ISE and ITAE. The values indicate that ANFIS with the lowest value of errors, plays the best role in rejecting the disturbance in uncertain environments when compared with ANN and PID.

7 Simulink model of the process

The above results show the dominance of ANFIS-based control over ANN-based control in the system. ANN-based control model is further investigated based on loop gain, peak gain, and stability by developing a Simulink-based model. Fig. 12 shows a control system diagram for a VCM distillation column, specifically to control the top and bottom composition of the column. The diagram includes a data sheet block of VCM column, a process model (DM), a controller (PI & PID), and a neural network (NNET) connected with distillation column block, with inputs representing the flow rate of the liquid and the vapor phases. Process model block converts controller's output, which is predicted by NNET, as input to generate the top product composition and bottom product compositions. The system also includes a reference signal for the desired output. The NNET is labeled as "1 input - 1 hidden layer - 1 output1". This suggests that the NNET is trained on data from the system and used to predict future behavior.

Table 9 Performance comparison of controllers based on ISE and ITAE on step disturbance basis

	ANFIS	ANN	PID
Top composition			
ISE	4.34E-5	1.65E-4	2.98E-2
ITAE	0.036	1.03	3.45
Bottom composition			
ISE	0.022	0.056	1.78
ITAE	0.86	2.12	7.54

The graph obtained from the above model is given in Fig. 13. A plot of the minimum and maximum loop gains for an open loop system is in the frequency domain, as shown in Fig. 13(a). The green line represents the singular value of the system at all frequencies, which is constant at 0 dB. The red line represents the target loop shape, which is a straight line with a slope of -20 dB per decade. The blue line shows the loop gains, with the solid line representing the scaled loop gains and the dashed line representing the loop gains themselves. The loop gains, within the specified tolerance are shown by the shaded area. The green for the minimum loop gain, while the red represents the maximum loop gain. Since, the loop gains are within the specified tolerance over the entire frequency range, which shows the system is stable and well-behaved.

The plot of overshoot as a peak gain constraint shows the actual closed-loop gain is in allowable range lower than the maximum allowed gain (15%) (Fig. 13(b)). The graph is a measure of how much a system's output exceeds its desired value.

The four graphs illustrate the step disturbance rejection of a system (see Fig. 13(c)). Each graph shows the response of the system to a step disturbance (blue line) in comparison with the reference response (purple dashed line) with two different input sources, *dL* and *dV*.

In Fig. 13(d) graph shows the stability margins of a system at plant inputs. The top plot shows the gain margin in decibels (dB) while bottom plot shows the phase margin in degrees as a function of frequency. The stability margins

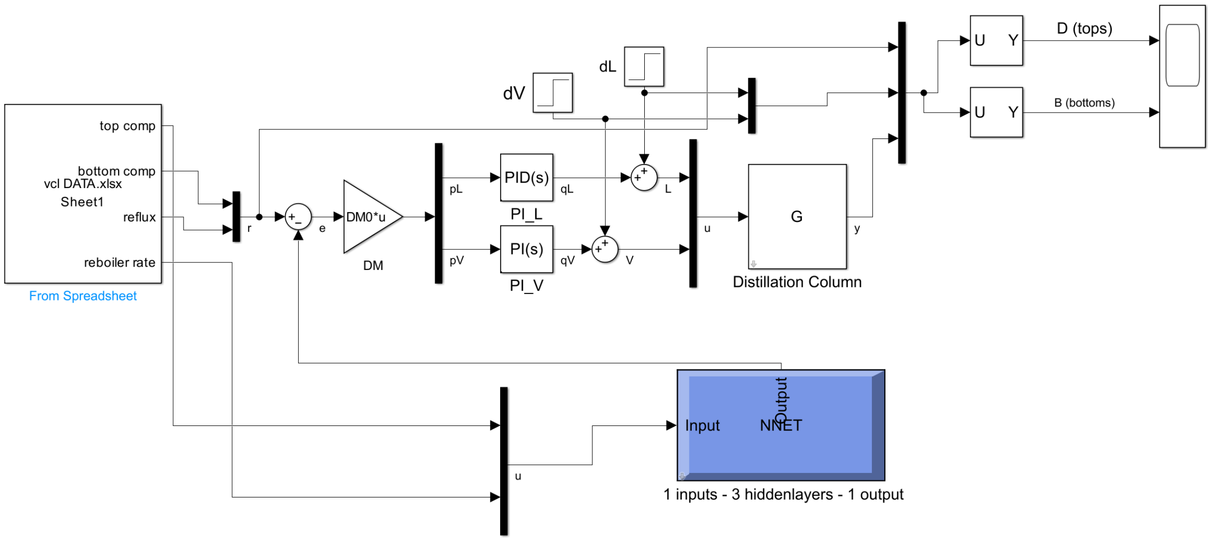

Fig. 12 Simulink model of an ANN-based control structure of a VCM distillation column

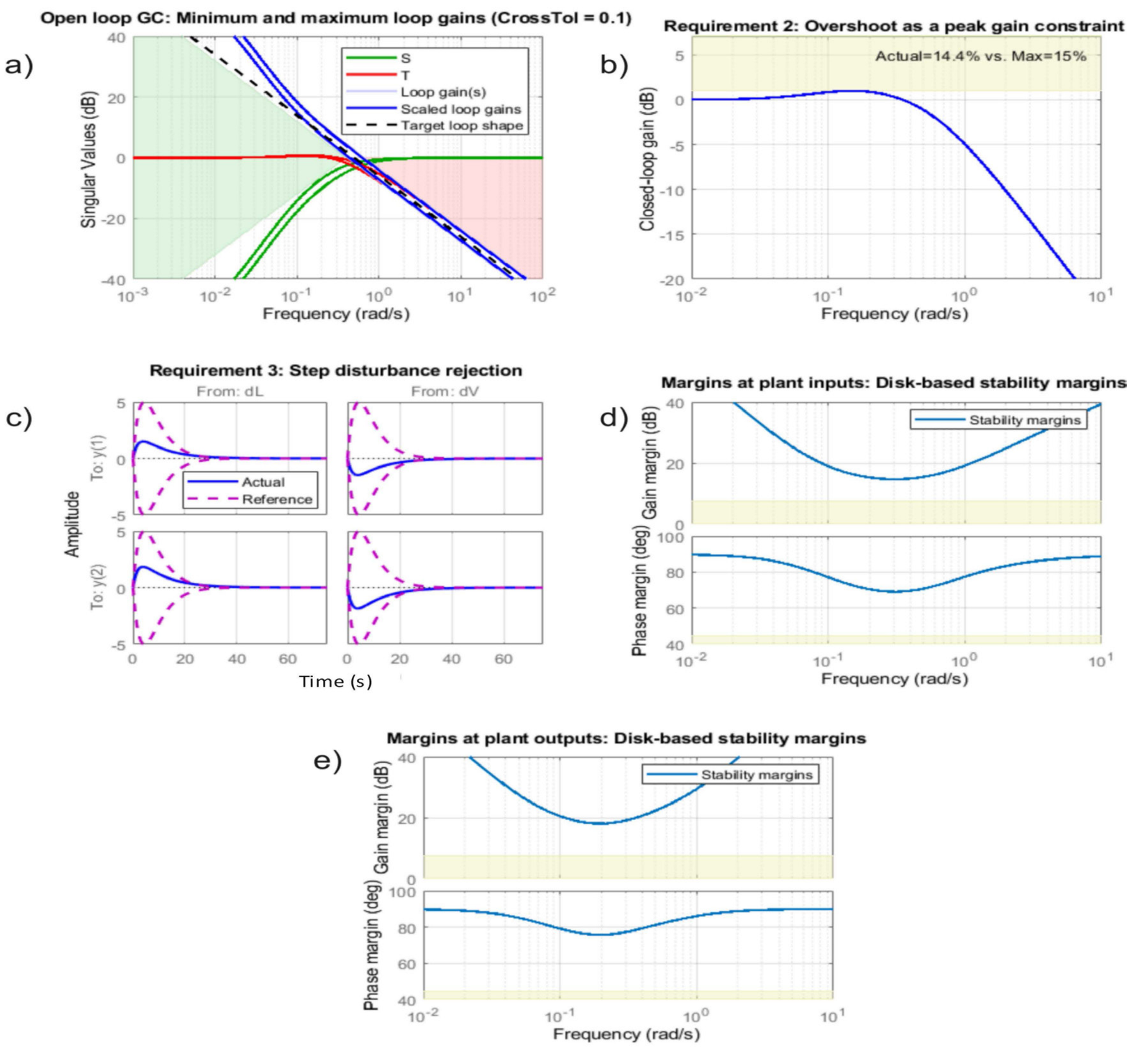

Fig. 13 (a) Minimum and maximum loop gains, (b) overshoot as a peak gain constraint, (c) step disturbance rejection, (d) margins at plant input and (e) margins at plant outputs are the minimum amount of gain or phase shift that can be added to the system before it becomes unstable. The yellow shaded areas indicate the acceptable range for the stability margins. The plot shows that the system has a gain margin of about 10 dB and a phase margin of about 90°. These values indicate that the system is stable and has a good amount of margin for stability.

Fig. 13(e) shows two graphs, one depicting gain margin and the other showing phase margin at plant outputs. The gain margin is relatively constant across the frequency range, while the phase margin is a horizontal line at around 90°.

Fig. 14 shows performance parameter of ANN model for training, validation, test, and all. The plots show the model's predicted outputs versus the actual target values. The plots include a line of best fit (labeled as "Fit") and a diagonal line representing the ideal scenario where the model predicts the target perfectly (labeled as "$Y = T$"). The R-squared values for each plot are given, indicating how well the model fits the data. The higher the R-squared value, the better the model's performance.

8 Conclusion

The paper presents the simulation-based study of the industrial VCM column using aspen plus dynamics software and the controllers. The performance of the controllers is validated through set point tacking after being tuned. The data generated from the simulation is processed through the system identification toolbox, in which the distillation column is identified as a nonlinear system and shows the highest Fit% in NLARX model. The top and bottom composition of the VCM column is controlled using different control structures, i.e. PID, ANN, and ANFIS. The performances of these controllers are compared based on set point tracking and disturbance

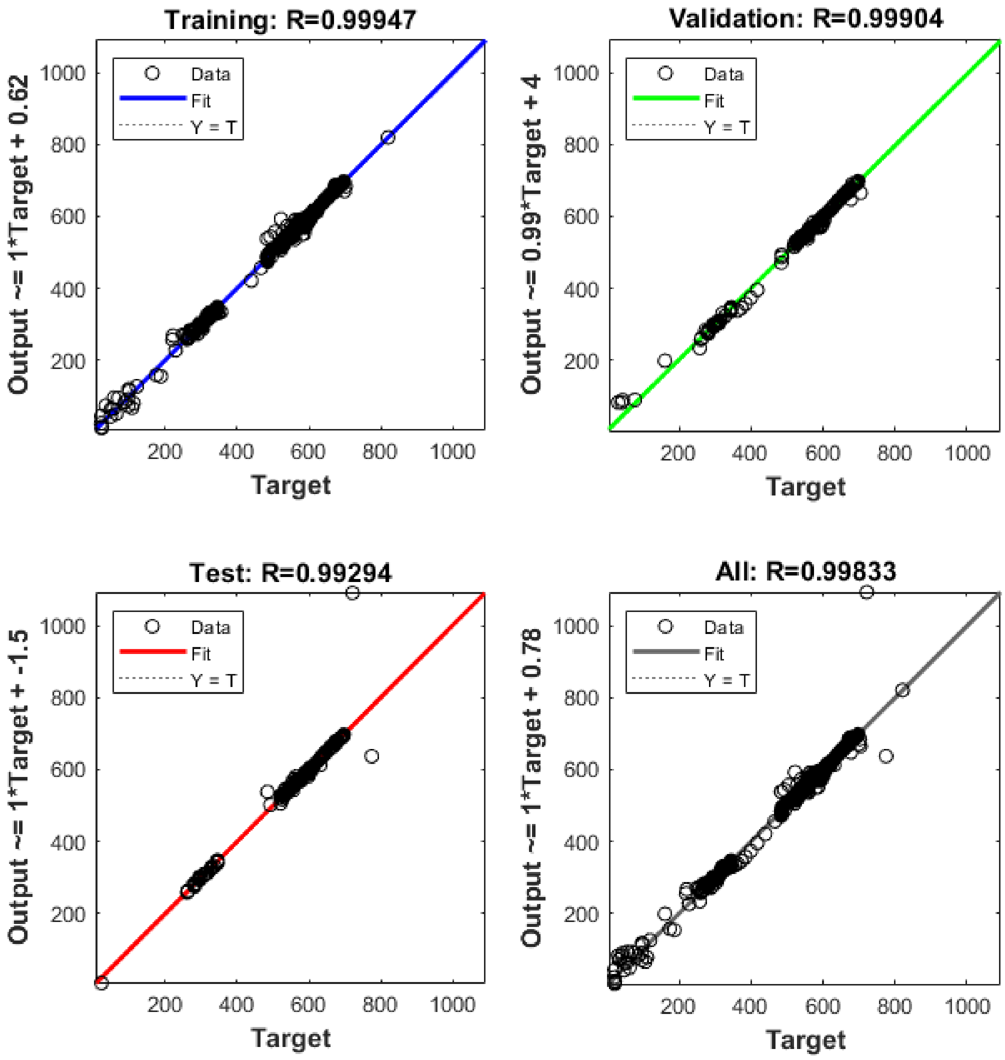

Fig. 14 Regression coefficient of ANN model

rejection. The results show PID controllers lag behind the intelligent controllers due to their incapability to handle nonlinear systems. However, the ANFIS-based controller outreaches the responses of ANN-based controllers owing to its ability to handle uncertainties as shown by the values of ITAE, MSE and ISE. Further, ANN-based controllers are investigated through a simulation model of the distillation column on Simulink and are checked for stability, overshoot, and gain values. Despite being stable and high value of regression coefficient, the hybrid nature of ANFIS allows it to manage nonlinearities and adapt more flexibly to system dynamics, providing better overall control and generalization compared to ANN. The work is beneficial in terms of developing understanding of nonlinear AI- based control of industrial VCM distillation column. However, the current study can be extended in domain of fault detection and diagnosis (FDD), Uncertainty and Robustness Analysis, Energy Optimization and Cost Analysis and Generalization to Other Industrial Systems. Additionally, the ANFIS model could be extended to multivariable control, managing multiple process variables like temperature, pressure, and flow rates simultaneously, thus improving robustness and adaptability. Beyond distillation, the model could be applied to other complex chemical processes such as reactors, crystallization, and extraction systems, showcasing its versatility. Future studies could also investigate hybridizing ANFIS with machine learning techniques like reinforcement learning or deep learning to further enhance its predictive capabilities.

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Conflicts of interest
The authors declare no conflict of interest.

Abbreviations

AI	artificial intelligence
ANFIS	artificial neural fuzzy inference system
ANN	artificial neural network
APC	advanced process control
ATV	auto-tune variation
COA	cuckoo optimization algorithm
EDC	ethylene dichloride
FIS	fuzzy inference system
FLC	fuzzy logic control
FOFPID	fractional-order fuzzy proportional-integral-derivative
FOPTD	first order plus time delay
FPE	final prediction error
GA	genetic algorithm
GMC	generic model control
HCl	hydrogen chloride
IMC	internal model control
ISE	integral square error
ITAE	integral time absolute error
LC	level controller
LLE	liquid-liquid equilibrium
LM	Levenberg-Marquardt
MF	membership function
MIMO	multiple-input-multiple-output
MISO	multiple-input-single-output
MSE	mean square error
NNET	neural network
NLARX	nonlinear autoregressive with exogenous inputs
NNMPC	non-linear model predictive control
NRTL	nonrandom two-liquid
O/H	overhead
PID	proportional integral derivative
PI	proportional integral
PVC	poly vinyl chloride
RBF	radial basis function
RMSE	root mean square error
SVM	support vector machine
TSK	Takagi-Sugeno-Kang
VCM	vinyl chloride monomer
VLE	vapor-liquid equilibrium

Nomenclature

A, B	membership function
dB	decibels
F	feed
f	activation function
K_p	proportional gain

K_i	integral gain	$u(t)$	control signal
K_d	derivative gain	ux	membership value of x
L	liquid reflux	V	vapors from reboiler
n_a	past outputs	w_{nk}	weight of connections between neurons
n_b	past inputs	x_D	top product composition
n_k	input delays	x_F	feed composition
Q	reboiler flowrate	x_B	bottom product composition
R	reflux flowrate	X, Y	fuzzy input variables
τ	time constant	y	output
t	time	θ	bias value
u	input	Π	firing strength of fuzzy rule

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