



COMPOSITION CONTROL BY TEMPERATURE INFERENCE USING FUZZY CONTROLLERS IN THE ETHYLBENZENE PRODUCTIVE PROCESS

Paulo Romero de Araujo Mariz

Emanuella Francisca Lacerda Vieira

Jonas Laedson Marinho da Silva Santos

Marcelo da Silva Pedro

Walter Yanko de Aragão Brandão

Leopoldo Oswaldo Alcázar Rojas

Arioston Araújo de Moraes Júnior

rom3romariz@gmail.com

emanuella_vieira@hotmail.com

jonas.laedson@hotmail.com

marcelopedrocz@hotmail.com

walteryanko@gmail.com

leopoldoalcazar@hotmail.com

aamj@ct.ufpb.br

Federal University of Paraíba

Technology Center, 58051-970, João Pessoa, Paraíba, Brazil

Abstract. *The nonlinearity, coupling, slow dynamics and interactivity are process characteristics that cause the need to develop new technologies and advanced control algorithms, capable to minimize these particularities. In these cases, fuzzy controller is suited to be employed, especially for multiple inputs and multiple outputs systems (MIMO), which*

there are significant interactions between the manipulated variables and controlled. In this paper, the methodology applied in the ethylbenzene productive process (EB), that is produced via alkylation reaction of benzene, was the employ of the fuzzy control algorithms and non-linear PID (proportional-derivative-integrative) technology and comparing their performance. After the chemical reaction, which occurs in two continuous stirred tank reactor (CSTR), the EB follows to the separation stage in two multicomponent distillation columns, C1 and C2, and should be recovered in the top stream of the second distillation column (C2), producing a high purity component ($\geq 99.9\%$). However, since the composition variable is an analytical quantity, its measurement and control are not performed directly, and the use of inferential temperature control is common to keep the compositions in its Setpoint. Through the techniques of selecting variables - decomposition of singular values (SVD), Relative Gain Array (RGA) and Non-Square Relative Gain Array (NRG) - the better pairs of manipulated variables (MV) and process variables (PV) were selected, after performing the control loop sensitivity analyses in the distillation columns C1 and C2. The selection step of variables proved satisfactory since every technique of variable selection (SVD, RGA and NRG) corroborated with the results. Finally, the nonlinear fuzzy controller was compared to the non-linear PID, presenting relevant minimization of transient disturbances, being employed criteria for evaluating the integral of the error to verify the quality of the controllers adjustment.

Keywords: Ethylbenzene process, Fuzzy controller, SVD, RGA, NRG and Inferential control.

1 INTRODUCTION

The Ethyl Benzene (C_8H_{10}) is an unsaturated aromatic hydrocarbon used in Styrene (C_8H_8) production by catalytic dehydrogenation. In the Styrene process, it is used as reactant of high purity, being the molar composition larger than 99,5%, to avoid secondary reactions and decrease its yield. The (C_8H_8) monomer is one of the high commercial value chemical intermediaries, being widely used in the manufacture of synthetic rubbers, plastics and copolymeric resin with annual production larger than 25 billion Kg worldwide (Hong et. al., 2008; Luyben, 2010).

In the ethyl benzene (EB) productive process the main equipment is two continuous stirred tank reactors (CSTR) and two multicomponent distillation columns. The compositions of distillates streams of columns are generally controlled through temperature controller because analyzers are expensive and there are no inline analyzers. Thus, the direct thermodynamic ratio between composition and temperature allows control by temperature inference. It is a popular method for this, due to high reliability of measurement and low maintenance of sensors, in addition to be a cheap and rapid implementation method (Kister, 1992).

The highly non-linear, interactive, and coupling process between variables, making the application of the theory of linear PID control limited to the control of some variables, which requires the classical controllers periodic tuning of their parameters. Alternatively, fuzzy logical non-linear controller presents some advantages, including the possibility to aggregate the expert knowledge of the process operation. In the fuzzy controller, the mathematical PID

algorithm is replaced by a base of rules developed from the convenient use of human knowledge that is generally an expert (Askari et al., 2017).

The satisfactory performance of the controller depends of the optimal structure of control in a process with multiple inputs and multiple outputs (MIMO), in addition to other factors (Smith and Corr pio, 2008). Thus, variables selection techniques are employed to know which variable must be manipulated (MV) and which variable must be controlled (PV), in a distillation process the PVs are the stages temperatures to maintain the interest compositions in their set-point. The main techniques used to define the optimal control structure is singular values decomposition (SVD), conditional number (CN), relative gain array (RGA), and the non-square relative gain array (NRG) systems.

The main purpose of this work is to propose the use of fuzzy controllers and the construction of a fuzzy rules base with the objective of controlling, by temperature inference, the molar compositions of benzene and the main product ethylbenzene, respectively, in the product of first and second column distillation process. The performance of the fuzzy controllers proposed were evaluated compared to the open loop condition of the plant and with the non-linear PID controllers. The ethylbenzene process proved interesting for the study, to see the difficulty of maintaining the compositions of the products in their set-point.

2 ETHYL BENZENE PROCESS

The flowsheet of the ethylbenzene production process is shown in Fig. 1. The ethylbenzene (EB) is produced from benzene (B) and ethylene (E) by liquid-phase alkylation into the first reactor (R₁).



But secondary reactions can occur in this process involving E and EB producing diethyl benzene (DEB) as by-product.



That is why ethylene is used as a limiting reagent and a second reactor CSTR is fixed in series, to convert all DEB in EB via transalkylation reaction, according Eq. 3.



Both reactors operate at high pressure to maintain the liquid phase present in the system, about 2026.5 KPa. The components present in the system are separated in two multicomponent distillations columns represented in flowsheet by C₁ and C₂. The distillate stream of first column (D₁) in wich its light key component is benzene (x_B>99.9%) that comes back for the first reactor as recycle stream (RC₁).

The second distillation column (C₂) is fed with the bottom rate (B₁) of C₁, providing a distillate rate (D₂) rich in EB (x_{EB}>99.9) and a bottom rate (B₂) rich in DEB (x_{DEB}>99.9). B₂ comes back to R₂ as recicle rate (RC₂) to convert all DEB in EB.

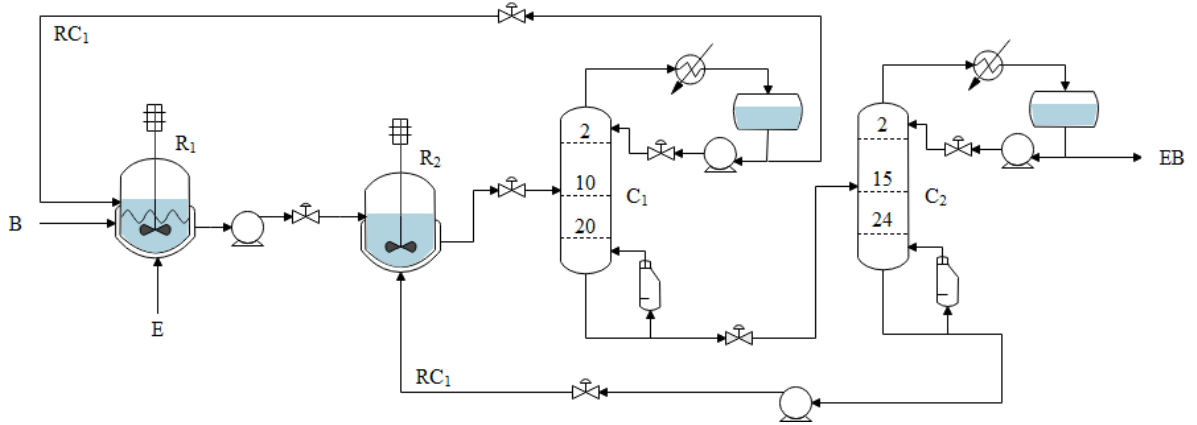


Figure 1: Ethyl benzene flowsheet. Adapted from (Luyben, 2010).

3 VARIABLE SELECTIONS

Several variable selection methods can be applied to select the relevant PV-MV variable pairs, and thus find the optimum control structure for the system. The most widely used are decomposition of singular values (SVD), relative gain array (RGA) and the relative gain array for non-square systems (NRG) that is an extension of the RGA method.

3.1 Singular Value Decomposition (SVD)

Decomposition in singular values was created by mathematician Bateman in 1908. It is a numerical algorithm based on the theory of linear algebra of eigenvalue and eigenvector (Morais et al., 2013). Consider a symmetric array K , formed by the gain in steady-state of the system, then its SVD is defined as,

$$K_{m \times m} = U D P^T = (u_1, \dots, u_m) \begin{pmatrix} \sigma_{11} & \dots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{m1} & \dots & \sigma_{mn} \end{pmatrix} \begin{pmatrix} p_1 \\ \vdots \\ p_n \end{pmatrix} \quad (4)$$

Where U and P , are orthonormal matrices and the singular values σ_N are the main diagonal elements of the diagonal matrix D . The corresponding eigenvalues of the array P are $\lambda_1, \lambda_2, \dots, \lambda_n$, arranged in such a way that: $\sigma_1 \geq \sigma_2 \dots \geq \sigma_n > 0$ and $\sigma_1 = \sqrt{\lambda_1}, \dots, \sigma_n = \sqrt{\lambda_n}$. Vectors $u_1, \dots, u_n$ and $p_1, \dots, p_n$ are singular vectors to the left and right, respectively. The reason between the maximum and minimal singular value is the conditional number (CN), defined as,

$$CN = \sigma_{11} / \sigma_{mn} \quad (5)$$

3.2 Relative Gain Array (RGA)

Bristol (1966) proposed a non-corrupted interaction measure by the units of the process variables, known as the relative gain array (RGA). The reason between the open loop gain

and the closed loop gain of the system makes the RGA an array whose elements are dimensionless numbers and therefore are more representative to indicate when the control structure is evaluated.

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1n} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \lambda_{n1} & \lambda_{n2} & \cdots & \lambda_{nn} \end{bmatrix} \quad (6)$$

Where the relative gain λ_{ij} is defined as,

$$\lambda_{ij} = \frac{(\partial CV_i / \partial MV_j)_{MV_{k,k \neq j}}}{(\partial CV_i / \partial MV_j)_{PV_{k,k \neq i}}} = \frac{\text{Open-loop gain}}{\text{Closed-loop gain}} \quad (7)$$

For a quadratic system whose matrix dimension is $n \times n$, the RGA is calculated from the steady-state gain matrix (Smith and Corripio, 2008).

$$\Lambda = K \otimes (K^{-1})^T \quad (8)$$

Where $\otimes$ is the element by element multiplication.

The relative gain is a value close to the unit, then there is interaction between the loops and the control can be designed. However, negative values indicate that the design of the control loops is not possible.

3.3 Non-Quadratic Relative Gain (NRG)

Chang and Yu (1990) proposed the NRG technique with the objective of measuring the interaction in a multivariable system for non-quadratic systems. The NRG has the same properties as the RGA and is defined as:

$$\Lambda^N = K \otimes (K^\dagger)^T \quad (9)$$

In that, the superscript † , represents the pseudo-inverse of the steady-state gain array.

4 CONTROL ALGORITHMS

There are numerous variations of the teproportional-integrative-derivative control (PID) algorithm, among which the ideal and parallel forms stand out. The non-linear PID controller parameters are the proportional gain (K_c), the derivative time constant (τ_D) and the integrative time constant (τ_I). These parameters need to be adjusted so that the process can reject the disturbances over the process variable.

4.1 Proporcional – Integrative – Derivative Control

The proportional - integrative - derivative technique is the most widely used in large - scale chemical processes (Seborg, 2011). The equation describing the PID controller in its ideal form is described by Eq. (10).

$$u(t) = K_c \left[e(t) + \frac{1}{\tau_I} \int_0^t e(t) dt + \tau_D \frac{de(t)}{dt} \right] + u_0 \quad (10)$$

Where u_0 is the off-set or bias of the controller action.

4.2 Fuzzy Logic Control

Fuzzy logic was introduced by Zadeh in 1965 to express the partiality that the intensive and extensive measurable variables present. The fuzzy logic control (FLC) is a feedback algorithm control that uses a verbal language acquired from a specialist's experience, to compose a rule base in the form *if - then* from the inference system.

4.3 Fuzzy Sets

According to Zadeh (1965), a fuzzy set is a continuous class with varying degrees of pertinence. Then, a fuzzy set A in a universe of speech U, is defined as a set of ordered pairs:

$$A \triangleq \{ \langle x, \mu_A(x) \rangle \mid x \in U \} \quad (11)$$

It is characterized by the membership function $\mu_A(x)$ that associates each element x with a real number with infinite values in the closed interval [0,1] (Zadeh, 1965; Jantzen, 2007). The membership function is a numerical function that assigns membership values to discrete values of a variable x in U. They can take different forms for the same fuzzy set, but are all convex, normal, and continuous. Numerous applications show that only four types are used in most cases: trapezoidal, triangular, gaussian and Gbell. Among these, the ones that are most widely used are those of the triangular and trapezoidal type (Ying, 2000).

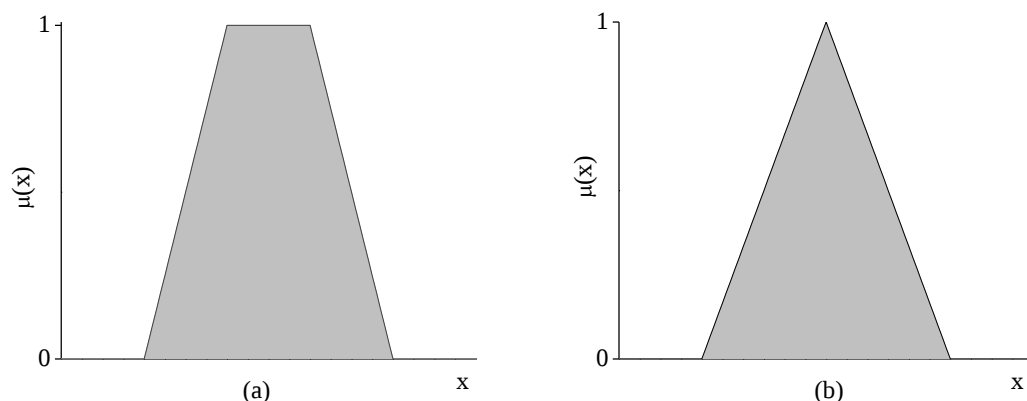


Figure 2. Types of membership functions: (a) Trapezoidal e (b) Triangular.

4.4 Controller and Fuzzy Inference Systems

The fuzzy controller is divided into three steps, as shown in Fig. 3. The controller input is a variable of the reals sets resulting from the measurement. The conversion of an exact input to the fuzzy domain is called the fuzzification step (Seborg, 2011).

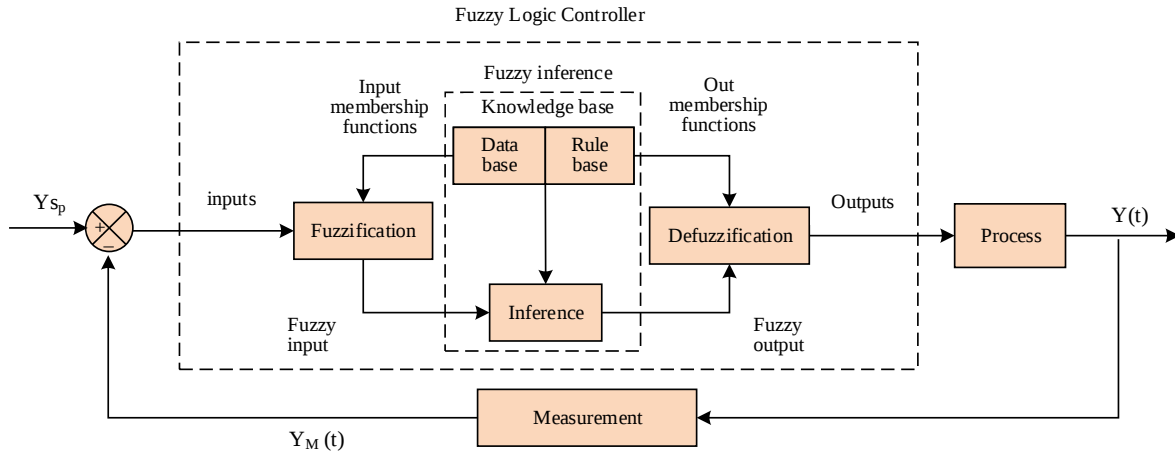


Figure 3: Fuzzy logic control structure. Adapted from Seborg (2011).

The second step is characterized by the inference system that is formed from a database provided by the expert and the fuzzy rules used to relate the input fuzzy sets to the output fuzzy sets. In this second step, the operations between the fuzzy sets of the *if-then* or *premise-consequence* type are performed to generate the output sets. There are several models of inference mechanisms in the literature, but the difference between them is only the consequence, in which the Mandani and Takagi-Sugeno models are the most used (Ross, 2004).

Finally, in the third step, the fuzzy set resulting from the inference step must be converted to a classical set before the controller signal arrives at the final control element. This change of set is called defuzzification (Jantzen, 1998). There are several defuzzification methods, however, there is no systematic procedure for choosing the most suitable defuzzification strategy. The most popular include:

- Maximum criterion (MAX): choose the point at which the inferred function has its maximum;
- Maximum of Average (MOA): represents the average value of all maximum points when there is more than one maximum;
- Center of Area (COA): Returns the area center of the inferred function.

$$u = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)} \quad (12)$$

$\mu(x_i)$, is the membership to a value of the variable x_i in a discrete universe, with closed interval $0 < \mu(x) < 1$.

4.5 PERFORMANCE CRITERIA

According to the type of control strategy used, the closed-loop system presents different responses to disturbances in the same input variable with equal amplitudes. The variation of time error is used as a performance criterion to indicate the best control structure to be used. One that minimizes the error integral criterion is the optimal control structure and the most used are:

- Integral of the absolute value of the error (IAE)

$$IAE = \int_0^{\infty} |e(t)| dt \quad (13)$$

- Integral of absolute error multiplied by time (ITAE)

$$ITAE = \int_0^{\infty} t |e(t)| dt \quad (14)$$

- Integral of the square error (ISE)

$$ISE = \int_0^{\infty} e^2(t) dt \quad (15)$$

5 METHODOLOGY

The process was first simulated in steady state in Aspen PlusTM software. The two reactors operate at a constant volume of 200 m³ each, the first being non-isothermal and the second isothermal. The distillation columns are multicomponent, operating under vacuum and with high purity compositions. The first column has 21 stages with feed in the 10th tray, while the second one has 25 stages with feed in the 15th tray. The distillation process has two degrees of freedom, and during the simulations were fixed the distillate stream (D1) and the reflux ratio (RR1) for column C1. For the second column (C2) were fixed the reflux ratio (RR2) and the bottom stream (B2). The thermodynamic model used to calculate the thermodynamic properties of the system's physical variables was that of Chao-Seader, which is a suitable method for systems containing hydrocarbons and light gases.

The simulations were initially performed in Aspen PlusTM software, so the equipment was designed for conversion to simulation of the steady state in the transient. Fig. 4 presents the flow diagram of the transient process, with the control structure proposed initially, implemented in Aspen DynamicTM.

To obtain the stationary gain arrays for columns 1 and 2 (C1 and C2), step perturbations with individually amplitude of 5% in D1, D2, B1, B2, R1, R2, RR1, RR2, heat duty of the C1 (Q1) and C2 (Q2).

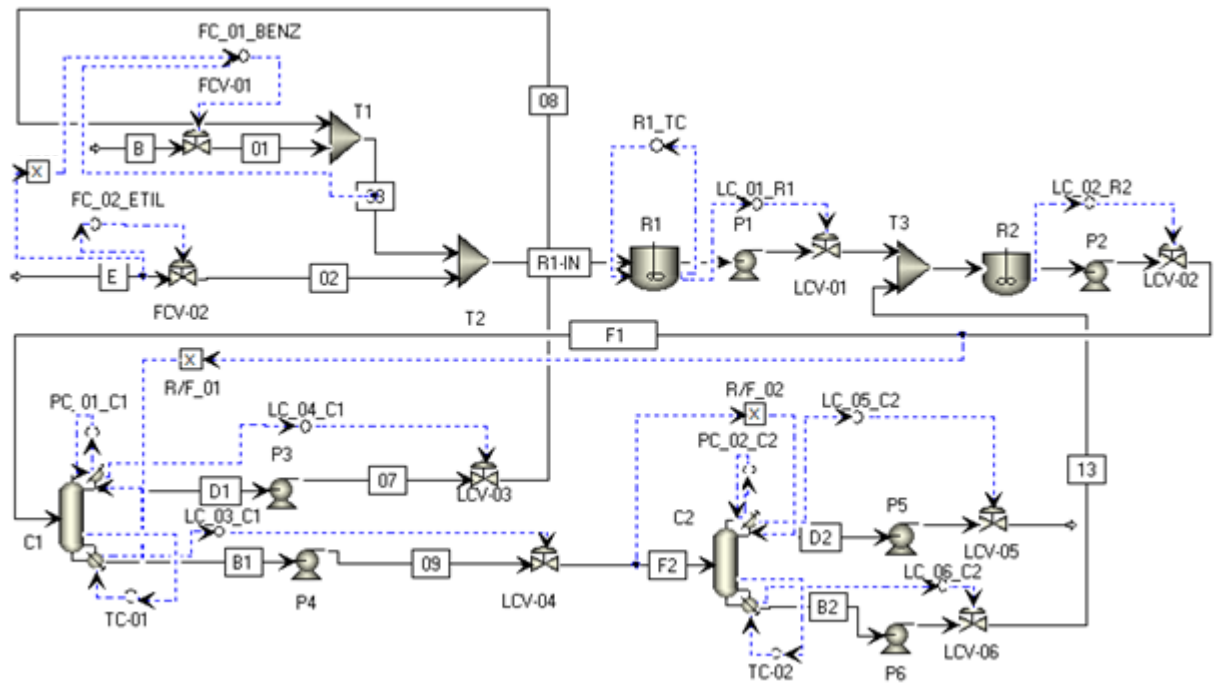


Figure 4: Ethyl benzene plantwide control structure in Aspen Dynamics.

The fuzzy controller rule base was implemented in MATLAB-Simulink® software. As the AM Simulation extension of Aspen Dynamics™ enabled the communication between the two software. Thus, the fuzzy control strategy was employed as shown in the block diagram of Fig. 5.

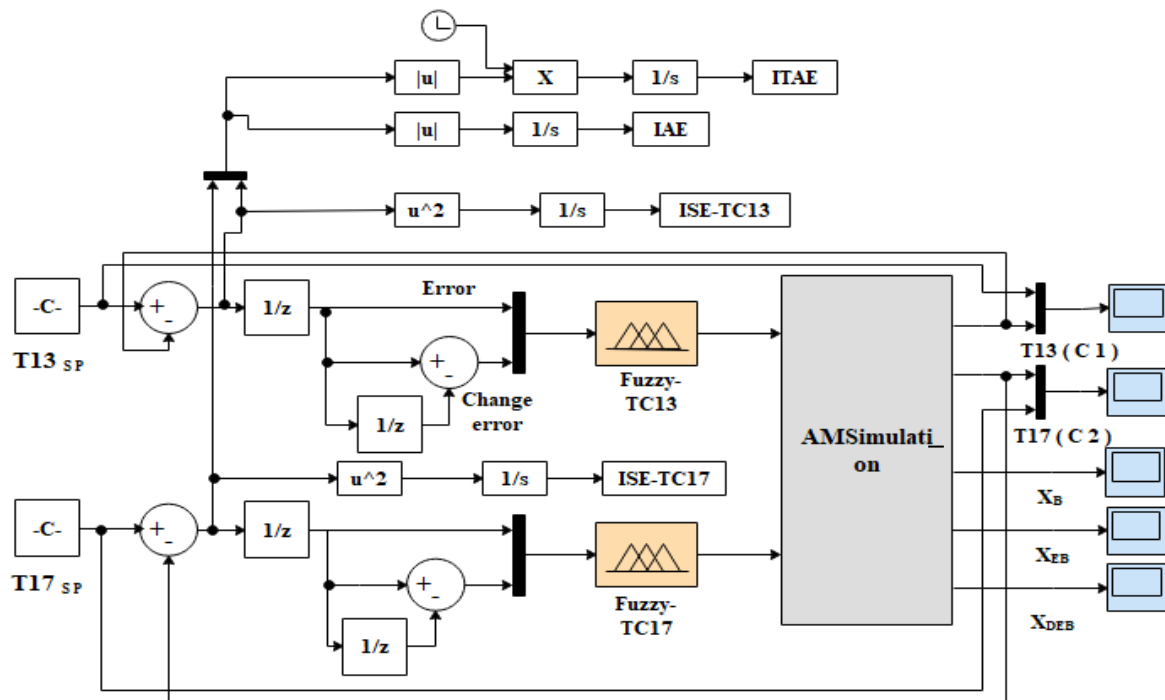


Figure 5: Block diagram for temperature fuzzy logic controllers.

The non-linear PID controllers were implemented directly in Aspen Dynamics TM, being tuned through the correlations of Tyreus-Luyben. The classical controller input is the error generated from the difference between the set-point of the process variable and the measured value at each time instant. Analogous to the non-linear PID, in the fuzzy logic controller, the error is also used as an input variable and, additionally, the change error.

In both controllers, the valve position output (VPO) that controls the steam flow rate on the reboiler is used as a manipulated variable to control the temperatures of the distillation columns. The inputs of the fuzzy-TC13 and fuzzy-TC17 controllers are represented by linguistic variable, Error (E) and change error (CE).

The VPO varies from 0% to 100% and the seven linguistic variables are created based on this variation, that is, completely closed (VPO_{CC}), very closed (VPO_{VC}), little closed (VPO_{LC}), normal (VPO_N), little open (VPO_{LO}), very open (VPO_{VO}), completely open (VPO_{CO}). For both input variables error and change error the linguistic values are negative big (NB), negative middle (NM), negative small (NS), zero (ZR), positive small (PS), positive middle (PM), positive big (PB). Thus, for the design of the fuzzy logic controller was first defined the rules with reverse action of the controller, as shown in Tab. 1.

Table 1. Rules for temperature fuzzy logic controller.

Rules	error						
change error	NB (VPO_{CC})	NB (VPO_{CC})	NB (VPO_{CC})	NB (VPO_{CC})	NM (VPO_{VC})	NS (VPO_{LC})	ZR (VPO_{NR})
	NB (VPO_{CC})	NB (VPO_{CC})	NB (VPO_{CC})	NM (VPO_{VC})	NS (VPO_{LC})	ZR (VPO_{NR})	PS (VPO_{LO})
	NB (VPO_{CC})	NB (VPO_{CC})	NM (VPO_{VC})	NS (VPO_{LC})	ZR (VPO_{NR})	PS (VPO_{LO})	PM (VPO_{VO})
	NB (VPO_{CC})	NM (VPO_{VC})	NS (VPO_{VC})	ZR (VPO_{NR})	PS (VPO_{LO})	PM (VPO_{VO})	PB (VPO_{CO})
	NM (VPO_{VC})	NS (VPO_{VC})	ZR (VPO_{NR})	PS (VPO_{LO})	PM (VPO_{VO})	PB (VPO_{CO})	PB (VPO_{CO})
	NS (VPO_{VC})	ZR (VPO_{NR})	PS (VPO_{LO})	PM (VPO_{VO})	PB (VPO_{CO})	PB (VPO_{CO})	PB (VPO_{CO})
	ZR (VPO_{NR})	PS (VPO_{LO})	PM (VPO_{VO})	PB (VPO_{CO})	PB (VPO_{CO})	PB (VPO_{CO})	PB (VPO_{CO})

The input variables were related by the operation *prod*, since it is continuous and as an aggregation the *max* operation was chosen. The center of gravity was defined by the defuzzification method, for both controllers. The tuning of the fuzzy logic controller was performed by adjusting the degree of support of the membership functions. Regarding the forms of membership functions, five triangular and two trapezoidal ones are used for each end since the defuzzification method for controllers is the center of area as shown in Fig. 6 and Fig. 7.

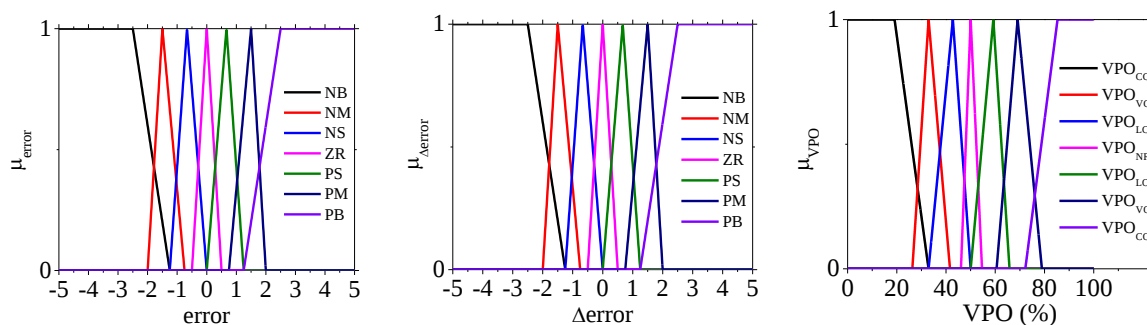


Figure 6. TC13 Membership functions.

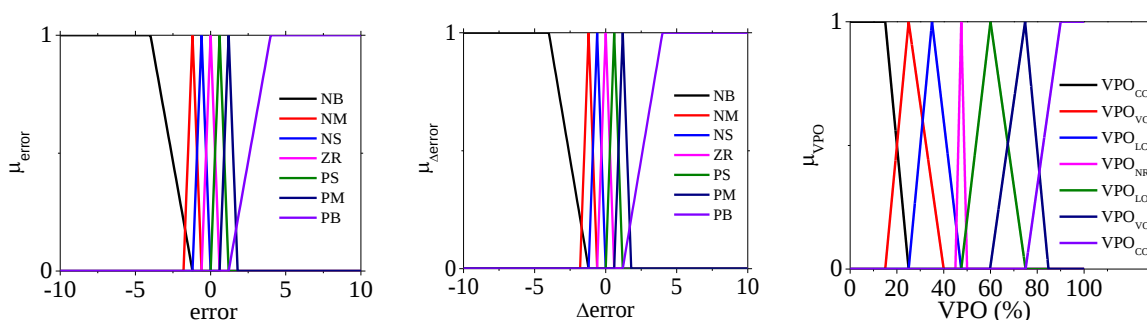


Figure 7. TC17 Membership functions.

6 RESULTS AND DISCUSSION

The results obtained with the simulations and with the performance of the proposed control loop are presented in this section. With the simulations of the steady-state process it was possible to obtain the profiles of the compositions of the four compounds of the mixture along the stages of columns C1 and C2, which are: ethylene (x_E), benzene (x_B), ethylbenzene (x_{EB}) and diethyl benzene (x_{DEB}); as shown in the graphs of Fig. 8 and Fig. 9, respectively.

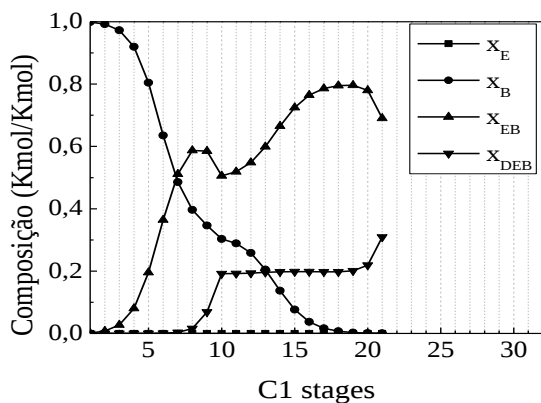


Figure 8. Profile of the molar composition in C1.

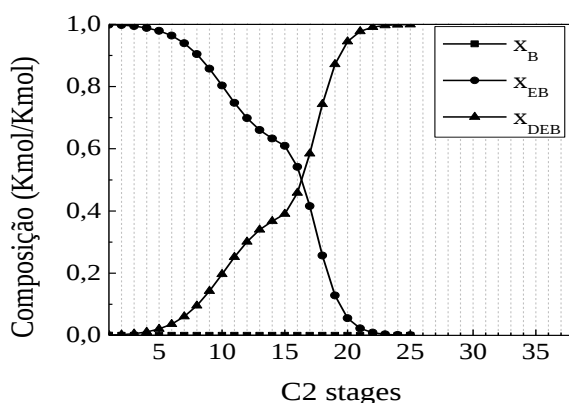


Figure 9. Profile of the molar composition in C2.

In the first distillation column, B is recovered in the 1st stage (condenser) with molar fraction $x_B > 99.9\%$ and the less volatile components EB and DEB leave in stage 20 of the column (base stream). In the second column EB and DEB are separated in stages 1 and 24

respectively. EB leave the column top with purity $x_{EB} > 99.9\%$ and the DEB is recovered at the base of the column with molar composition $x_{DEB} > 99.9\%$.

6.1 SELECTION OF VARIABLES PAIRS

The conditional number shown in Tab. 1 and Tab. 2 defines the reflux ratio and reboiler heat duty as the best pair of manipulated variables most suitable for controlling the temperature in both distillation columns. The other pairs that presented smaller conditional numbers were not selected because some of the variables are used as MV for other control loop.

Table 2. Conditional number for C1.

Pairs	CN
D ₁ e R ₁	1,856
RR ₁ e Q ₁	18,809
D ₁ e Q ₁	118,798
D ₁ e RR ₁	489,080
R ₁ e Q ₁	4500,0584

Table 3. Conditional number for C2.

Pairs	CN
D ₂ e R ₂	2,257
B ₂ e R ₂	9,217
B ₂ e Q ₂	19,476
RR ₂ e Q ₂	20,330
D ₂ e Q ₂	94,667

The sensitivity array for columns 1 and 2 are shown in Fig. 10 and Fig. 11. It is not possible to say which input variable is the most sensitive to disturbances with amplitude of 5% because of the difference between the quantities that each variable assumes. But for the column 1 the 13th tray exhibits greater sensitivity to the disturbances in the reboiler heat duty and the 16th tray is the most sensitive when carried out disturbances on the ratio of reflux. In the second column, the sensitivity array indicates the 17th tray as being the most sensitive to variations in the reboiler heat duty and 21st tray for reflux ratio.

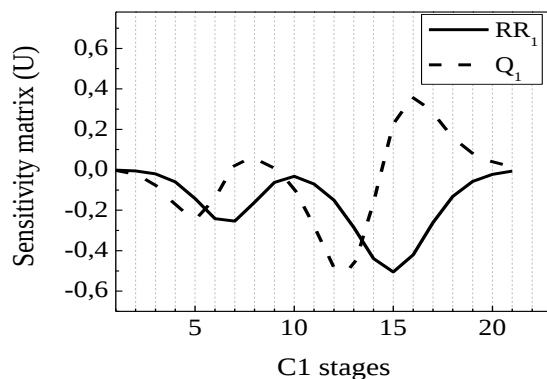


Figure 10. Sensitivity matrix for C1.

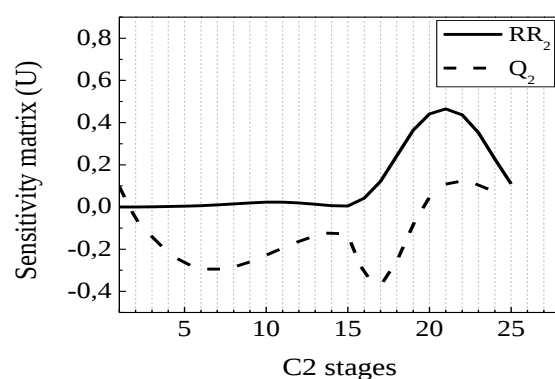


Figure 11. Sensitivity matrix for C2.

The RGA and NRG indicates the formation of the optimal control structure, who are assigned the responsibility of filtering the best MV among the two indicated by the SVD. The PV-MV pairs closest to the unit, according to Tab. 4 and Tab. 5 are T13-Q1 for column 1 and T17-Q2 for column 2, respectively. The same control structure is observed in the graphical representation of the NRG according to Fig. 12 and Fig. 13.

Table 4. RGA results for C1.

Pares	RR ₁	Q ₁
T ₁₃	-0,1825	1,1825
T ₁₇	1,1825	-0,1825

Table 5. RGA results for C2.

Pares	RR ₂	Q ₂
T ₁₇	-0,02581	1,02581
T ₂₁	1,02581	-0,02581

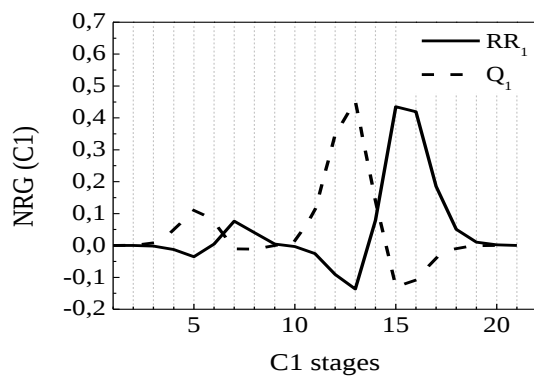


Figure 12. NRG for the RR1 and Q1 pair by 5% disturbances.

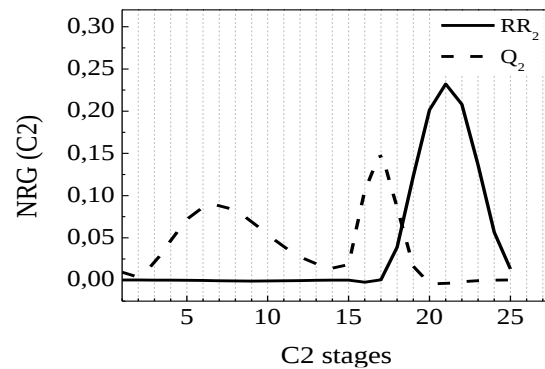


Figure 13. NRG for the RR₂ and Q₂ pair by 5% disturbances.

Figure 14 shows the transient behavior of the temperature in stage 17 in open-loop of column C2 when it is subjected to step perturbations, with amplitude of + 5% at the instant of time of 5 hours and -5% at the instant of time of 20 hours, in the following variables: feed flow of column C2 (F2), composition of diethyl benzene in the process feed of pure benzene stream (x_{DEB}) and bottom rate of C2 (B2).

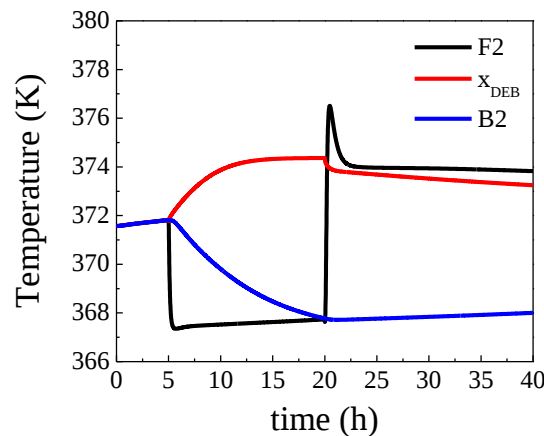


Figure 14: Temperature profiles in the tray 17 of C2.

It is verified that the temperature undergoes more sudden changes when subjected to the perturbations in F2, reaching a new steady state after the perturbation at the instant of time of 20 hours.

Based on the above information, it was the initial goal of this work to develop a controller that can heal the most influential disturbances in the two distillation towers, eliminating any offsets that may arise. In Fig. 15 and Fig. 16, the results concerning the transient behavior of temperatures T13 (in C1) and T17 (in C2) are presented when step time is inserted of + 5% at time of 5 hours and -5 % at time instant of 10 hours in feed flowrate of each column.

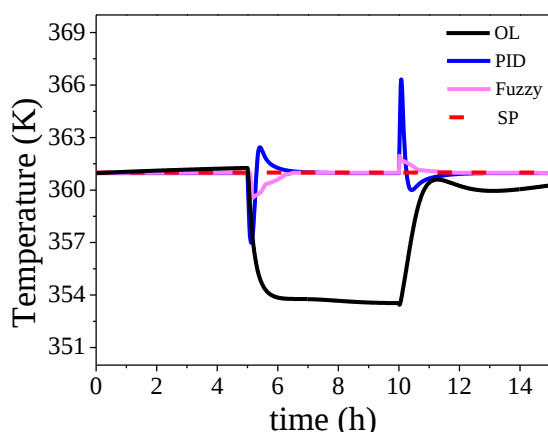


Figure 15: Temperature profiles in 13th tray of C1.

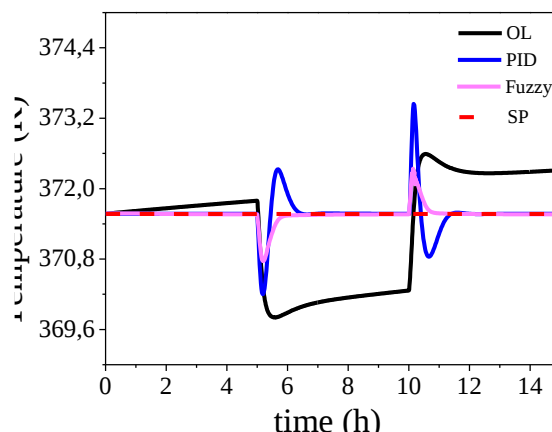


Figure 16: Temperature profiles in 17th tray of C2.

The black, blue and pink lines indicate, respectively, the open-loop (OL) condition, with the non-linear PID and fuzzy control algorithm. The set-point is represented by the dotted red line (SP).

According to the graph of Fig. 15, we can observe that the non-linear PID control strategy presents a rise time of 0.1 hour and overshoot of approximately 1.35%, whereas the fuzzy controller presents only 0.8 hour and an approximate overshoot of 0.22%. The same performance, non-linear PID versus fuzzy, is observed in the temperature responses for the control strategies of column 2, according to Fig. 16. The process rise time with the non-linear PID strategy is 0.16 hour and approximate overshoot of 0.5%, and the fuzzy logic control has a rise time of 0.1 hours and an approximate overshoot of 0.15%.

Thus, it is verified that the fuzzy logic control is more robust to the point of rejecting the disturbances and does not show oscillation in the temperature transient response. Finally, it was desired to know to what extent the non-linear PID and fuzzy temperature control would be able to maintain, by inference, the composition of the product (ethylbenzene at the top and diethyl benzene at the base of column C2), as shown in the graphs of Fig. 17 and Fig. 18, respectively.

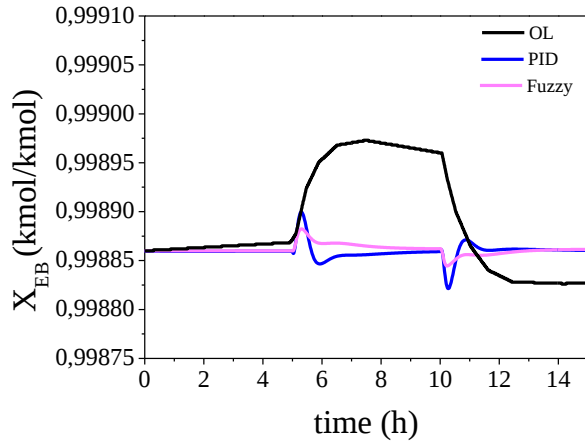


Figure 17: Composition profiles in D2.

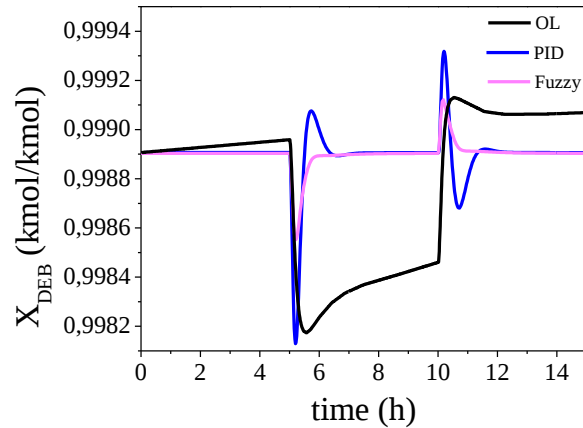


Figure 18: Composition profiles in B2.

According to the graphs shown in Fig. 17 and Fig. 18, we observed that the non-linear PID and fuzzy controllers presented similar behavior. They can keep the value of the composition within its set-point. However, the fuzzy controller proved to be more efficient in minimizing off-set of the variable x_{EB} and x_{DEB} .

In a quantitative analysis, integral error criteria were used to evaluate the performance of non-linear PID and fuzzy temperature controllers, TC13 and TC17.

Table 6. Performance criteria for C1 temperature control algorithm.

Control algorithm	ITAE	IAE	ISE
Non - linear PID	9,645	1,452	2,858
Fuzzy	2,632	0,418	0,119

Table 7. Performance criteria for C2 temperature control algorithm.

Control algorithm	ITAE	IAE	ISE
Non - linear PID	5,082	0,716	0,614
Fuzzy	2,212	0,446	0,217

According to Tab. 6 and Tab. 7, the fuzzy controllers TC13 and TC17 presented lower integral error values according to the three evaluated criteria: ITAE, IAE and ISE.

7 CONCLUSION

In this study, intelligent controllers were proposed in an industrial ethyl benzene production plant, to maintain the compositions of critical compounds in their set-point of operation. Traditionally, the composition control in distillation columns is affected by direct temperature inference in a feedback control strategy. However, the non-linearity, coupling, slow dynamics and interactivity are processes that cause the need to develop new technologies and advanced control algorithms, capable of minimizing these particularities. In these cases, fuzzy controller is suited to be employed, especially for MIMO systems, which there are significant interactions between the manipulated variables and controlled.

The process under study proved to be relevant for the application of the developed methodology, where the process was simulated in steady state and transient in Aspen PlusTM and DynamicsTM software, where the molar compositions of benzene (distillate of C1) and ethyl benzene (distillate of C2) are the control objective variables. Through the techniques of selecting variables SVD, RGA and NRG the better pairs MV-PV were selected, after performing the control loop sensitivity analyses in the distillation columns C1 and C2. The selection step of variables proved satisfactory and corroborated with the results. Stages 13 and 17 were selected with the most sensitive temperatures in the distillation columns C1 and C2, respectively.

It was verified that the two distillation towers present as higher operating disturbances the flow rates, F1 and F2, respectively. The non-linear PID and fuzzy controllers were proposed for T13 and T17, represented by TC13 and TC17. It was verified that the fuzzy logic control is more robust than the non-linear PID to the point of rejecting the disturbances and does not show oscillation in the temperature transient response. For this assertion, we have evaluated some transient terms, such as: rise time and overshoot. In addition, in the quantitative analysis, the fuzzy temperature controllers, TC13 and TC17, also presented lower values for the integral error criteria. Finally, it was observed that the non-linear PID and fuzzy controllers presented similar behavior, related to transient operation of the x_{EB} and x_{DEB} compositions. However, the fuzzy controller proved to be more efficient in minimizing off-set.

ACKNOWLEDGEMENTS

The authors thank God for spiritual strength, the department of chemical engineering and technology center for support.

REFERENCES

- Askari M. R.; Shahrokhi M.; Talkhonchek M. K., 2017. Observer-based adaptive fuzzy controller for nonlinear systems with unknown control directions and input saturation. *Fuzzy Sets and Systems* 314, 24–45.
- Bristol, E. H., January, 1966. On a New Measure of Interaction for Multivariable Process Control. *IEEE, Transactions on Automatic Control*, pp. 133-134.
- Chang, J. -W., and Yu, C.-C., 1990. The relative gain for non-square multivariable systems. *Computers and Chemical Engineering*, pp. 1309-1323.
- Hong, D-Y.; Vislovskiy, V. P.; Hwang, Y. K.; Jhung, S. H.; Chang, J-S, 2008. *Catalysis Today*, 131, pp. 140-145.
- Jantzen, J., 1998. Design of Fuzzy Controllers.
- Jantzen, J., 2007. Foundations of Fuzzy Control. Wiley, New York.
- Kister, H. Z., 1992. Distillation Design. McGraw-Hill, Inc.
- Luyben, W. L., 2010. Design and Control of the Ethyl Benzene Process. *Process System Engineering*. vol. 57, n. 3.

Morais JR, A. A., 2011. Elaboração de um Analisador Virtual Utilizando Sistema Híbrido Neuro-Fuzzy para Inferenciar a Composição em um Processo de Destilação. Dissertação de mestrado, Universidade Federal de Alagoas.

Ross, T. J., 2004. Fuzzy Logic with Engineering Applications. John Wiley and Sons, Inc.

Seborg A. R., Edgar, T., Mellichamp, E. D., 1989. Process Dynamics and Control. John Wiley and Sons, Inc.

Smith C. A. and Corripio A.B., 2008. Principles and Practice of Automatic Process Control, 2nd Edition, New York: John Wiley.

Ying H., 2000. Fuzzy Control and Modeling: Analytical Foundations and applications.

Zadeh, L., 1965. *Fuzzy sets, information and control*. Vol. 8, pp. 338-353.