

Artificial Intelligence for Inferential Control of Crude Oil Stripping Process

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Abstract

Stripper columns are used for sweetening crude oil, and they must hold product hydrogen sulfide content as near the set points as possible in the faces of upsets. Since product quality cannot be measured easily and economically online, the control of product quality is often achieved by maintaining a suitable tray temperature near its set point. Tray temperature control method, however, is not a proper option for a multi-component stripping column because the tray temperature does not correspond exactly to the product composition. To overcome this problem, secondary measurements can be used to infer the product quality and adjust the values of the manipulated variables. In this paper, we have used a novel inferential control approach based on adaptive network fuzzy inference system (ANFIS) for stripping process. ANFIS with different learning algorithms is used for modeling the process and building a composition estimator to estimate the composition of the bottom product. The developed estimator is tested, and the results show that the predictions made by ANFIS structure are in good agreement with the results of simulation by ASPEN HYSYS process simulation package. In addition, inferential control by the implementation of ANFIS-based online composition estimator in a cascade control scheme is superior to traditional tray temperature control method based on less integral time absolute error and low duty consumption in reboiler.

Keywords: Stripping Column, Composition Control, Inferential Estimator, Adaptive Network Fuzzy Inference System

1. Introduction

Stripping multi-component mixtures is one of the most common separation operations in the petroleum upstream industry. Stripping process takes place at the lower section of distillation columns. The stripping control system must hold product composition as near the set point as possible in the faces of upsets. The control is difficult because the product quality cannot be measured easily and economically online. This is because the instrumentation is either very expensive, and / or measurement lags and sampling delays make designing an effective control system impossible.

A solution to this problem is the use of tray temperature control method. The temperature control is

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based on the assumption that the product composition can satisfy its specification when an appropriate tray temperature is kept constant at its set point. If tray temperatures are to be used, the issue is selecting the best tray or trays on which temperature is held constant. This problem has been discussed in the distillation literature for over half a century. Hundreds of papers, each of which uses one particular method for temperature control and tray selection, have been presented. The discussion of one approach to this problem is given by Jorgensen et al. 1998.

Tray temperature control method is a proper option for binary distillation columns at a constant pressure, but where feed composition or feed flow rate changes in a multi-component distillation/stripping tower, it is quite difficult to keep product quality at its set point by using temperature control; this is due to the fact that the tray temperature does not correspond exactly to the product composition. Moreover, pressure changes also cause temperature variation. To solve this problem, secondary measurements in conjunction with a mathematical/empirical model of process can be used to estimate the product quality.

The distillation/stripping process can be modeled using input-output data from experimental tests. Regression and neural network modeling techniques are commonly used for this purpose.

Sivakumar et al. 2010 proposed a fuzzy model predictive control strategy for multivariable nonlinear control problem in distillation columns. They reported that fuzzy model predictive controller offers better control response than conventional PID controllers for multivariable processes.

Tonnang et al. 2010 developed a neural network controller for the control of an industrial distillation process. Field data was used for the development and testing the effectiveness of the controller. The developed controller performed optimally when compared with the installed distributed control system based on proportional integral and derivative algorithm.

Barcelo-Rico et al. 2011 designed a fuzzy controller for distillation process based on local fuzzy models and velocity linearization. The results showed that the fuzzy controller was able to keep the target output in the desired range for different input disturbances, changing smoothly from a predefined target output to another.

Rani et al. 2011 used intelligent controller to control the temperature profile of the reactive distillation process. Four intelligent controllers were designed based on fuzzy logic, adaptive linear network (Adaline), and hybrids of these two techniques. The fuzzy logic controller provides a better steady state response whereas the adaptive linear network controller provides better transient responses. The hybrid fuzzy-neural network controller and fuzzy Adaline controller were proposed to combine the advantages of the two techniques.

Araromi et al. 2012 developed a hybrid fuzzy Hammerstein (FH) model consisting of nonlinear fuzzy model and linear state space model for a reactive distillation column. The developed model was compared with linear autoregressive input exogenous (ARX) and nonlinear autoregressive input exogenous (NARX). The results showed that the FH model can provisionally capture the nonlinear dynamic behavior of reactive distillation system and the model can be found suitable for real time applications.

Gupta et al. 2013 designed an adaptive neuro-fuzzy controller to control a binary distillation process. The designed controllers were tested for set point tracking and disturbance rejection in feed composition. It was observed that the proposed ANFIS controller performed better than the conventional PID controllers.

Al-Naimi et al. 2013 used different control strategies to control the distillate and bottom composition of a packed distillation column to separate the mixture of methanol and water. They reported that adaptive fuzzy logic controller is better than feedback, PID fuzzy logic, and artificial neural network controllers because it uses an auxiliary variable used as another input to select the region in which the process is operating.

Popoola et al. 2013 investigated the expert system design and control of crude oil distillation column using an artificial neural networks model which was validated using experimental data. They concluded that an artificial neural networks model is an effective tool for the design and control of crude oil distillation column.

Popoola et al. 2013 presented a comprehensive review of various traditional systems of crude oil distillation column design, modeling, simulation, optimization, and control methods. Artificial neural network, fuzzy logic, and genetic algorithm framework were chosen as the best methodologies for design, optimization, and control of crude oil distillation column.

Giwa et al. 2013 developed ANFIS models for the reactive distillation process used for the production of isopropyl alcohol from the hydration reaction of propylene. The high fit values and low means of absolute error obtained respectively from the training and testing of the ANFIS models have revealed that the developed ANFIS models represented the reactive distillation process very well.

Arumugam et al. 2014 proposed a fuzzy logic controller for methanol/water arrangement of bubble cap distillation column. It was concluded that the fuzzy logic control led to lower integral square error, smaller integral absolute error, and smaller integral time absolute error compared to the PID controller.

Miccio et al. 2014 developed a type-1 and a type-2 fuzzy logic PID controller for the control of a binary distillation column, the mathematical model of which is characterized by both high nonlinearities and parameter uncertainties. The performance of the type-1 fuzzy logic controller was compared with that of the type-2 fuzzy logic controller, and the robustness and effective control action of each fuzzy controller, with evident advantages for the type-2 controller, were investigated.

Ahmadi et al. 2014 modeled and optimized an industrial hydrocracker unit by means of adaptive neuro fuzzy inference system. The obtained networks were used to predict the plant optimum operating condition in order to maximize the volume percent of gas oil, kerosene, heavy naphtha and light naphtha as objective functions.

Sangster et al. 2016 developed a fuzzy supervisory controller which included a feed forward and two feedback controllers for the purpose of improving the dual product quality control of an existing pilot binary distillation column. Positive results were achieved as the majority of the simulated controller outputs were within 10% of the actual values.

In this research, we used a novel inferential composition control approach based on adaptive network fuzzy inference system (ANFIS) for a stripping process. In previous studies, ANFIS has been used for the identification of the process or the estimation of controller output, but the composition of the product was not reported as the measured variable of the controller. The main aim of this paper is to present a novel nonlinear modeling and control study concerning an industrial stripping column using adaptive network fuzzy inference systems with different learning algorithms. ANFIS structure is used for building a nonlinear model of the column. The investigated column operates the separation of hydrogen sulfide from the outlet stream of a production unit. The H₂S concentration in the bottom product has to be controlled.

2. Methods

The research work was carried out in the following steps: (i) the steady state simulation of the process; (ii) the dynamic simulation of process; (iii) the nonlinear modeling of process; (iv) the inferential control of process based on the empirical model of the system; and (v) a comparison between the proposed inferential control and the traditional tray temperature control strategy. The flow chart of the method used is presented in Figure 1.

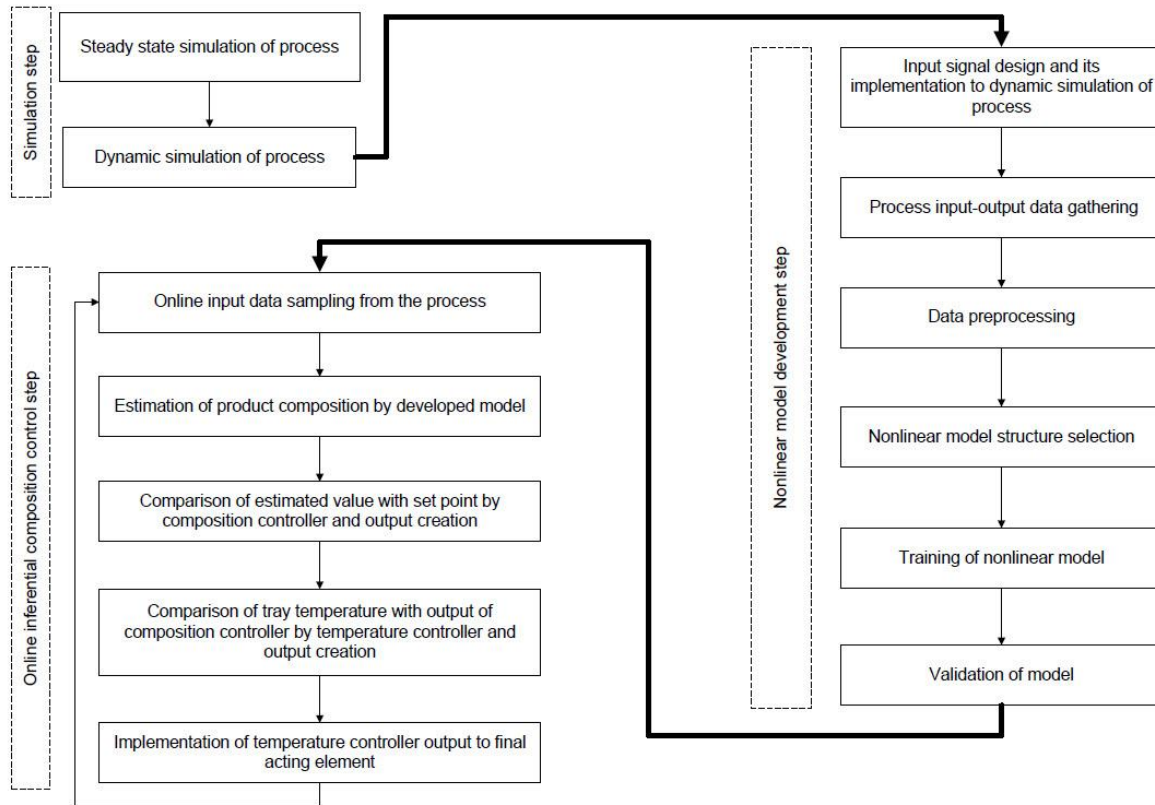


Figure 1

Flow chart of the method used for the identification and inferential control of oil sweetening process.

2.1. Steady state simulation of the process

A schematic representation of the examined column is given in Figure 2. The column has 20 valve trays, and the feed enters at tray 20; the bottom and top products are removed at trays 1 and 20 respectively.

The composition of the feed stream is illustrated in Table 1. The column was simulated by means of ASPEN HYSYS process simulation package, and the steady state operating conditions of the column are reported in Table 2.

The column feed stream is the outlet stream from the second stage separator in oil production unit. The purpose of this column is to reduce the H_2S concentration in the bottom product, which is sent to storage tanks.

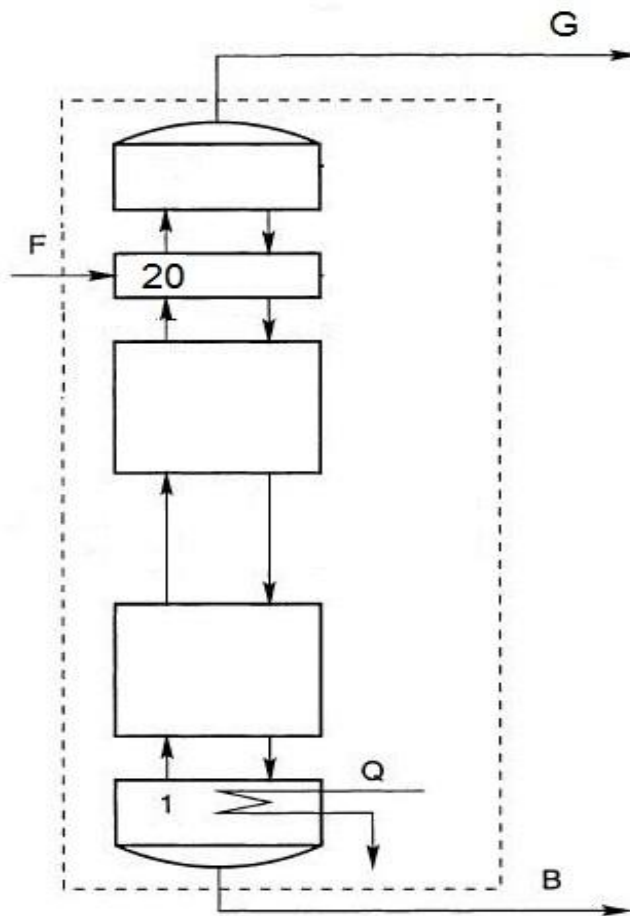


Figure 2
Schematic layout of the column.

Table 1
Composition of the column feed.

Component name	Concentration (wt.%)	
Methane	0.0011	
Ethane	0.0066	
Propane	0.0149	
iButane	0.0062	
nButane	0.0186	
iPentane	0.0128	
nPentane	0.0162	
Hexane	0.0396	
Hydrogen sulfide	0.0089	
Carbon dioxide	0.0005	
C_7^+	0.8745	
C_7^+ Properties	Molecular weight	199
	Specific gravity	0.8632

Table 2
Steady state operating conditions of the column.

Stream			
Feed	Flow rate	kg/hr.	115000
	Temperature	°C	60
	H ₂ S concentration	PPM	8900
Gas	Flow rate	kg/hr.	4800
	H ₂ S concentration	PPM	211852
Bottom	Flow rate	kg/hr.	110200
	H ₂ S concentration	PPM	60
	Reboiler duty	kJ/hr.	1.45×10 ⁷

2.2. Dynamic simulation of the process

The dynamic behavior of the column was simulated by ASPEN HYSYS DYNAMIC simulation package. Tray liquid hydraulic was predicted by Glitsch procedure, and the equilibrium constants were calculated by the SRK relation. The simulation model takes into account the stripper tower as well as all the auxiliary apparatus (reboiler, measuring devices, and control elements).

As illustrated in Figure 3, for the design of stripper column control system, it is proposed that the tower pressure is controlled by manipulating top gas flow rate, that the reboiler liquid level is controlled by manipulating bottom product flow rate, and that tray 2 temperature is controlled by manipulating reboiler duty in order to keep the bottom product H₂S concentration constant.

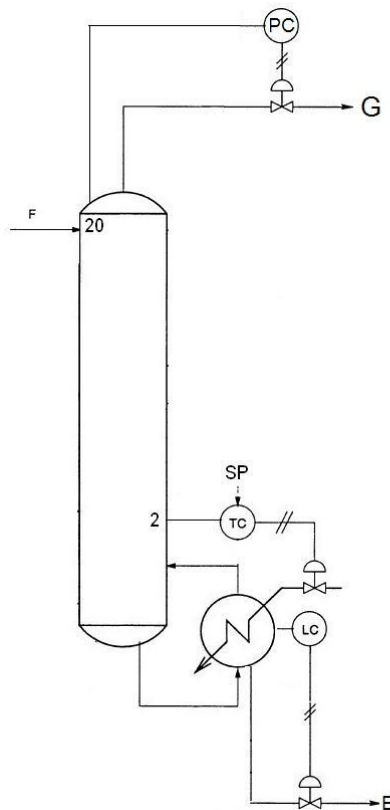


Figure 3

Traditional tray temperature control technique applied to the stripping column.

2.3. Nonlinear modeling

2.3.1. Input signal design and data collection

The simulated data for building inferential estimator are obtained under the following conditions. The pseudo random binary signals of bound and varying amplitude are introduced as the feed temperature (within $\pm 5\%$ of the steady state values) and total flow rate changes (within $\pm 20\%$ of the steady state values) during simulations. For realizing slow composition changes, each signal is filtered by a first order lag model. Total simulation time is 48 hours, and process data are sampled every one minutes.

The simulated data for validating inferential models are obtained in almost the same conditions as described above. The total simulation time is 24 hours.

If the input-output data described above are obtained when the temperature controller is in the automatic mode, the data do not include the operational conditions when the controlled temperatures undergo large changes. However, when inferential composition control, instead of temperature control, is applied, the trays temperature fluctuates greatly. Thus, when an inferential model is used for composition control, the accuracy of estimation may deteriorate due to large changes of tray temperature. In order to improve the accuracy, the inferential model must be built using appropriate data, which include large fluctuation of the temperature. For this purpose, the proportional gain of the bottom temperature controller is changed between $\pm 50\%$ of the base controller gain in the simulation in order to change the reboiler duty. Figures 4a, 4b, and 4c represent the input signals applied to the process for collecting identification data.

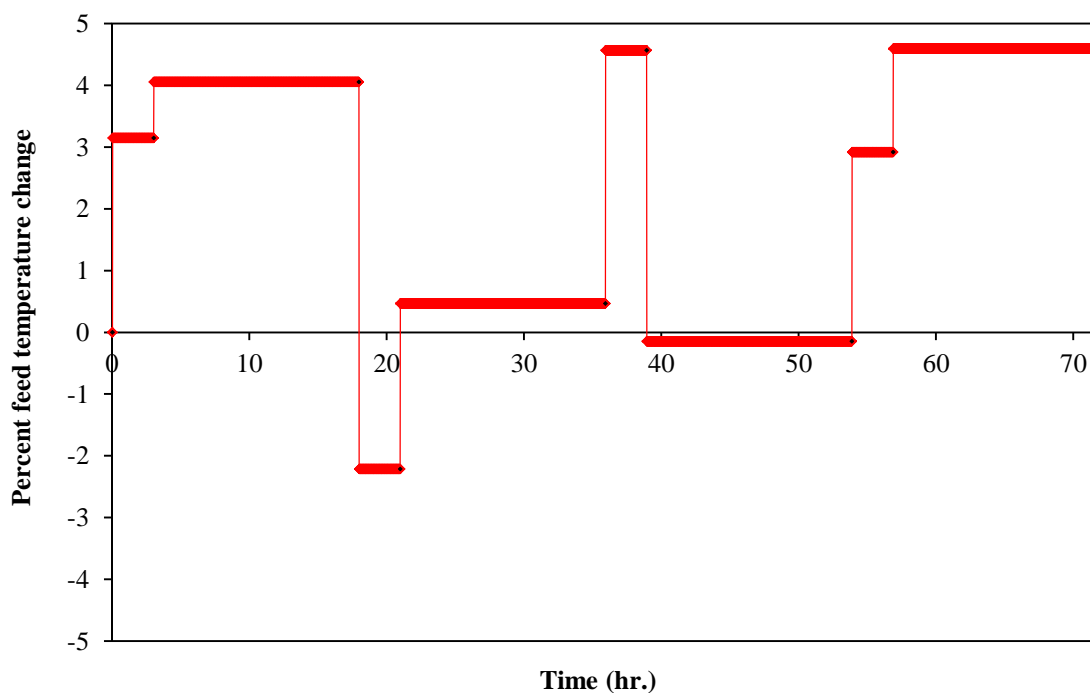
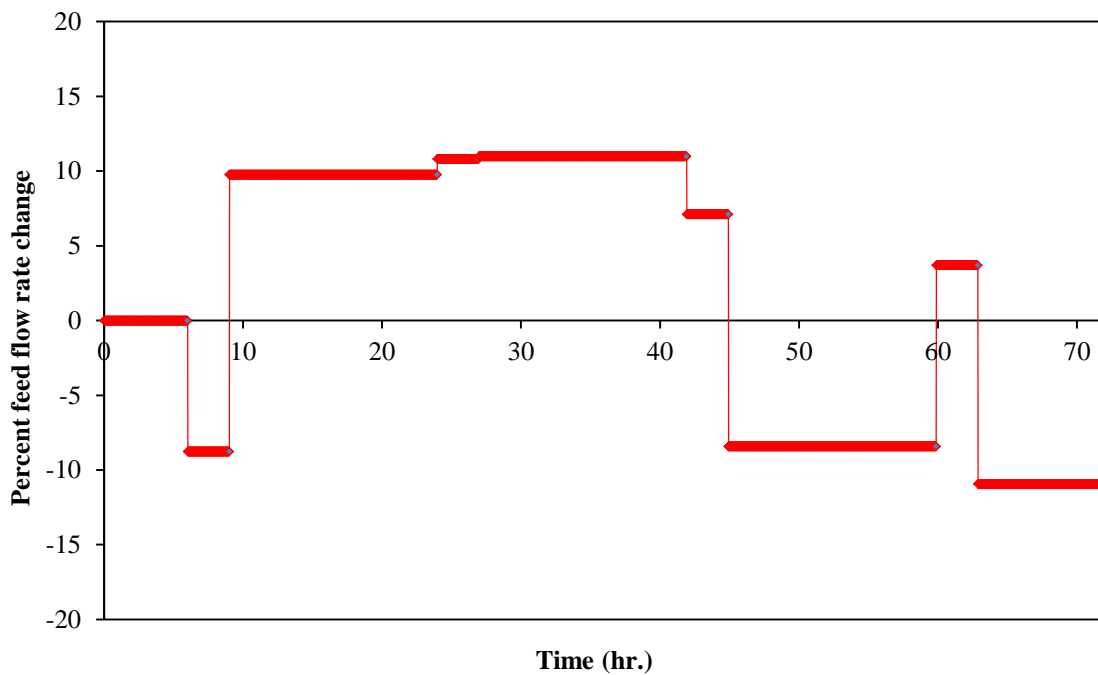
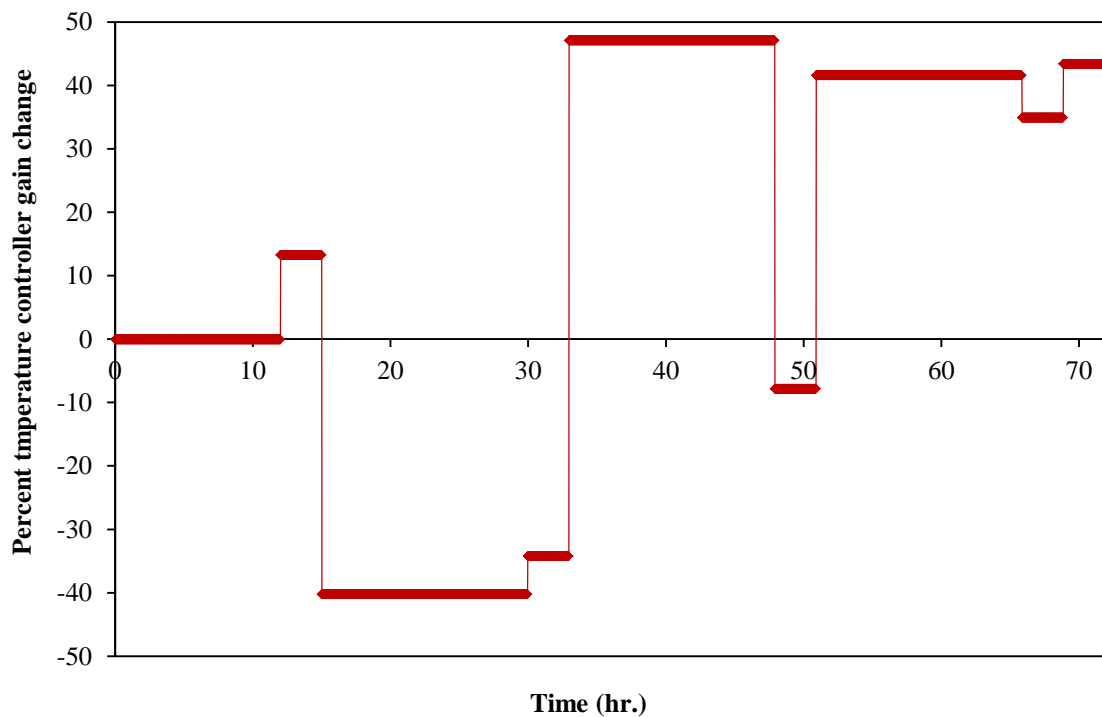


Figure 4a

Input signal (feed temperature change) applied to the process for collecting identification data.

**Figure 4b**

Input signal (feed flow rate change) applied to the process for collecting identification data.

**Figure 4c**

Input signal (temperature controller gain change) applied to the process for collecting identification data.

2.3.2. Data preprocessing

The collected data have different magnitudes depending on the units adopted. This can cause larger magnitude variables to be dominant over smaller ones during the training process. Data scaling is

therefore needed. Min-max normalization method is one of the common scaling methods; min-max normalization is given by:

$$a' = \frac{a - \min_a}{\max_a - \min_a} (\max_{a'} - \min_{a'}) + \min_{a'} \quad (1)$$

Where, a is the unscaled variable, and a' is the scaled variable; \min_a is the minimum value of the unscaled variable, and \max_a is the maximum value of the unscaled variable; $\min_{a'}$ is the minimum value of the scaled variable, and $\max_{a'}$ is the maximum value of the scaled variable.

In this research, the collected data are scaled to [0, 1] interval. Since the collected data are the results of the simulation and have no inconsistent data, other preprocessing operations such as outlier detection, missing value replacement, and data de-noising are not required.

2.3.3. Model structure selection

One modification of a neural network structure is to replace some of or all of the components of neuron by fuzzy logic operations. Conventional neural networks are used to approximate functions from numerical input-output data. Fuzzy-neural networks are a more general computational structure with which function approximation can be extended to linguistic data.

To illustrate the use of neural networks for fuzzy inference, consider a fuzzy rule base consisting of only two Sugeno-Takagi rules:

$$R_1: \text{If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1, \text{ then } y = f_1(x) \quad (2)$$

$$R_2: \text{If } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2, \text{ then } y = f_2(x) \quad (3)$$

where, A_i and B_i are fuzzy sets and

$$f_1(x) = Z_{11}x_1 + Z_{12}x_2 + Z_{13} \quad (4)$$

$$f_2(x) = Z_{21}x_1 + Z_{22}x_2 + Z_{23} \quad (5)$$

When numerical input $x = (x_1, x_2)$ is presented, the inference mechanism will produce the numerical output:

$$y^* = \frac{A_1(x_1)B_1(x_2)f_1(x) + A_2(x_1)B_2(x_2)f_2(x)}{A_1(x_1)B_1(x_2) + A_2(x_1)B_2(x_2)} \quad (6)$$

A fuzzy neural network for implementing the above formula is shown in Figure 5. The observed input $x = (x_1, x_2)$ is presented to layer 1 by input layer 0. The output of layer 1 is given by:

$$(O_{11}, O_{12}, O_{13}, O_{14}) = (A_1(x_1), A_2(x_1), B_1(x_2), B_2(x_2)) \quad (7)$$

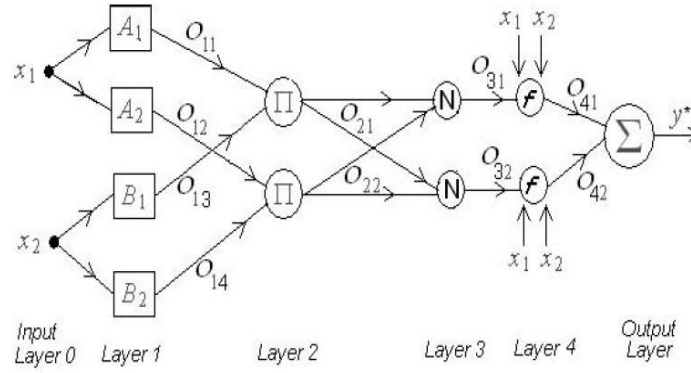


Figure 5
First order Sugeno fuzzy model with two rules.

Layer 2 consists of fuzzy neurons with an aggregation operator being some T-norm. If product T-norm is used the output of layer 2 is defined by:

$$(O_{21}, O_{22}) = (A_1(x_1)B_1(x_2), A_2(x_1)B_2(x_2)) \quad (8)$$

Layer 3 is normalizer. The output of layer 3 is:

$$(O_{31}, O_{32}) = \left(\frac{O_{21}}{O_{21} + O_{22}}, \frac{O_{22}}{O_{21} + O_{22}} \right) \quad (9)$$

The fuzzy neurons in layer 4 output the below values:

$$(O_{41}, O_{42}) = (O_{31}f_1, O_{32}f_2) \quad (10)$$

Finally, the output layer calculates the estimated output by summing:

$$y^* = O_{41} + O_{42} \quad (11)$$

Of course, this neural network type for representing the inference procedure for a rule base of two rules can be extended in an obvious way to an arbitrary number of rules.

In the ANFIS structure, the parameters of the premise and consequence play the role of weights in neural network systems. The ANFIS learning algorithm consists of adjusting the mentioned parameters from sample data $((x_1^k, x_2^k), y^k), k = 1, \dots, N$.

2.3.4. Validation of model

The estimated model can be evaluated on the basis of the mean squared error of the prediction (MSEP), which is calculated by applying the models to the validation data.

$$MSEP = \frac{1}{N} \sum_{n=1}^N (b(n) - \hat{b}(n))^2 \quad (12)$$

where, b is a measurement of the product composition, and \hat{b} is its estimate; N is the number of measurements.

3. Results and discussion

3.1. Inferential model

The output variable to be estimated is the H_2S concentration of the bottom product. The inputs to the inferential estimator are various combinations of 20 tray and reboiler temperatures and feed, gas, and bottom stream flow rates. Sample numbers 1 to 2880 are used for training ANFIS structure, and sample numbers 2881 to 4320 are used for the validation of the model. Training ANFIS structure is performed with four methods as described below:

1. Back propagation learning rule (BPLR);
2. Back propagation learning rule the number of fuzzy rules of which is determined by subtractive clustering (BPLRC);
3. Genetic algorithm (GA);
4. Particle swarm optimization method (PSO);

Table 3 illustrates the MSE of the validation data for the following combinations of inputs to the inference system.

IN1. $T_2, T_3, T_4, RebT, F, B$

IN2. $T_1, T_2, T_3, T_4, RebT$

IN3. $T_2, T_4, T_6, T_{16}, T_{18}, T_{20}$

IN4. $T_1, T_{10}, T_{20}, RebT, F, B$

IN5. $T_9, T_{11}, RebT, F, B$

IN6. $T_1, T_5, T_{10}, T_{15}, T_{20}, RebT$

where, T_i is tray i temperature, and $RebT$ is the reboiler temperature; F is feed stream flow rate, and B is the bottom product flow rate;

Table 3
MSEP of the validation data.

Inputs	Training algorithm	Inference system properties		MSEP for bottom product
		Number of fuzzy rules	Number of parameters	H_2S concentration ($\times 10^{-3}$)
IN1	BPLR	64	484	921.41
	BPLRC	2	38	349.77
	GA	2	38	123.54
	PSO	2	38	254.62
IN2	BPLR	32	222	131.94
	BPLRC	2	32	14.41
	GA	2	32	31.49
	PSO	2	32	28.45
IN3	BPLR	64	484	3.32
	BPLRC	2	38	0.79

Inputs	Training algorithm	Inference system properties		MSEP for bottom product H ₂ S concentration ($\times 10^{-3}$)
		Number of fuzzy rules	Number of parameters	
	GA	2	38	54.26
	PSO	2	38	87.35
IN4	BPLR	64	484	1.86
	BPLRC	2	38	0.37
	GA	2	38	8.27
	PSO	2	38	2.40
IN5	BPLR	32	222	9.31
	BPLRC	2	32	5.49
	GA	2	32	922.54
	PSO	2	32	124.78
IN6	BPLR	64	484	1.01
	BPLRC	2	38	0.73
	GA	2	38	10.36
	PSO	2	38	2.10

The examination of various combinations of the inputs show that the combination recommended in case IN4 is the most efficient for the estimation of H₂S concentration in the bottom product based on MSEP.

The stripping process is a complicated process, and any change in the feed condition does not change the product quality simultaneously; on the other hand, the system has some time delay. This time delay can also be considered in the selection of the inputs to the ANFIS structure. Table 4 illustrates the MSEP of the validation data for the following combination of the delayed inputs to inference system. The numbers in bracket correspond to the number of the sampling time delay.

IN7. $T1[1]$, $T5[3]$, $T10[5]$, $T15[6]$, $T20[6]$, $RebT[0]$

IN8. $T1[1,2]$, $T5[3,4]$, $T10[5,6]$, $T15[6,7]$, $T20[6,7]$, $RebT[0]$

IN9. $T1[1]$, $T10[5]$, $T20[6]$, $RebT[0]$, $F[6]$, $B[0]$

IN10. $T1[1,2]$, $T10[5,6]$, $T20[6,7]$, $RebT[0]$, $F[6,7]$, $B[0]$

Table 4

MSEP of the validation data for the delayed inputs to the ANFIS structure.

Inputs	Training algorithm	Inference system properties		MSEP for bottom product H ₂ S concentration ($\times 10^{-3}$)
		Number of fuzzy rules	Number of parameters	
IN7	BPLR	64	484	0.90
	BPLRC	2	38	0.48
	GA	2	38	7.51
	PSO	2	38	5.20
IN8	BPLR	2048	16130	1.52
	BPLRC	2	68	0.84

Inputs	Training algorithm	Inference system properties		MSEP for bottom product
		Number of fuzzy rules	Number of parameters	H ₂ S concentration ($\times 10^{-3}$)
IN9	GA	2	68	6.32
	PSO	2	68	6.74
	BPLR	64	484	2.08
	BPLRC	2	38	0.29
	GA	2	38	5.37
	PSO	2	38	2.48
IN10	BPLR	1024	8081	2.11
	BPLRC	2	62	0.38
	GA	2	62	4.33
	PSO	2	62	4.86

From the above analysis, it can be concluded that the inference system represented in Table 5 is the most efficient model for the estimation of the H₂S concentration of the bottom product. The best training algorithm for the ANFIS structure is the back propagation learning algorithm accompanied by subtractive clustering. Figure 6 illustrates the block diagram of the proposed model.

Table 5

Property of the optimum model for the estimation of the bottom product H₂S concentration.

Inputs to ANFIS structure	Training algorithm	MSEP for bottom product H ₂ S concentration ($\times 10^{-3}$)
<i>T1</i> [1], <i>T10</i> [5], <i>T20</i> [6], <i>RebT</i> [0], <i>F</i> [6], <i>B</i> [0]	BPLRC	0.29

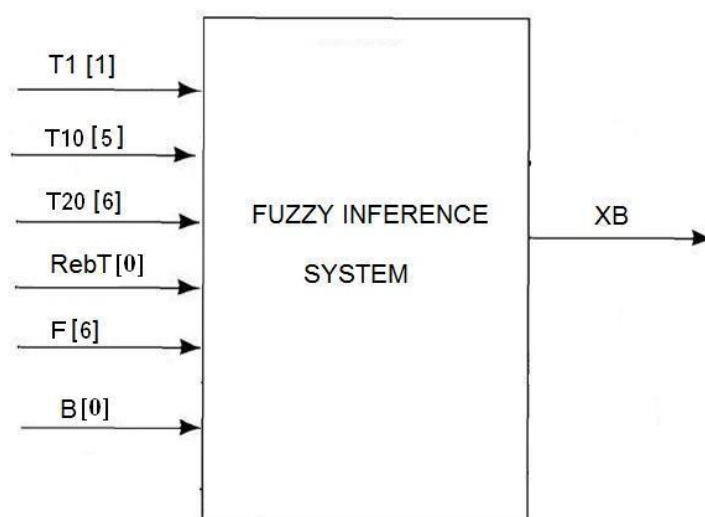


Figure 6

Block diagram of the proposed model for the estimation of the bottom product H₂S concentration.

Figure 7 visualizes the estimated values versus the actual ones for both the training (sample numbers 1 to 2880) and the validation data (sample numbers 2881 to 4320) of the proposed model. It is

obvious that the estimated values are in good agreement with the actual ones, and the model is satisfactory.

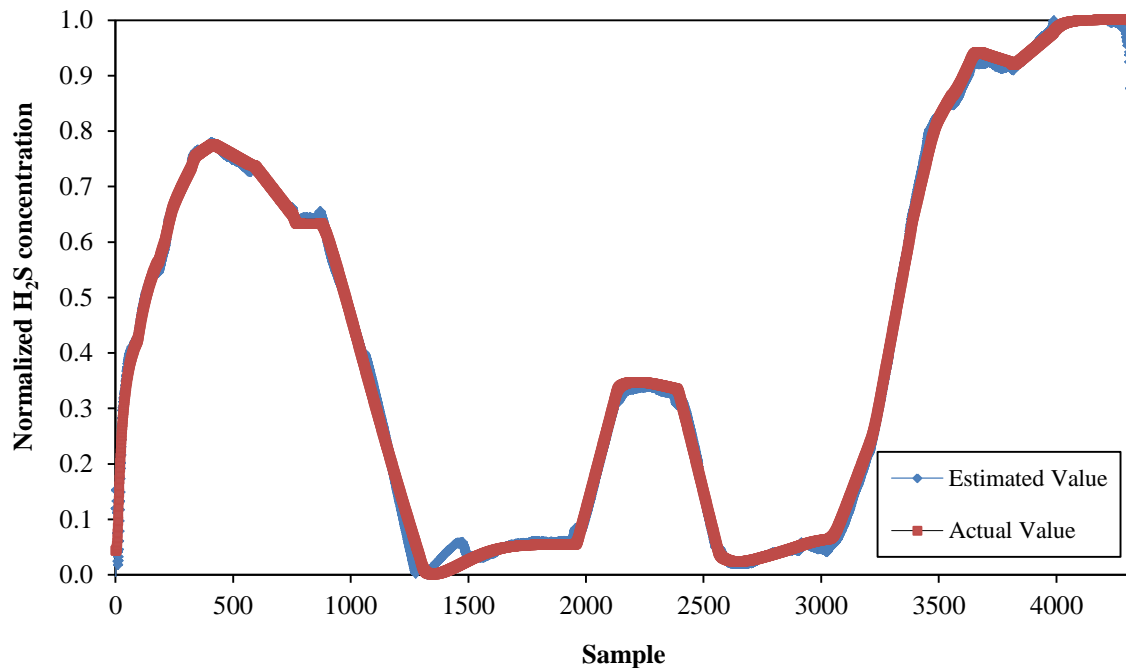


Figure 7

Estimated and actual values of the H_2S concentration of the product stream.

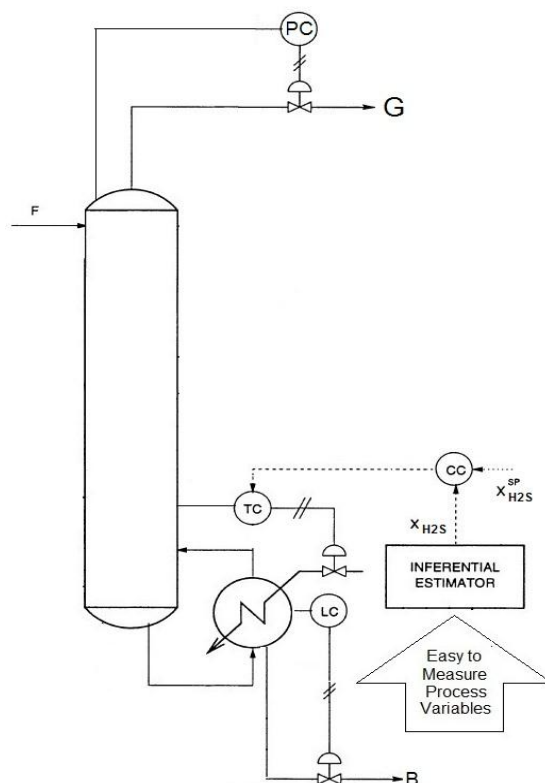
For the prediction of the bottom product H_2S concentration, the optimum inputs to the inference system are:

- Tray 1 temperature with one sample time delay;
- Tray 10 temperature with five samples time delay;
- Tray 20 temperature with six samples time delay;
- Reboiler temperature with zero sample time delay;
- Feed stream flow rate with six samples time delay;
- Bottom product flow rate with zero sample time delay;

3.2. Control strategy and results

On the basis of the control analysis reported in section 3.1, the inferential control strategy of the column shown in Figure 8 was adopted. A cascade control scheme has been assumed for control variable, with H_2S concentration on the primary (master) loop and tray temperature on the secondary (slave) one.

The efficiency of the control strategy was examined on the basis of the responses of the process to step the changes of H_2S composition of the feed stream ($\pm 10\%$), feed stream temperature ($\pm 5\%$), and total feed flow rate ($\pm 10\%$). The evaluation of control efficiency was conducted by calculating the integral time absolute error (ITAE) (see Table 6) over a horizon of 2 hours after the implementation of disturbance.

**Figure 8**

Layout of column inferential control configuration.

Table 6

ITAE of H₂S concentration for different control schemes.

Disturbance	Control strategy	ITAE
H ₂ S composition of feed (+10%)	Tray temperature	1.30
	Inferential	2.24×10^{-4}
H ₂ S composition of feed (-10%)	Tray temperature	1.95
	Inferential	2.41×10^{-4}
Temperature of feed (+5%)	Tray temperature	166.10
	Inferential	9.36×10^{-4}
Temperature of feed (-5%)	Tray temperature	15.32
	Inferential	8.97×10^{-4}
Total flow rate of feed (+10%)	Tray temperature	5.93
	Inferential	3.45×10^{-4}
Total flow rate of feed (-10%)	Tray temperature	7.95
	Inferential	2.82×10^{-4}

The responses of the system to step changes of the H₂S composition of the feed stream, feed stream temperature, and total feed flow rate when the H₂S concentration of the product stream is controlled by the cascade inferential scheme or by keeping the relevant tray temperature constant are compared in Figures 9-14. Tray temperature control method leads to a decrease in H₂S concentration below the set point (60 ppm) in Figures 9a, 12a, and 13a, and this is favorable from a process point of view;

however, from an economic point of view, this is not reasonable because considerable heat duty is consumed in the reboiler to decrease the H₂S below the set point without any necessity to do so (see Figures 9b, 12b, and 13b).

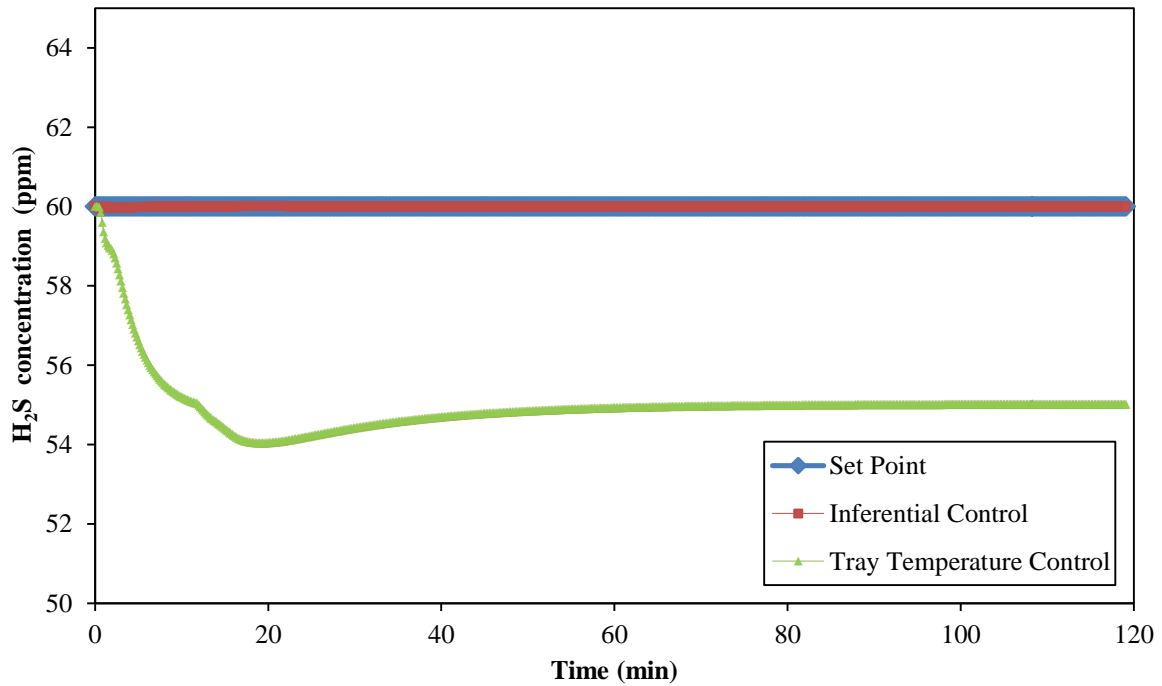


Figure 9a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +10% in the feed stream H₂S concentration.

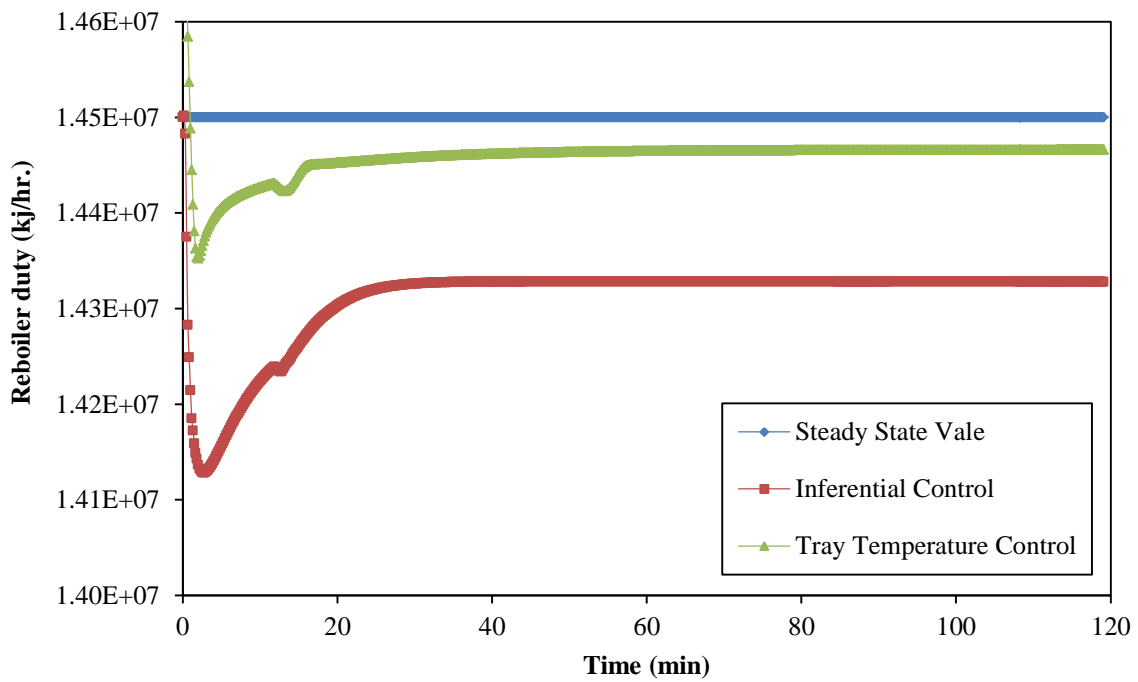


Figure 9b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +10% in the feed stream H₂S concentration.

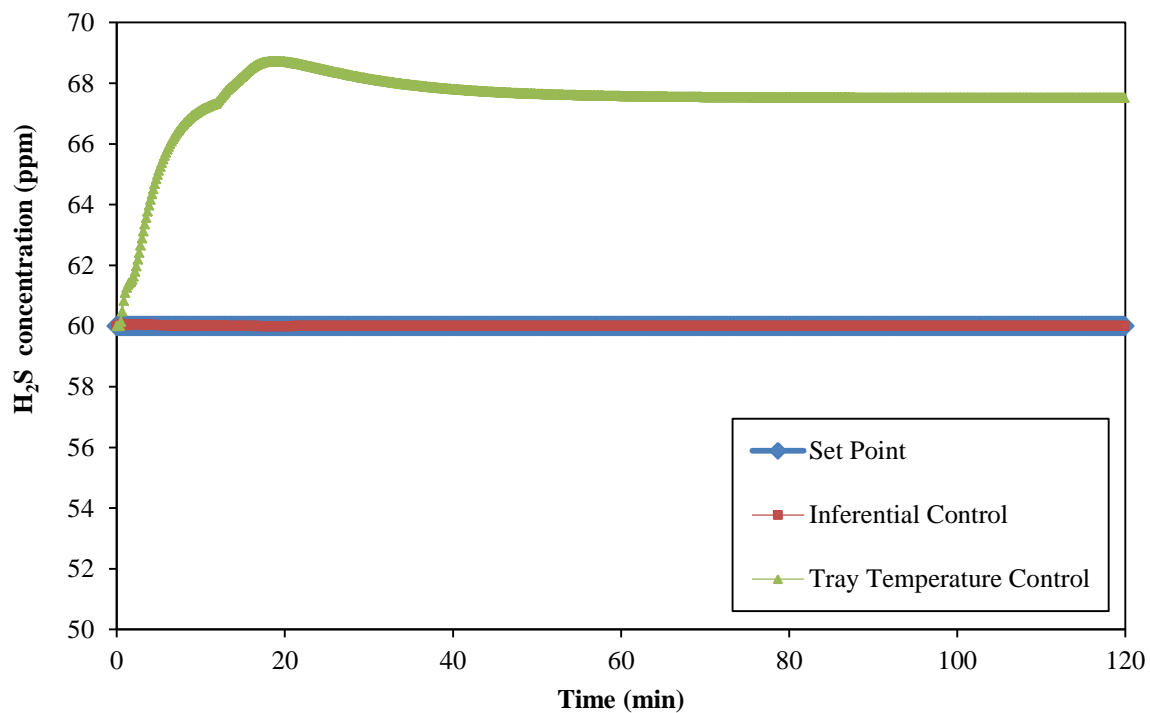


Figure 10a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -10% in the feed stream H_2S concentration.

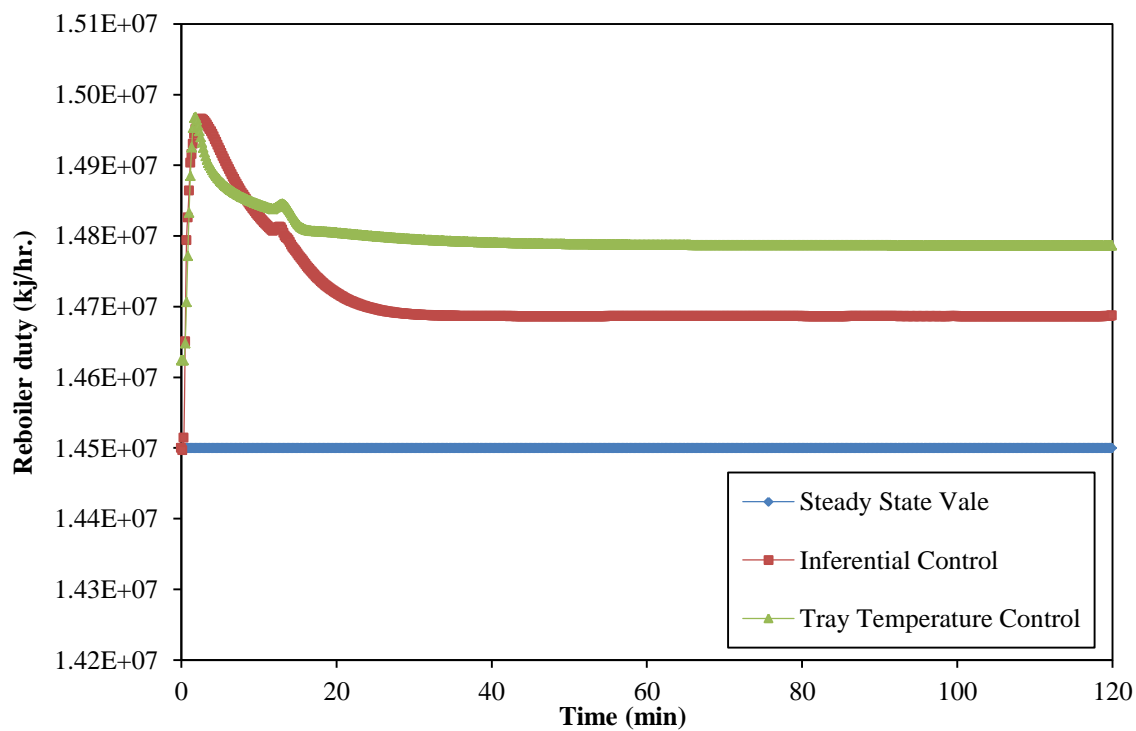


Figure 10b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -10% in the feed stream H_2S concentration.

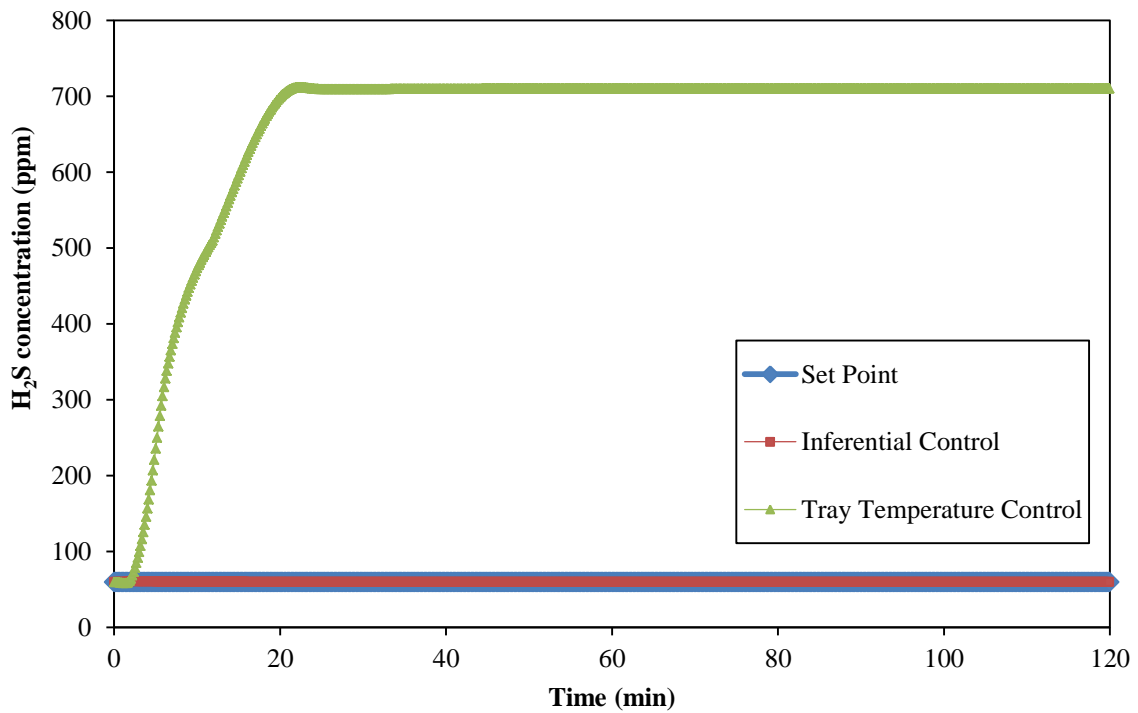


Figure 11a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +5% in the feed stream temperature.

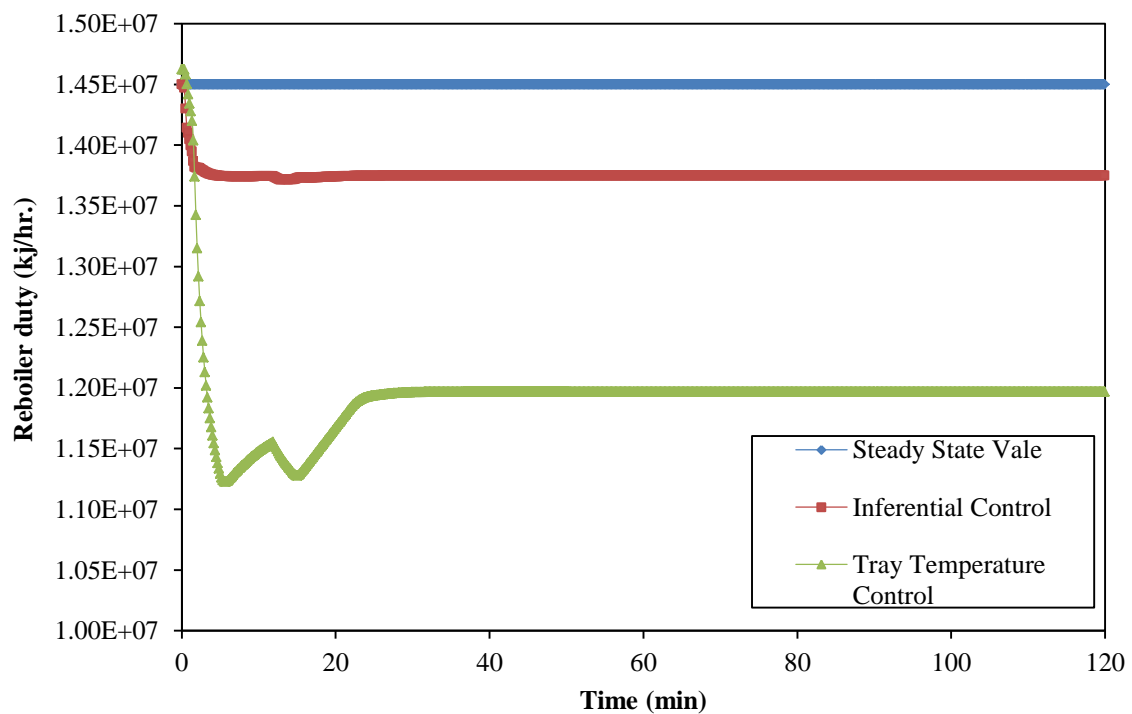


Figure 11b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +5% in the feed stream temperature.

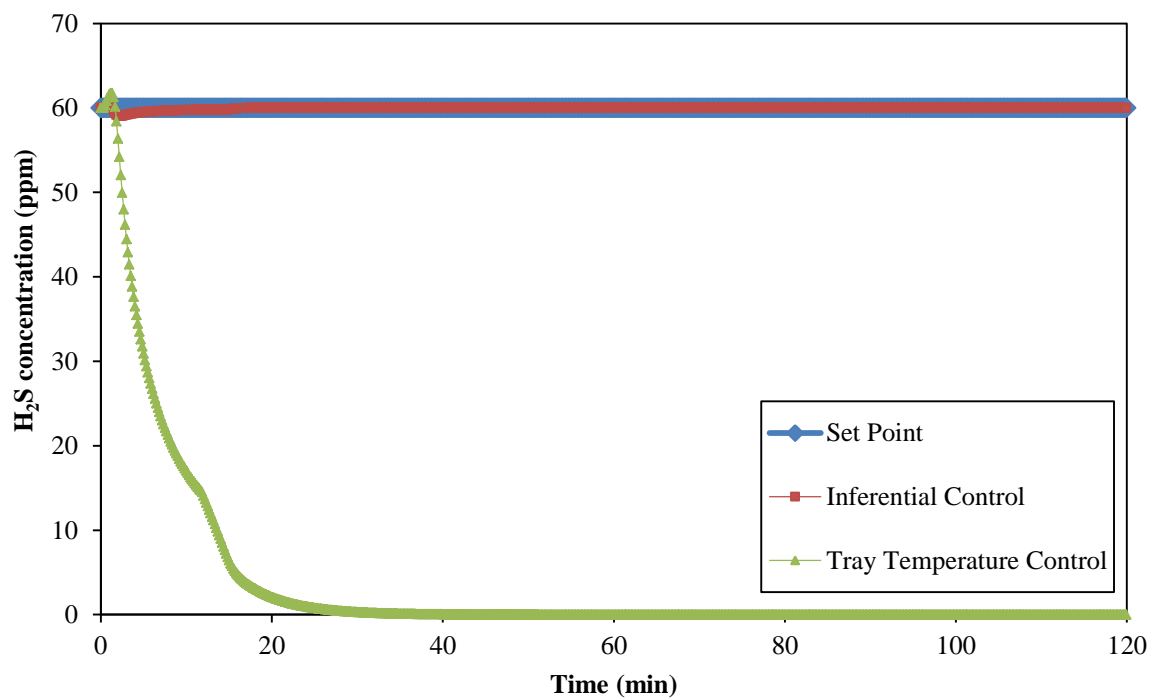


Figure 12a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -5% in the feed stream temperature.

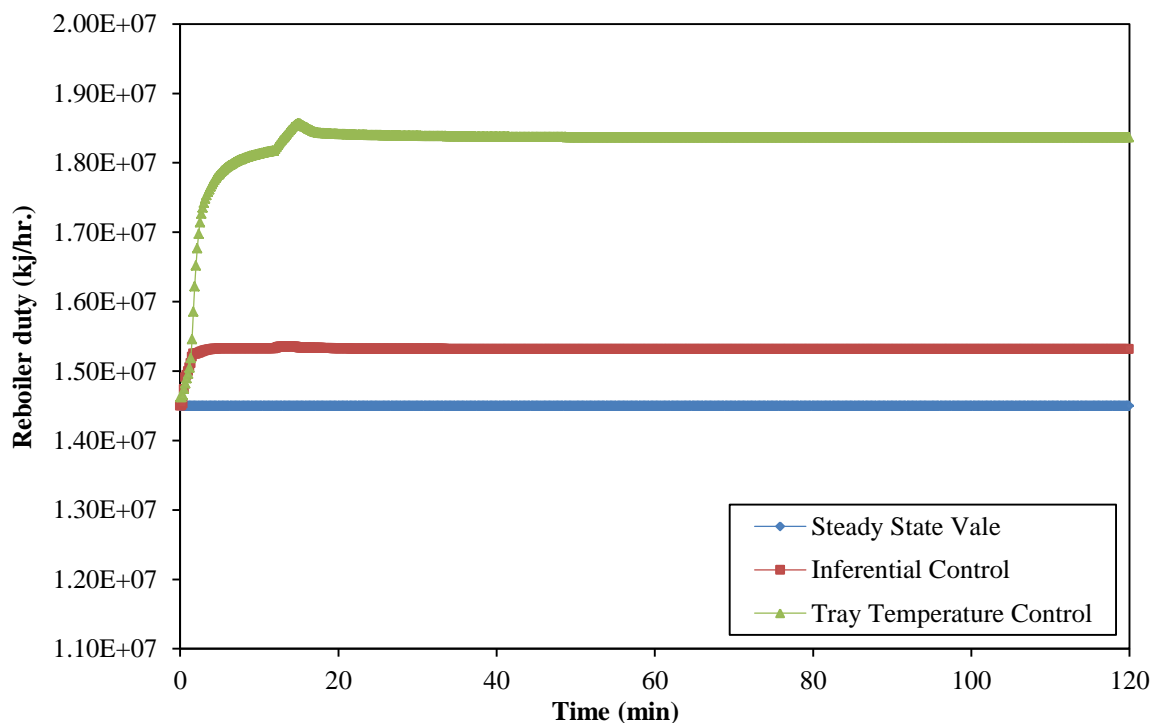


Figure 12b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -5% in the feed stream temperature.

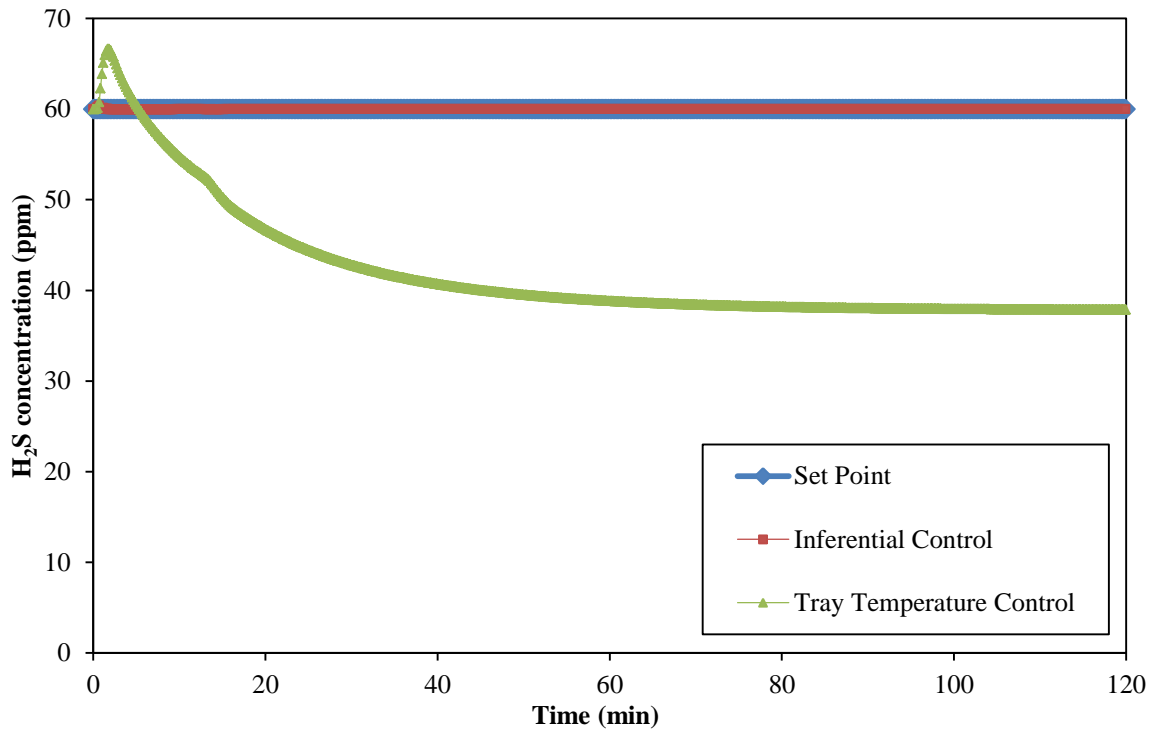


Figure 13a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +10% in the feed stream total flow rate.

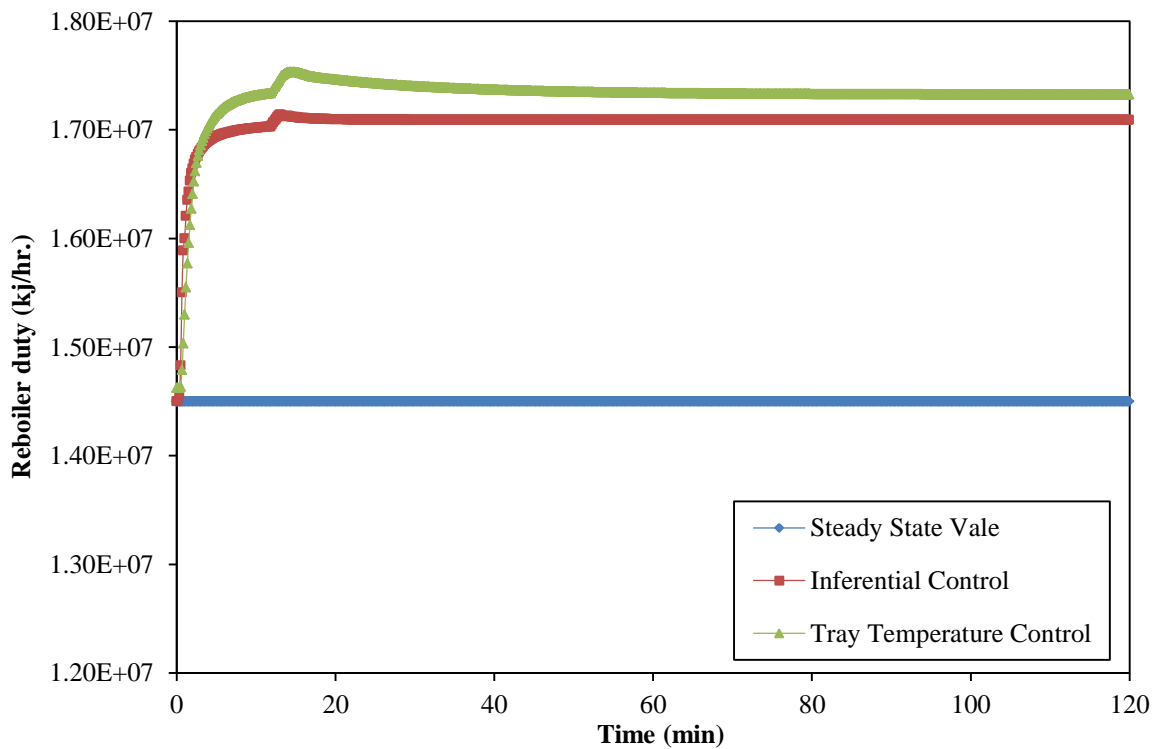


Figure 13b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of +10% in the feed stream total flow rate.

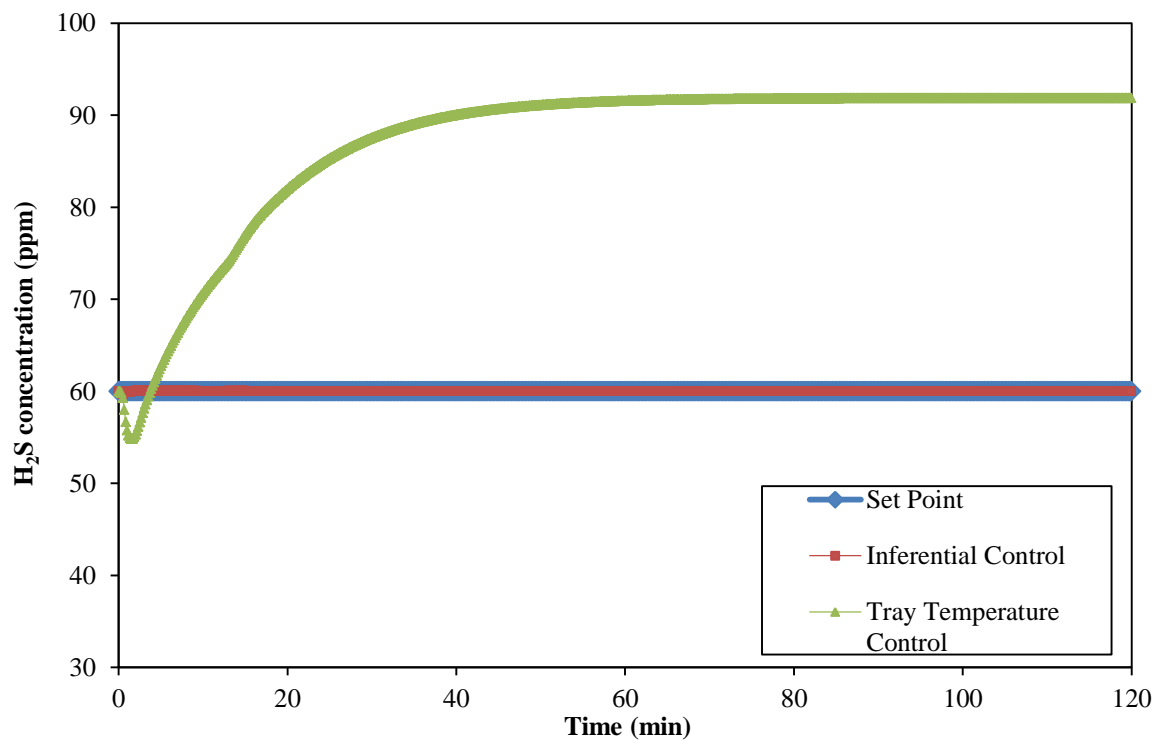


Figure 14a

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -10% in the feed stream total flow rate.

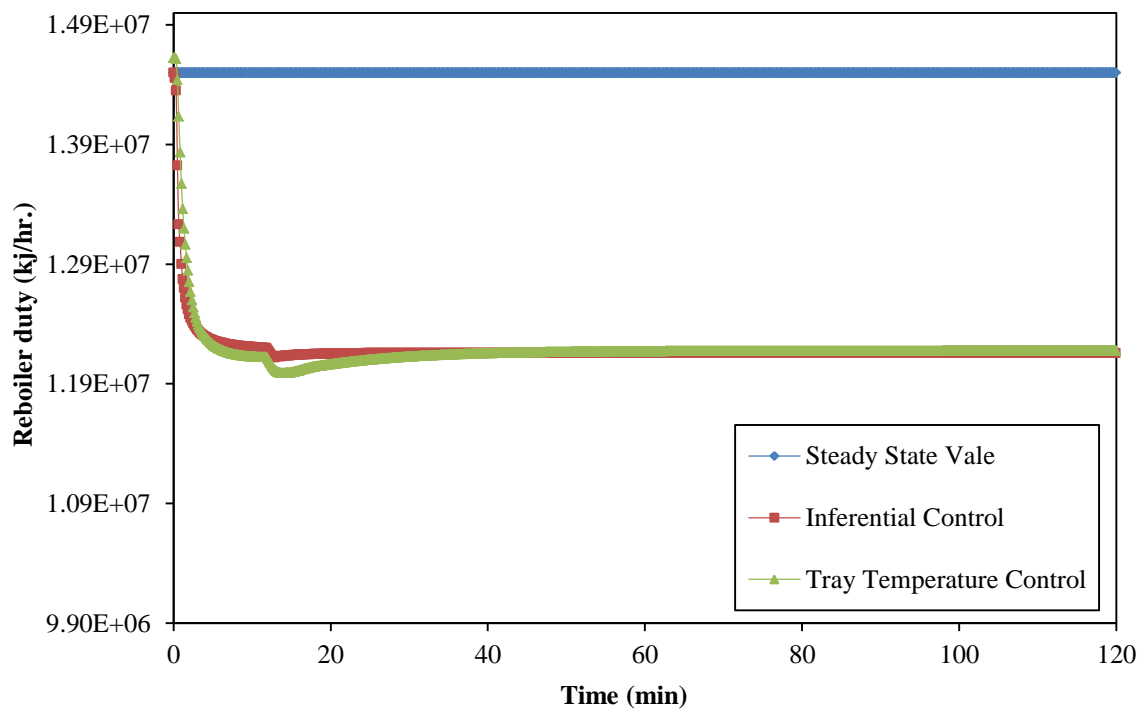


Figure 14b

Comparison between the performance of the traditional and inferential bottom product controller in response to the step change of a magnitude of -10% in the feed stream total flow rate.

4. Conclusions

In this paper, a novel inferential control system was developed based on ANFIS composition estimator for a stripper column. Four training algorithms (back propagation, back propagation with subtractive clustering, genetic algorithm, and particle swarm optimization method) are used for training ANFIS structure in an offline mode, and it is observed that back propagation algorithm with subtractive clustering is the best algorithm of training based on the mean squared error of the prediction of the validation data of the model.

The simulation results show that the proposed ANFIS-based composition estimator leads to the predictions that are in good agreement with the results of the simulation by ASPEN HYSYS process simulation package. ANFIS online composition estimator is also used in a cascade control scheme to control the quality of the product of a stripper column. It is observed that the inferential control of stripper column by the implementation of ANFIS-based online composition estimator is superior to traditional tray temperature control method based on less integral time absolute error and low heat consumption in the reboiler.

Nomenclature

B	: Bottom stream flow rate (kg/hr.)
CC	: Composition controller
F	: Feed stream flow rate (kg/hr.)
G	: Gas stream flow rate (kg/hr.)
H ₂ S	: Hydrogen sulfide
IN _i	: Input <i>i</i> to ANFIS structure
LC	: Level controller
PC	: Pressure controller
PPM	: Part per million
Q	: Reboiler duty (kJ/hr.)
RebT	: Reboiler temperature (°C)
SP	: Set point
TC	: Temperature controller
T _i	: Tray <i>i</i> temperature (°C)
Wt.	: Weight (kg)
X	: Mass fraction

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