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CONTROL PROPOSAL FOR A HIGH PURITY COLUMN BASED ON THE SEPARATION OF VARIABLES BY THE INDEPENDENT COMPONENT ANALYSIS METHOD

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Abstract - Many industries are complex when it comes to operation mode. In order to reduce the problems related to strong coupling in these processes, the search for the incorporation of artificial intelligence devices has shown an increasing trend in recent years. Due to this complexity and control in multivariable processes, diagnosis and fault monitoring in the processes have become increasingly difficult. Therefore, the application of these devices has achieved satisfactory results regarding the procedures performed with human operators. Independent Component Analysis (ICA) is a signal separation technique that is based on the use of higher order statistics to estimate each of the unknown sources, through observation of various mixtures generated from these sources. Although there are recent works on using the ICA in industrial processes, few studies have been made in cases involving distillation columns. This paper proposes a control strategy based on the ICA technique, which makes the control loops decoupled and hence the performance easier. Compared to the conventional method, the technique provided a great improvement in control performance. Control structures were implemented in Simulink/Matlab® in communication with a 1,2-dichloroethane (1,2-EDC) plant simulated in Aspen Plus Dynamics™.
Keywords: Independent Component Analysis (ICA); Control; Distillation column.

INTRODUCTION

The continuous search for improvements in industrial plants is associated with the highly competitive market and the need to raise increasing profit margins and operational safety. Engell (2007) showed that the purpose of a control system is not only to keep the variables in their setpoints, but, moreover, is to operate the plant while maximizing economic returns in the presence of disturbances in the process. In order to reduce the problems of the strong interactions in industrial processes, the incorporation of artificial intelligence devices in production processes has shown an increasing trend in recent years. The application of these systems for monitoring, diagnostics and maintenance of the good performance of the equipment has achieved satisfactory results regarding the procedures performed only with human operators.

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In chemical industries, among the equipments that require greater attention are the distillation columns, since in most manufacturing industries, 80% of the energy operating costs are due to this unit operation (Delgado *et al*., 2012; Gil *et al*., 2012; Modla, 2013; Chen and Law, 2013).

Besides the disadvantage of high energy consumption, if the mixture presents behavior that is not ideal in relation to the equilibrium phases, there may be azeotrope formation. This prevents separation of the components by conventional distillation and they are usually separated by extractive distillation or azeotropic distillation.

The occurrence of azeotropes in the chemical industry is relatively common. As its main feature, azeotropy is highly sensitive to disturbances, which can result in deterioration of products, multiple steady states and great difficulty to return to normal operation. The most addressed solution to minimize transient operation is the implementation of advanced control techniques. However, even with the use of complex algorithms, a long time for the process to reject a disturbance is observed. This difficulty to stabilize the processes is due to the strong interactions between the variables and is inherent to multivariable processes.

One of the most widespread and applied methods to reduce the strong interaction in these processes is the ICA. ICA is a technique applied in the separation of unknown sources, which is based on the use of higher-order statistics to estimate each of the sources by observing various mixtures generated from these sources (Silva, 2009). Few studies found in the literature use this technique in industrial processes involving distillation columns. Among the main ones the following can be cited:

Bo *et al*. (2010) applied an integrated approach based on an independent component analysis - support vector machine (SVM-ICA), which was used to detect and diagnose disorders in a cracking process for separating butadiene. Due to the complexity existing in the industrial distillation process, which presented non-Gaussian features, the ICA statistics detected more information about the type of applied disturbances in the separation than information about the statistics of the PCA. Chen *et al*. (2013) demonstrated that ICA-based monitoring techniques used in a cryogenic air separation process presented a very satisfactory fault diagnosis using ICA.

The use of this technique in this work had as its main characteristic the reduction of the strong coupling among the variables that complicate this type of column, thereby improving the performance of the proposed control loop. The algorithm chosen for the ICA performance was Fast ICA. Besides being the simplest among the others in requesting the step of adaptation, this algorithm has fewer interactions in the precision of separation (Zargoso, 2006). By comparing the ICA technique with a conventional control method, a significant improvement was observed in the results, both in instability reduction and in the shorter operating time required for the controlled variables to reach their desired setpoints.

STATE-OF-THE-ART REVIEW

Azeotropic distillation is highly sensitive to disturbances, which can result in deterioration of the products or a very difficult return to normal operation. The most used solution to minimize transient operation is the implementation of advanced control techniques. Monitoring and processes diagnostic became very important in the chemical industry because of the increasing complexity of operation and multi loop control.

In many practical situations the use of sensors is required to collect information and there is generally the problem of the signals supplied by the sensors being mixed signals (sources). Also, in general, there is no way to observe the sources directly, nor is it known how the sources were mixed. According to Moretto (2008), this problem is known as the problem of blind source separation (BSS), and one of the most widespread methods for BSS is ICA. The ICA technique has been applied in various types of industrial processes in order to reduce or to eliminate this strong interaction between the variables.

Independent Components Analysis

The goal of the technique is the analysis or separation of statistically independent sources from a given template mixture of original sources. What differentiates ICA from other existing techniques is precisely the fact that it works with components that are both non-Gaussian and statistically independent, as occurs in most industrial processes. This technique contributed to the reduction of the existing coupling between a set of variables present in a specific system. ICA estimates the mixing matrix A, which considers the signs or sources observed, and independent sources that make up the matrix S. Figure 1 shows a schematic representation of the ICA for source separation. In this paper the Fast ICA algorithm is applied to ICA operation performance.

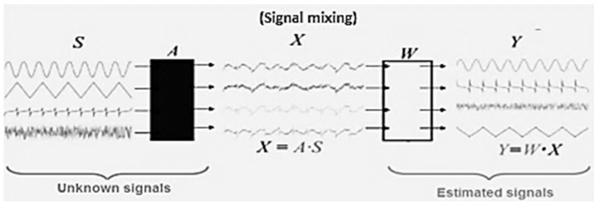


Figure 1: Mixture Separation Process through ICA.

The problem is finding the separation matrix W. This matrix W is the inverse of matrix A, and the estimated independent signal sources must be equal to the signs of the original independent sources. The Fast ICA algorithm (Hyyvarinen and Oja, 1997) is based on a fixed point interactive strategy with the goal of sequentially determining the maximum non-Gaussian components. The algorithm consists of a sequence as follows:

1. Remove the average value of observations x (Centralization).
2. Make the whitening of observations getting z. (Orthogonalization)
3. Choose a weight vector w.
4. After taking:

$w^+ = E\{x.G(w^T.x)\} - wE\{G'(w^T x)\}$, where G' is derived from a non-quadratic function G that is used in the contrast function for solving the ICA problem.

5. Doing $w = w^+ / \|w^+\|$.
6. If there is no convergence, go back to stage 4.

Before applying the Fast ICA algorithm, it is necessary to perform pre-processing on the input data, thereby facilitating the algorithm convergence and serving as standards for the calculation of negentropy, which measures the entropy of the data analyzed. That is, the more unpredictable the observed variable, the greater is its entropy. The pre-processing consists of two major operations: the Centralization and the Whitening. The centralization subtracts the average for each component belonging to a set of variables, making it zero average, and the whitening makes the set of uncorrelated data. The appropriate choice of the non-quadratic function G(.) makes the algorithm perform a conceptually simple approach that is computationally fast and has interesting statistical properties such as robustness. Some of the most used standard functions are cubic, hyperbolic tangent and Gaussian.

The present Fast ICA algorithm calculates only an independent component at a time. It is possible to calculate all components running Fast ICA a number of times equal to the number of independent components, in addition to varying the initial 'w' vector. However, there is a risk that the same maximum spot is calculated more than once. To eliminate this problem, the property with orthogonal ‘w_i’ vectors is used, step 2 described above. This is due to the orthogonality of the new mixing matrix A obtained after whitening.

Since $A^{-1} = A^T$, ‘w_i’ vectors are the A^{-1} rows and the A^T columns, so to avoid that the same local maximum is calculated more than once, it is necessary to make vectors 'W' orthogonal on each iteration of the algorithm. For this, two methods may be used: deflationary and symmetrical orthogonalization. In deflationary orthogonalization, independent components are calculated one by one, so it has the disadvantage that estimation errors propagate to subsequent components.

For this reason, another orthogonalization technique of symmetrical nature may be interesting. In this technique the components are not calculated sequentially, but in parallel. Thus, as the independent components are calculated all at once, there is no estimation error propagation. In the symmetric orthogonalization, a Fast ICA algorithm iteration is performed in each 'w_i' vector in parallel. After the main iteration, all vectors 'w_i' are orthogonalized by using the symmetrical method presented in this section.

Although it is possible to find recent work on the use of ICA in industrial processes, very little for found in processes involving distillation columns. Bo *et al*. (2010) applied an integrated method based on ICA-SVM to detect and diagnose disorders in a cracking process for separating butadiene. Because of the complexity existing in the distillation process industry, due to its non-Gaussian features, the ICA statistics detected greater information on the type of applied disturbances in the separation of the statistics of the principal component analysis (PCA). Chen *et al*. (2013) showed that ICA-based monitoring techniques used in a cryogenic air separation process with fault detection and diagnostic capability showed better results when compared to applying the PCA technique to the same process.

METHODOLOGY

The distillation column under study belongs to a commercial plant producting 1,2-EDC, one of the steps prior to obtaining the final product PVC (polyvinyl chloride). Figure 2 shows the flowchart of the column process in the Aspen Plus Dynamics™ simulator used in this study.

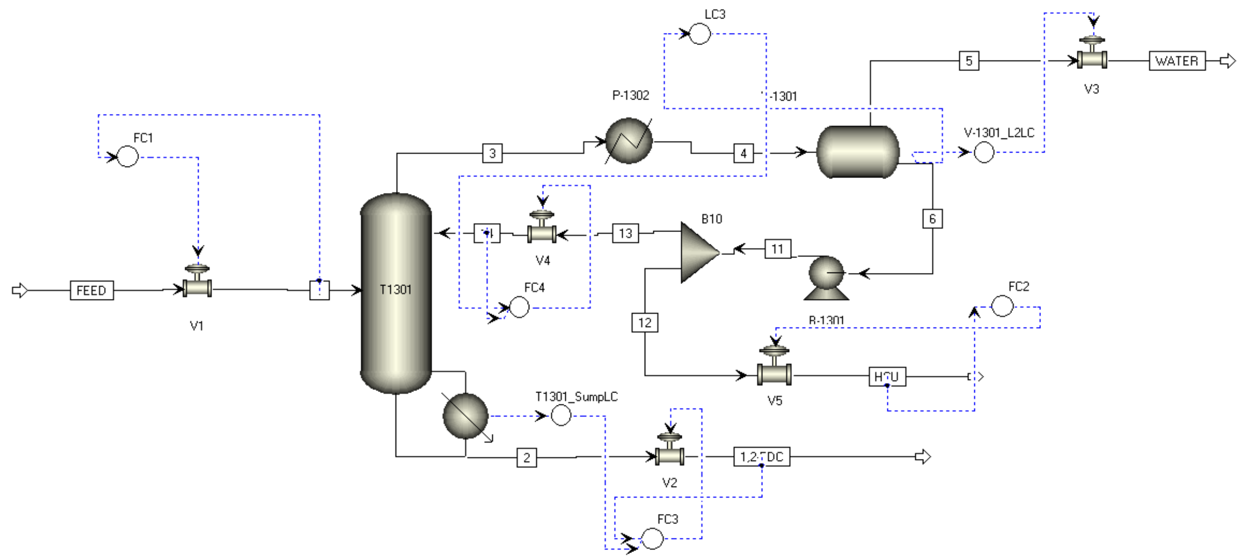


Figure 2: Flowchart of the 1,2-EDC column with flow controllers and level.

The feed stream of the industrial column under study comprises 98 to 99% of 1,2-EDC, and other organic substances, of which carbon tetrachloride (CCl_4) and chloroform ($CHCl_3$) are the components of interest. The purpose of this column is to dry 1,2-EDC and to remove most of the lighter components from the basic product.

The column has 70 plates, a total condenser, and a decanting vessel as reflux drum. Water forms a minimum boiling point azeotrope with 1,2-EDC and other chlorinated hydrocarbons. The top vapors are cooled and condensed in the condenser and flow into the column reflux vessel. The reflux vessel is designed to separate the most dense organic phase from the aqueous phase. The organic phase is pumped back to the tower under level control, maintaining a constant reflux ratio. The decanted aqueous phase in the reflux vessel is drained to the wastewater treatment.

The column is regarded as a non-conventional heterogeneous azeotropic distillation column, since the addition of an entrainer to perform separation of the components is not necessary because this agent is already present in the feed.

Characterized as a high purity distillation column, the base product is essentially 1,2-EDC (99%). Because of its catalytic effect on a chemical reaction that occurs in a later stage of the process (pyrolysis of 1,2-EDC), the presence of a given concentration of CCl_4, when properly controlled, is desirable in the column base product. However, the presence of $CHCl_3$ is not desirable, since it is a cracking inhibitor for 1,2-EDC. The 1,2-EDC produced is purified and goes to the cracking area, where monovinylchloride (MVC) and hydrochloric acid (HCl) are produced.

Communication Aspen Plus Dynamics™ x Simulink/Matlab®

A Simulink/ Matlab® was built in a block diagram for communication with Aspen Plus Dynamics™, through an AMSimulation block, Figure 3, where all the information directly stemming from the 1,2-EDC plant was received. In the process input five signals were simultaneously applied with different amplitudes and frequencies, in order to obtain, in the block diagram of the output, the transient behavior of the process variables to be controlled, under the influence of this signal mixture. The signals applied were respectively: Sinusoid, Sinusoid, Ramp, Sinusoid and Step. Both the input signals and the output signals to model the Aspen were specified in the AMSimulation. The signals applied at the process input had varying amplitudes and frequencies, as shown in Table 1.

Through this communication it was possible to obtain the data for the mixed output components, Figure 3, and submit them to ICA through the application available for Hyyvarinen (2005), thus obtaining the independent variables and consequently reducing the existing strong coupling between them. This application has in its structure the Fast ICA algorithm, which is the method that is responsible for making the components as mixed in the independent variables as possible, resulting in easier and more robust control of the variables in the process. Initially, the five acquired signals x1, x2,..., x5, corresponding to mixtures of the 5 signals applied to the sources (input variables) in the process, were inserted into the ICA application, which aims to provide the estimates y1, y2,..., y5, referring to the output variables of the respective individual signals.

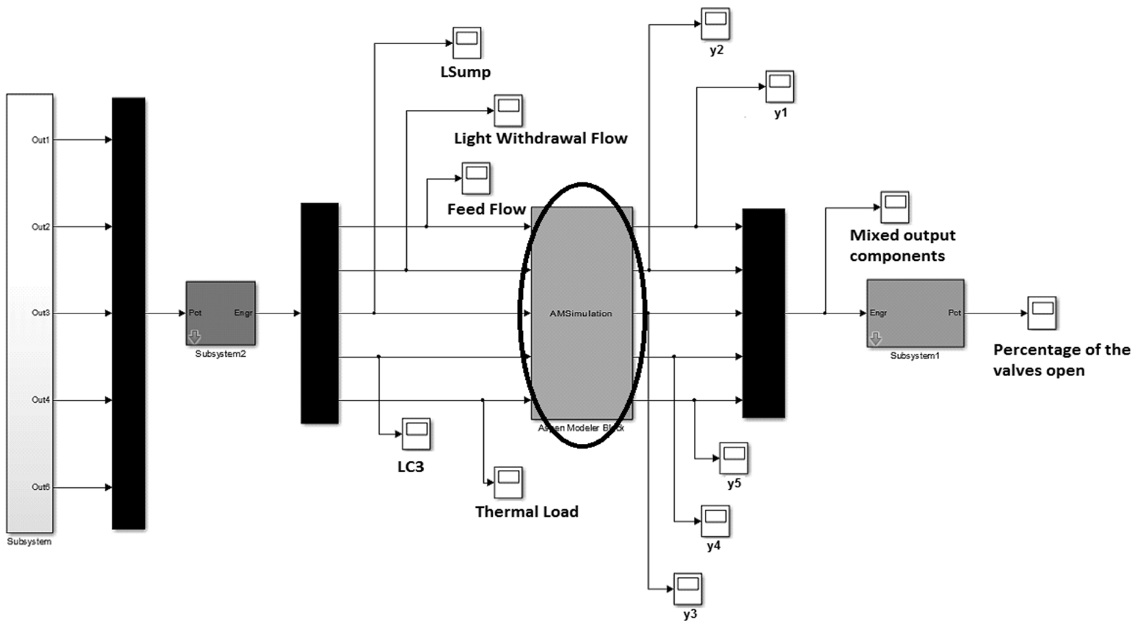


Figure 3: Communication Aspen Plus Dynamics^{TM} x Simulink/Matlab®.

Table 1: Applied input signal amplitudes and frequencies.

Signals	Amplitudes	Frequencies
Signal 1 - Sinusoid	5	1.5
Signal 2 - Sinusoid	4	1
Signal 3 - Ramp	Slope = 5	
Signal 4 - Sinusoid	0.3	2
Signal 5 - Step	Slope = 2.5	

Application of Independent Components Analysis

The data were then treated to reduce the complexity of the algorithm during the simulation. For this, the pre-processing was accomplished through the centering and whitening and, immediately after this, the Fast ICA algorithm was applied. Thus, independent output components extraction was obtained. The purpose of whitening was to make uncorrelated random variables and the variance equal to one. The use of the technique afforded the separation matrix W, which was used in the control structure proposed in the online work. According to Silva (2011), the most relevant characteristics of Fast ICA algorithms are listed below:

- No adjustment is necessary in the adaptation step when compared to gradient-based algorithms. It is simpler;
- The low amount of interactions, between 5 and 10, which are necessary in most cases, makes the method have a maximum accuracy with a small number of iterations;
- The algorithm finds the source directly of virtually any non-Gaussian function;
- The performance of the algorithm can be improved according to the choice of nonlinear function that is used;
- It can be used to identify independent components one by one.

Control Proposals

The importance of maintaining industrial plants running close to their optimum operating points allows the process to operate safely, as well as to guarantee the best yields. The objective is to use a signal separation technique capable of creating independent variables, thus allowing the control to act individually on each variable and thus obtain a better control performance. In order to verify the performance provided by the ICA technique, the work proposed two control strategies:

- Offline Control based on models that ruled the procedure, but did not act directly in the 1,2-EDC plant simulated in Aspen Plus Dynamics^{TM}. Its use was helpful in obtaining the PID controller tuning parameters, which were used in the online control structure;

▪ Online control performed in real time directly on the setpoints of the controlled variables (CV's) in 1,2-EDC plant;

▪ Each one of the strategies mentioned above was assessed in two different situations:

▪ First situation: Conventional control over coupled control loops through the PID component;

▪ Second situation: Control based on the application of the ICA technique as a means of decoupling the control loops using the PID for this component.

For a better comprehension, the proposals were named as follows:

▪ Control loop 1 – Conventional Offline Control on the coupled control loops, based on the identified process models.

▪ Control loop 2 – Offline Control based on the application of the ICA technique as a way of decoupling among the control loops, using the models identified after the application of the technique.

▪ Control loop 1A – Conventional Online Control on the coupled loop control, acting directly on CV's setpoints in the 1,2-EDC plant;

▪ Control loop 2A – Online Control on decoupled loops after applying the ICA technique, acting directly on the setpoints of CV's in the 1,2-EDC plant;

The pairing between the manipulated variables (MV) and controlled variables (CV) was determined by analysis after the administration of tests in the 1,2-EDC plant. Excitations to simulate plant input variables had the intent to verify the sensitivity shown by each output variable controlled in the process. The excitation signal was applied to the PRBS, and from this component disturbances were conducted into the Feed flow, adopted as a process disturbance, and in the other variables (reflux flow rate, cascading reflux flow with LC3.SP, Flow 1,2-EDC (Base) in cascade with SumpLC.SP and Thermal Load), which at first were individually observed, and then chosen as MV.

In most systems, the base composition or base level is controlled by the thermal load or the flow of the base. Likewise, the composition of the distillate or reflux vase level is controlled by the flow rate of distillate or reflux flow. The choice for the use of setpoints of the level of the organic phase and the sump as manipulated level was due to the fact that the disturbances that often occur in industrial plants trigger abrupt changes like emptying or over-flowing at these two levels, making it difficult to do any analysis on their transient behavior.

Therefore, the handling of these set points allows a better understanding of what happens in a wider range of operation, thus enabling a safer understanding of the strategy and benchmarks for control. Table 2 shows the VM and CV annealing used in the proposed control structures.

Table 2: Pairing between Manipulated and Controlled Variables.

Manipulated Variable	Controlled Variable
Light Withdrawal Flow (U2)	1.2EDC composition on top (y1)
* SumpLC (Setpoint) (U3)	Sump level (y4)
** LC3 (Setpoint) (U4)	Organic phase level in the reflux vessel (y3)
Thermal Load (U5)	CCl_4 composition in the base (y2)

*Cascading with output Flow 1,2-EDC
** Cascade with Reflux Flow

OFFLINE Control

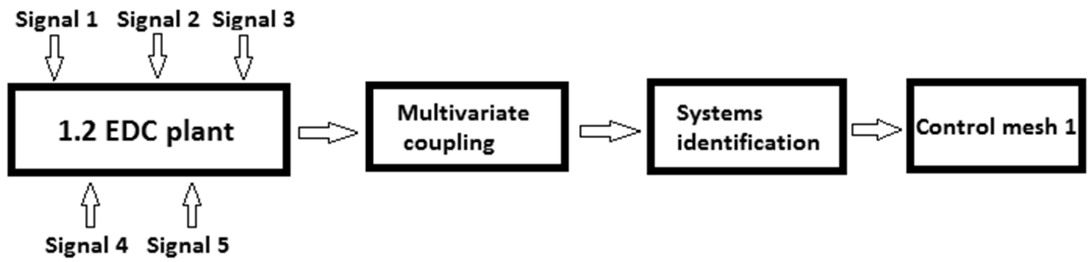
The first step was to obtain the mathematical models ruling the 1,2-EDC plant process. Once obtained, it was possible to analyze system performance. For this, the tool Matlab® ident software was used, which enables the creation of a dynamic system model from the data generated, characterizing the transient behavior of each variable in the analysis process. In possession of the data of the output components obtained directly through communication, as well as of the data of independent components extracted after passing through the ICA, we could begin the process of modeling. Offline control was useful to understand the behavior of each output variable to be controlled in the process, and was also handy for obtaining the initial controller parameters. The setpoints to be achieved by each CV are shown in Table 3.

Table 3: Reference values for controlled variables.

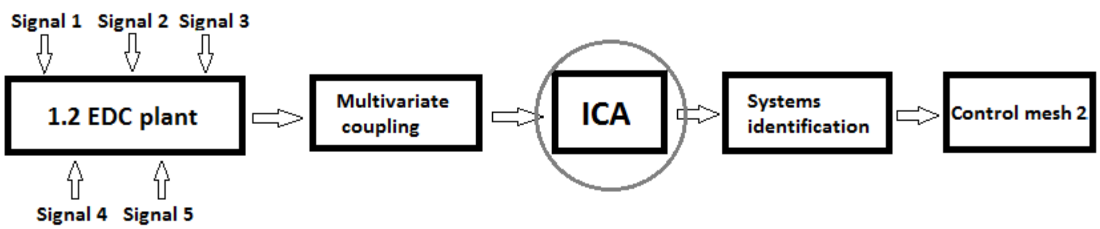
Controlled variables	Setpoint	Unit
1.2EDC composition on top (y1)	0.028	kg/kg
CCl_4 composition in the base (y2)	0.00265	kg/kg
Sump level (y4)	1.275	m
Organic phase level in the reflux vessel (y3)	0.29	m

In Figures 4(a) and 4(b) a schematic flow diagram used in each of the control motions offline is shown.

Both control loops 1 and 2 had the same format in this first moment, Figure 5. The only difference between them was the models used. Models were implemented within the blocks called 'subsystem', where for each MV/ CV pair relationship there was a distinctive style.



(a)



(b)

Figure 4: (a) Control loop 1 scheme fluxogram; (b) Control loop 2 scheme fluxogram.

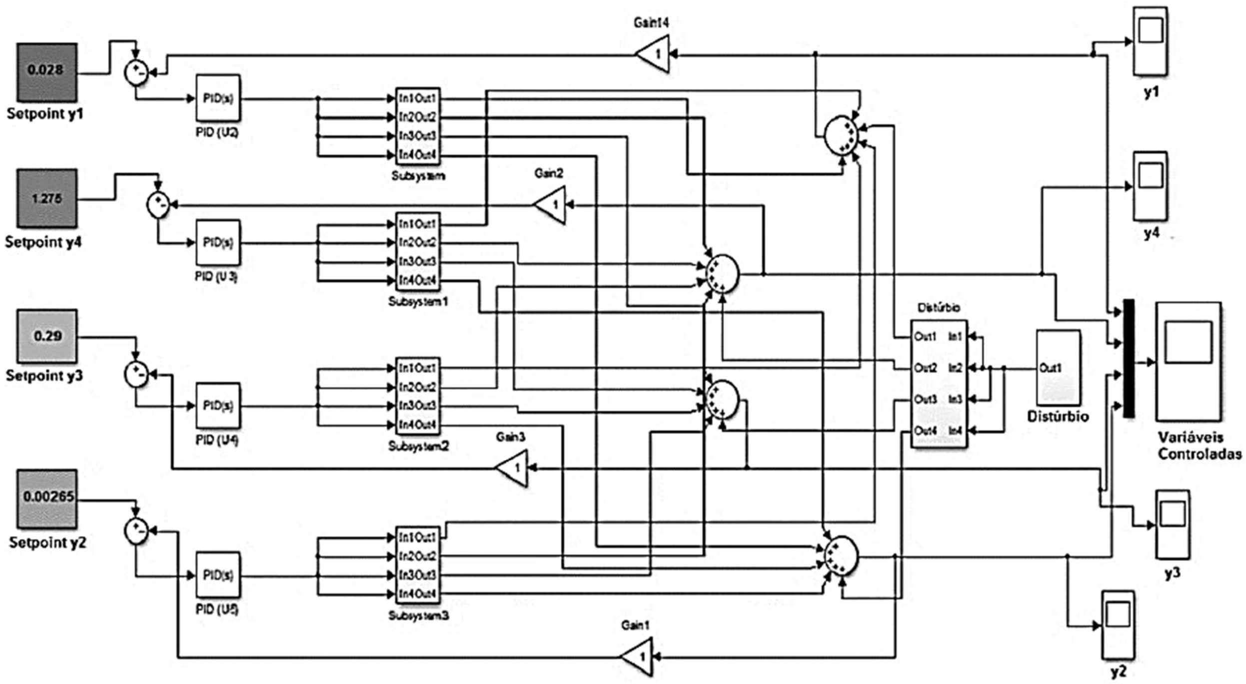


Figure 5: 1,2-EDC plant offline control proposal.

ONLINE Control

Then, after checking the performance achieved by the offline control, two new structures were proposed. The present work proposes two control structures in order to make a comparison between the conventional method of using Control Loop 1A, Figure 6, and the control method for decoupling variables using the ICA - Control Loop 2A, Figure 7. The control loop 2A used the separation matrix W obtained after applying ICA to promote decoupling of the variables in order to reduce the strong interaction between them. Both proposals used the base structure communication of Simulink/Matlab® x Aspen Plus Dynamics™, Figure 3.

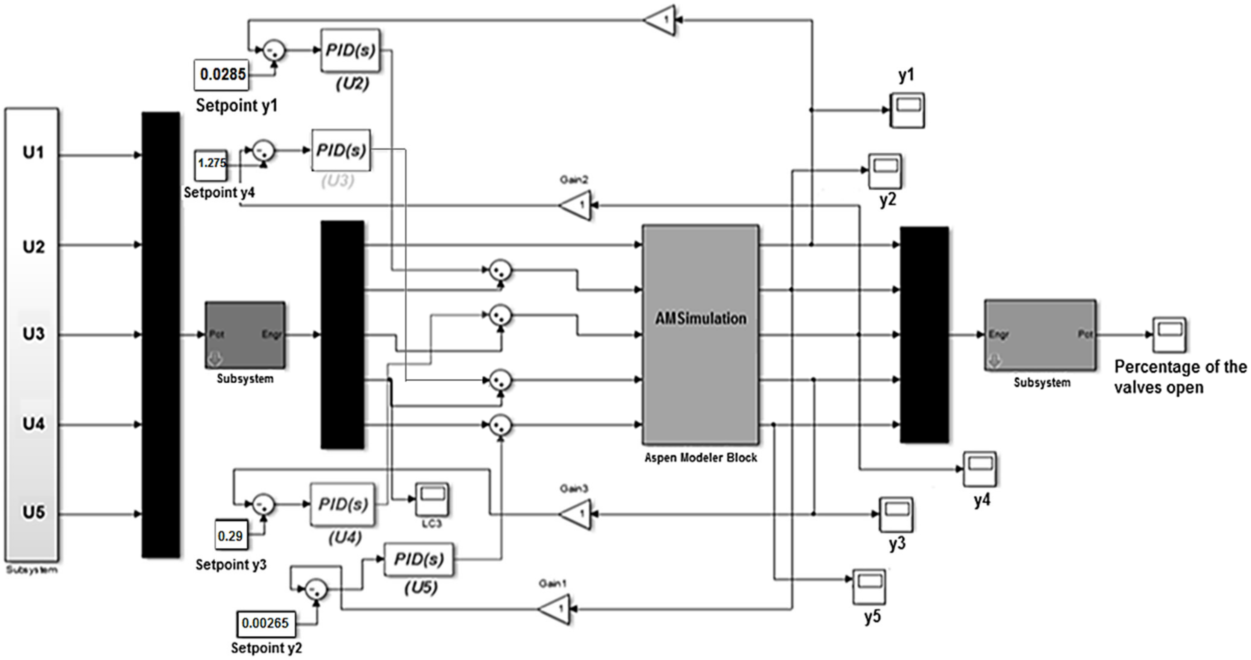


Figure 6: Control Proposal 1A.

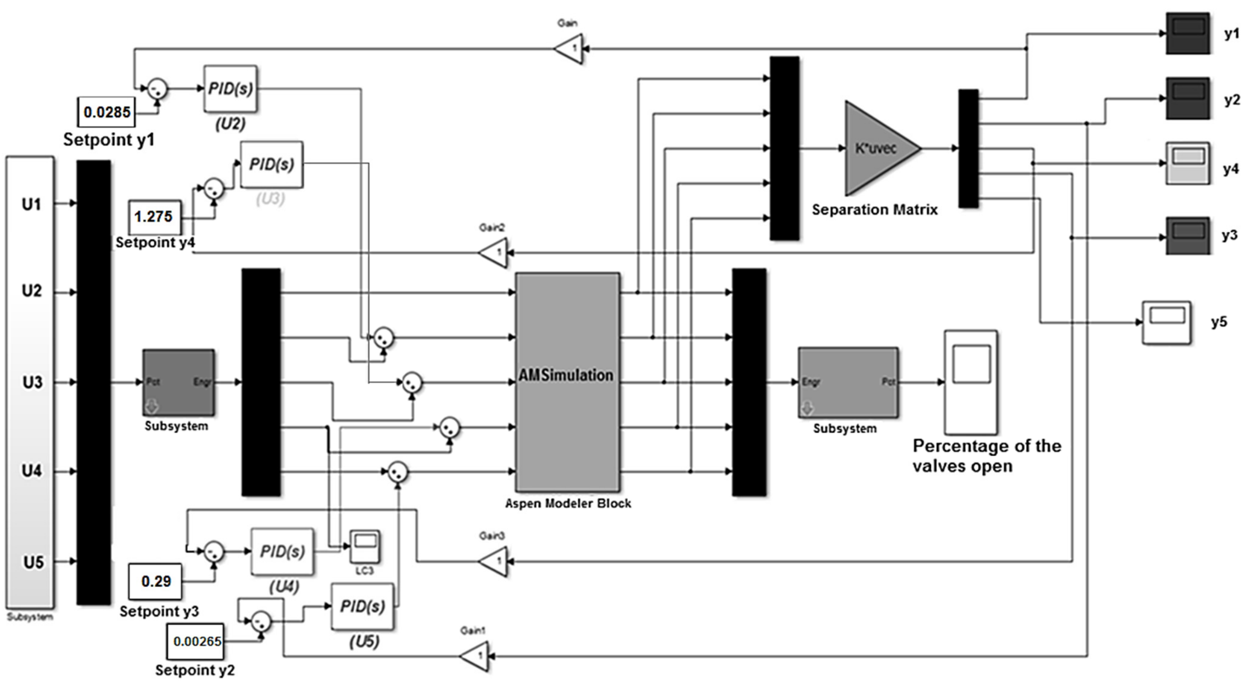


Figure 7: Control Proposal 2A.

The Control Loop 1A used the same precept of Control Loop 1, but, in this case, the control was directly applied to the 1,2-EDC plant, and not based on the models ruling the process, as can be seen in Figure 6. Figure 7 shows the addition of the separation matrix in order to reduce the existing strong coupling between the variables contained in the process, and this control was also applied in real time on the setpoints of CV's in the 1,2-EDC plant simulated in AspenPlus Dynamics™.

The tuning of the parameters of the controllers was based on the Ziegler Nichols method. However the initial starting line took place through the automatic tuner, and initial values were obtained during the tuning of the offline control loops. A system can be considered to have optimal control when the adjusted autotuning parameters provide a minimum error; thus, we used the Integral criterion of absolute error (IAE) to evaluate the performance of each proposed control system. The IAE criterion considers the error module and is much used in simulations because it is easy to implement and understand.

For Balestrino *et al*. (2006), the criterion of the IAE is a good economic measure of performance because the size and length of error in both directions is proportional to loss of income. In addition, an optimal system designed with this criterion is a system that has a reasonable damping, i.e., a response with overshoot, but is not too oscillatory and had a satisfactory transient response.

RESULTS AND DISCUSSION

The PRBS component allows us to observe the behavior triggered at each output variable after excitations are applied to the input variables. Thus, it was possible to identify and select the VM and CV pairs to be used in the control structure proposed in the work.

After provoked excitement of the Feedflow, the CCl_4 composition exceeded 3000 ppm, an amount required for maximum conversion of 1,2-EDC in cracking, the subsequent step of purification of 1.2–EDC; this factor may cause coke formation in the cracking furnaces. The composition of $CHCl_3$, despite suffering variations, still remains within the limits specified for safe operation of the plant, less than 400 ppm.

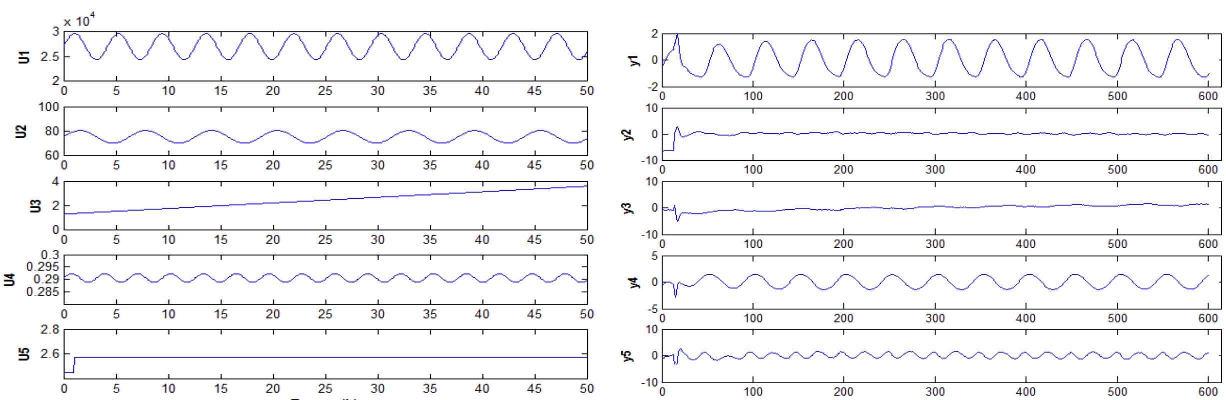
Therefore, the importance of the control of CCl_4 composition as opposed to $CHCl_3$ composition is proved by testing, since CCl_4 is more sensitive to disturbances in the system. By controlling $CHCl_3$ automatically, it is held below the maximum limits allowed for satisfactory safe operation of the process.

The level of the organic phase in the reflux vessel presented significant oscillations and its setpoint must be kept around0.3m. Otherwise the organochlorine components pass through the water output current. Finally, the sump level and the composition of 1,2-EDC in the distillate stream were evaluated.

Since there are rapid changes in the sump level, either upwards or downwards, liquid may overflow and flood the distillation column, thereby preventing the separation of the components. Also, if the sump is emptied, the pump that provides the circulation flow within the column may burn, what may cause the premature shutdown of the plant.

The variations in the 1,2-EDC composition in the distillate may reduce the purity of the product and this is not interesting for the purification process step under study. Therefore, this is one of the variables chosen for the control, along with the level of the organic phase of the reflux vessel, the level in the sump and the CCl_4 composition in the basic chain.

Especially in azeotropic distillation columns of high purity, the strong interaction and engagement between the variables is inherent in the process, a factor that is due to the high complexity present. Through the ICA it was possible to reduce this strong coupling, gain and extraction of independent signals obtained from the output variables (y1, y2, y3, y4 and y5), as shown in Figure 8.



(a) (b)

Figure 8: Components separated by ICA - (a) the original signals on the input variables; (b) signals recovered through the output variables.

For the best performance in separation, the orthogonalization methods were tested: deflation and symmetry, alternating together with non-quadratic functions. Thus, it was noted that the deflation method and the Gaussian function were the best pair for use in maximizing the decoupling data.

Several models have been evaluated in order to get the best fit for the relationship MV/ CV, namely: Transfer Functions, State Space, non-linear, polynomial models and correlation models. Those that presented the best results were ARX. For this choice some factors were taken into consideration, such as the correlation coefficient; the transient response that allows us to observe the system after the model adjustment, whether the system will reach stability for control purposes if certain disturbances occur in the process. Besides the two criteria outlined above, we analyzed the value of the final prediction error (FPE), where this criterion provides a measure of the quality of the model. After calculating several different models, it is possible to compare them using this criterion.

OFFLINE Control

As seen before, two control structures were proposed: Control Loop 1 and Control Loop 2. Both structures were implemented in the Simulink Matlab® environment. After analyzing the transient behavior of CVs monitored in the study, it was established what the best pairing would be between VM's and CV's, as seen previously. In Figure 9, the behavior of y1 is shown after tuning the controllers in both control loops.

As seen before, y1, besides presenting greater instability, requires a longer time to reach the desired setpoint when subjected to the control loop 1. As a result, it reaches a composition that is over 0.04% in mass in the distillate stream when the disorder is applied, which means a loss of 1.2 in the EDC overhead stream of the column, higher than is actually acceptable in the drying step. Therefore, the improved results are clear when control loop 2 is used because variable stabilization occurs in less than 5 hours of simulation, while control loop 1 takes about 25 hours. In Figure 10 the behavior of y2 can be observed.

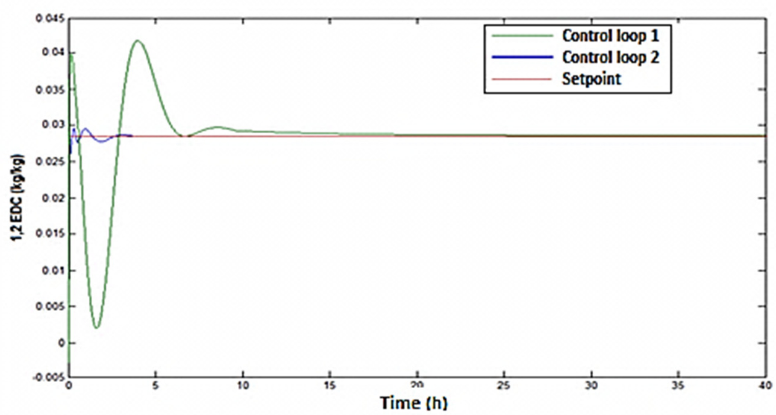


Figure 9: Behavior of y1 after controller tuning in Control loop 1 and loop 2.

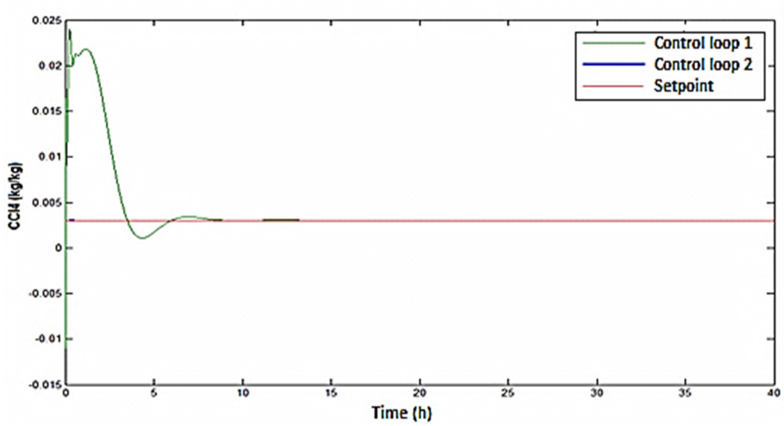


Figure 10: Behavior of y2 after controller tuning in Control loop 1 and loop 2.

The results were similar to those discussed above for y1. Again, the control loop 2 presents more satisfactory results when compared to those obtained through control loop 1. The value of y2 after the disorder reaches an approximate value of 0.024 kg/ kg (24 ppm), which exceeds 3000 ppm and is desirable for the drying and purifying value of 1.2EDC. Excessive fluctuations in y2 in the base product cause changes in the content of this component in feeding the cracking furnaces for 1,2-EDC, causing variations in the exchange rate and affecting the entire downstream process.

Adequate control of y2 in the feeding of the furnaces potentially reduces the formation of coke and leads to premature shutdown of the plant. In relation to the control loop 2, it is apparent that it reaches the setpoint in a short time. Besides, it has almost no instability. Seeing this, the ICA provides great benefit to the distillation columns with such specifications. The tests also verified the importance of controlling the levels of the organic phase and of the sump level. In Figure 11, it is observed that the level in the sump under the influence of control loop 2, although having almost no deviations from the desired setpoint, reached the setpoint at a time close to 1 hour, which is faster than required in control loop 1. Finally, the levels of the organic phase in the reflux vessel were analyzed, Figure 12.

As can be seen, the level of the organic phase under control of control loop 1, reached 0.7 m, a figure well above the setpoint value, which is 0.3 m. This level higher than the limit specified for the setpoint can cause a loss of organochlorine through the water output current at the top. Similarly, if the level drops to empty, it may lead to problems such as cavitation in the pump that carries the liquid flow into the column. In control loop 2, instability remained quite close to the setpoint, thus avoiding any risk of passage of organochlorines to the current output of the aqueous phase, besides achieving variable control at a time inferior to control loop 1.

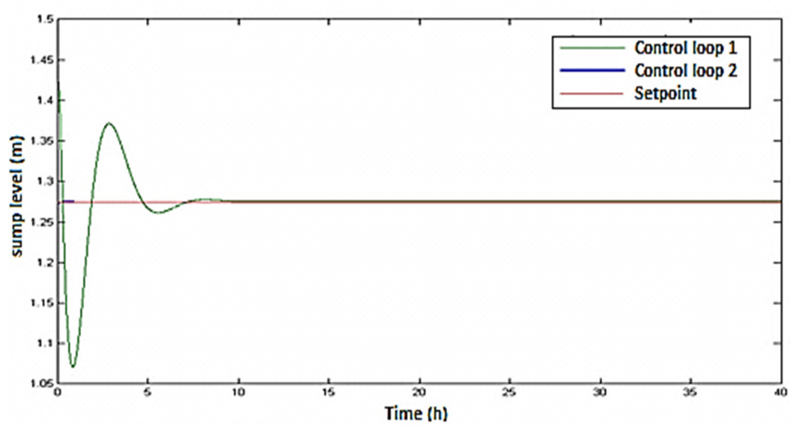


Figure 11: Behavior of y4 after controller tuning in Control loop 1 and loop 2.

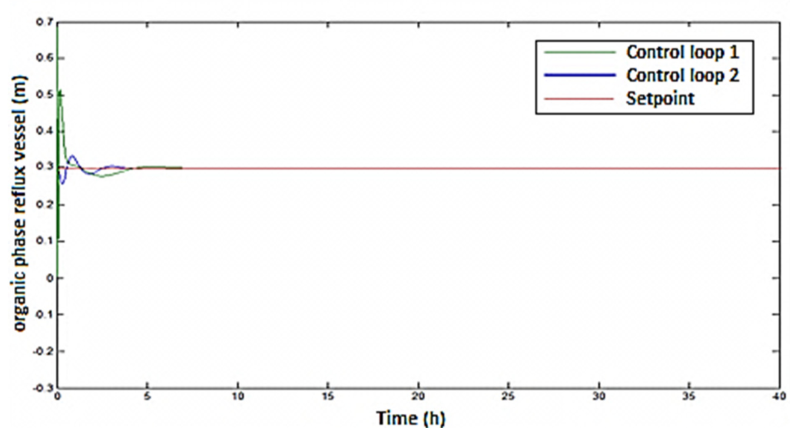


Figure 12: Behavior of y3 after controller tuning in the Control loop 1 and loop 2.

ONLINE Control

After implementation of the offline control loops in Simulink/Matlab®, the communication with Aspen Plus Dynamics™ was performed to promote real-time control of the CV in the 1,2-EDC plant. Figure 13 shows the reproducibility of results obtained in the offline control proposal when the ICA technique was used. It shows that, in this case, the identified models acquired real characteristics of the analyzed process.

The composition y1 submitted to control through control loop 1A showed a higher IAE value. The performance of this control is lower than that obtained through the control loop 2A. As can be seen, the variable y2 exhibits outliers in loop 1A, which implies losses until reaching the reference value, i.e., loss of 1,2-EDC in the distillate stream, which is not good for the process.

Furthermore, the variable presents oscillation even after reaching the setpoint value, which can be explained by the interference from other variables due to the existence of coupling.

After 30 hours of simulation, the variable y1 subjected to the control loop 1A, suffers a new instability and moves away from the desired set point, taking it to an integrator behavior in a longer time simulation. This causes difficulties for controlling the variable within a multivariable process, where the variables have a strong influence on one another. Thus, the control loop 2A showed much more robust results.

The variable y2 showed better control when subjected to control loop 2A, Figure 14, once again proving the technical benefit in the decoupling technique of the control loops, which can be justified by the value of IAE. As for variable y1, variable y2 presented outliers before reaching the setpoint value (control loop 1A); this factor leads to reduced conversion of 1,2-EDC in the cracking furnace, a posterior stage to the drying stage of 1,2-EDC. Furthermore, the time required for the control loop 1A to achieve the desired variable setpoint is well above that required by the mesh control 2A.

Although the levels of the sump and the organic phase did not present oscillations after reaching the desired setpoint, the occurrence of outliers was similarly found in the offline control. Analyzing the

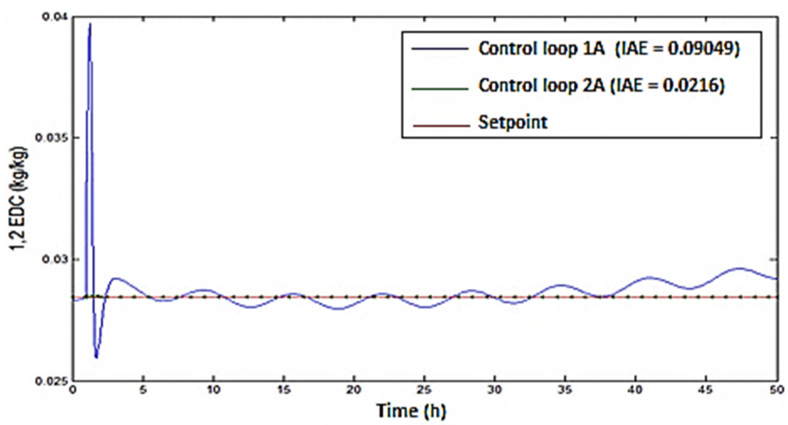


Figure 13: Behavior of y1 after controller tuning in Control Loop 1A and loop 2A.

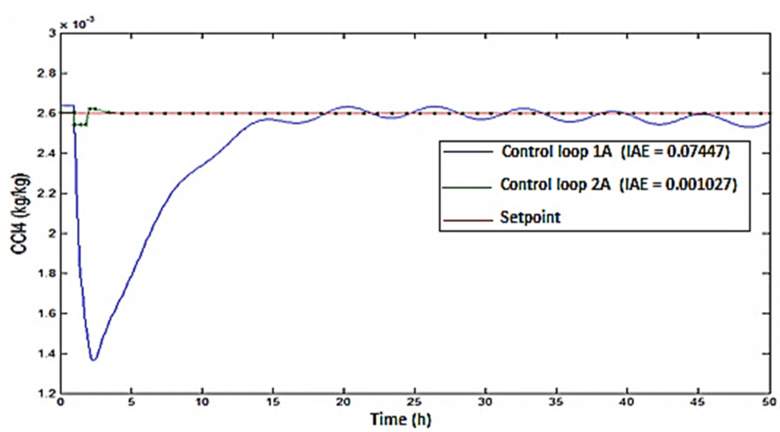


Figure 14: Behavior of y2 after controller tuning in Control Loop 1A and loop 2A.

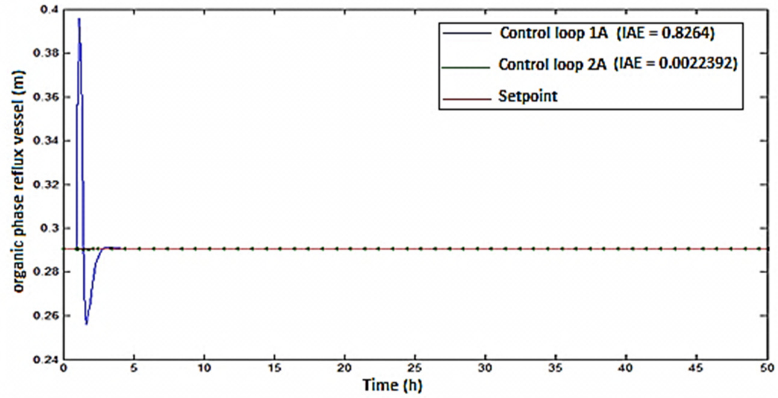


Figure 15: Behavior of y3 after controller tuning in Control loop 1A and loop 2A.

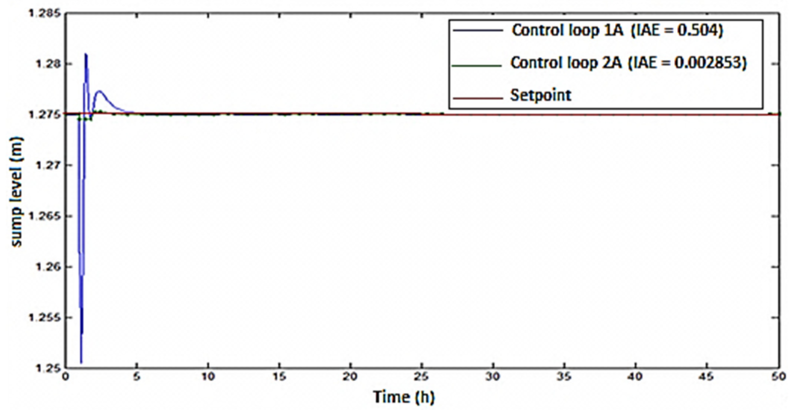


Figure 16: Behavior of y4 after controller tuning in Control loop 1A and loop 2A.

control levels, it is observed that, for both y3 (Figure 15) and y4 (Figure 16), the separation matrix applied to the control loop 2A showed improved results, which once again reflects the benefit of the technique robustness in the control, both as regards the reduction of instability and the convergence time to reach the setpoint. The two factors presented are justified through the IAE values found.

CONCLUSIONS

Through the excitement caused by the PRBS component to the system, it was possible to establish which control variables are required in the process. The top pressure of the column showed insignificant variations in the face of disturbance, so the control over this was discarded. Application of the ICA technique in the distillation column provided a significant improvement in control performance robustness, since by making the variables independent, the control could act individually on each CV, thus avoiding interference among the variables caused by the existing strong engagement in the process. Comparing the performance of the control strategy using the ICA with the strategy presented by the conventional method, the improvement was clear, besides reducing the settling time required for the variables to achieve the desired setpoint. The deviations over the set points were reduced. The tuned PID controller, analyzed by IAE criterion for the strategy using the ICA technique, has a satisfactory transient response, taking a shorter accommodation time and an overshoot below the conventional method of control. Reproducibility of the results presented by the two ICA technique offline control loops was observed. The identified models acquired real process characteristics, as well as providing a separation and efficient retrieval of the variables. When the loops were analyzed by the conventional method, it was clear that the online loop had higher deviations and required a longer time to reach the setpoint, when compared to the offline proposal, demonstrating that the models were not able to represent the dynamics of the process well because of the strong coupling between variables.

NOMENCLATURE

ICA	independent components analysis
SVM	support vector machine
BSS	blind signal separation
PCA	principal components analysis
PVC	polyvinyl chloride
1,2-EDC	1.2-dichloroethane
CCl_4	carbon tetrachloride
$CHCl_3$	chloroform
HCl	hydrochloric acid
MVC	vinyl chloride monomer
CV	controlled variable
CV's	controlled variables
MV	manipulated variable
MV's	manipulated variables
PRBS	pseudorandom binary sequence
IAE	Integral absolute error
ARX	autoregressive with exogenous input

Variables

Sump LC.SP	Sump level setpoint
LC3.SP	Organic phase level in the reflux vessel setpoint
U1	Feed flow
U2	Light withdrawal flow
U3	Sump.LC setpoint (Sump level setpoint)
U4	LC3.setpoint (Organic phase level in the reflux vessel setpoint)
U5	Thermal load
y1	Composition of 1,2-EDC in the distillate
y2	Composition of CCl_4 in the base of the column
y3	Organic phase level in the reflux vessel
y4	Sump level
y5	Top pressure of the column
A	Mixing matrix
A^{-1}	Inverse matrix of A
A^T	Transposed matrix of A
D	Diagonal matrix
W	Separation matrix

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