Decoupling of Multivariable Control Systems Using Mod-ICA

Dissociação de sistemas de controle multivariável usando Mod-ICA

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ABSTRACT

Sensors usage in process control systems is of vital importance for industrial plants proper operation and monitoring. In turn, process signals may have interference from other sources, and in some cases, it is not possible to observe the individual signs of the sources directly. Because of this, techniques of processing and separation of signals has been used to extract the information from the sources contained in mixed signals. The main signal separation techniques are associated with the technique ICA (Independent Component Analysis), which has undergone significant evolution since its creation in the 80's. This growth had also received contributions from PCA technique (Principal Component Analysis), and the development of computational processing power. However, these methods have two fundamental problems, which are the deviation of amplitude, and phase change, with issues such as limiting its use in control systems. Thus, this work aims to present a solution to the amplitude problem of ICA's techniques for use in obtaining uncoupling of multivariable systems. The proposed correction, based on the stage of whitening of ICA algorithms, generating the technique MOD-ICA, has been used as an alternative to the breaking of the correlation between variables of multivariate systems, with the goal of achieving the decoupling of MIMO (Multiple Input Multiple Output) systems. In the study case, proposed in this work, it was observed a better estimation of the parameters of decoupling models for the control system. The variables, after using the

ICA modified technique, are independent and do not present the influence of disturbances arising from other variables in the process, resulting in a more robust control system for process variations.

Keywords: Signal processing**,** ICA, decoupling, Process control

RESUMO
O uso de sensores em sistemas de controle de processo é de vital importância para a operação e monitoramento adequados de plantas industriais. Por sua vez, os sinais do processo podem ter interferência de outras fontes e, em alguns casos, não é possível observar os sinais individuais das fontes diretamente. Por conta disso, técnicas de processamento e separação de sinais têm sido utilizadas para extrair as informações das fontes contidas em sinais mistos. As principais técnicas de separação de sinais estão associadas à técnica ICA (Independent Component Analysis), que sofreu uma evolução significativa desde a sua criação na década de 80. Esse crescimento também recebeu contribuições da técnica PCA (Análise de Componentes Principais) e do desenvolvimento da capacidade de processamento computacional. No entanto, esses métodos têm dois problemas fundamentais, que são o desvio de amplitude e a mudança de fase, com questões como a limitação de seu uso em sistemas de controle. Assim, este trabalho tem como objetivo apresentar uma solução para o problema de amplitude das técnicas do ICA para utilização na obtenção de desacoplamento de sistemas multivariáveis. A correção proposta, baseada na etapa de clareamento dos algoritmos ICA, gerando a técnica MOD-ICA, tem sido utilizada como uma alternativa para a quebra da correlação entre variáveis de sistemas multivariados, com o objetivo de alcançar o desacoplamento de MIMO (Multiple Sistemas de entrada e saída múltipla). No caso de estudo, proposto neste trabalho, observou-se uma melhor estimativa dos parâmetros dos modelos de desacoplamento para o sistema de controle. As variáveis, após a utilização da técnica modificada ICA, são independentes e não apresentam a influência de perturbações decorrentes de outras variáveis no processo, resultando em um sistema de controle mais robusto para as variações do processo.

Palavras-chave: Processamento de sinais, ICA, desacoplamento, Controle de processo

1 INTRODUCTION

In signal measurements, the sensors for collecting information may contain problems with interferences and mixtures of the desired signals. Moreover, in general, there is no way to observe the sources directly, nor is it known how the tables were mixed [1].

Studies of Bode and Shannon at the end of the 1940s and the early 1950s [2], started the temporal filtering study [3]. The emergence of new separation techniques has been stimulated by the need to overcome the theoretical limits of classical methods, allowing resolution of problems, such as image separation, application in sensors and multivariate systems, with the processing of MIMO signals - Multiple Output).

Most multivariate systems present interactions between their inputs and outputs. In the context of process control, the consolidated control methods for SISO (Single Input

- Single Output) systems are not always efficient in the control of MIMO systems [4]. Consideration of interactions in control systems is essential because a large part of the modern industrial system involves a considerable number of variables with a certain degree of interrelation [5]. In these MIMO signal processing problems, it is desirable to find a transformation of the data to decrease the structure degree of interaction.

Decoupling method essence is to introduce dynamics that cancel the interactions among the process variables, allowing independent control to be made for each of the system control loops [6]. Among several alternatives, used in this type of process can be mentioned: Learning not Supervised; Principal Component Analysis (PCA); Analysis of Factors; Independent Components Analysis (ICA).

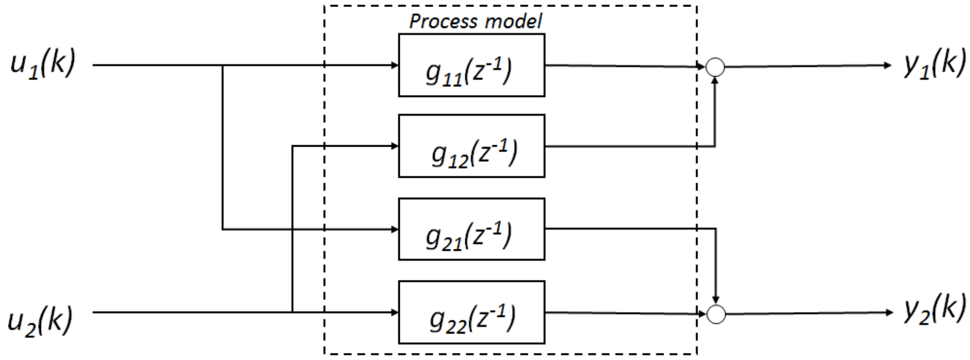
Signal processing technique by ICA is a stochastic and computational method, whose purpose is to search for a linear representation of non-Gaussian data so that these components are statistically independent or have their statistical dependence minimized. Previous work, such as that of [7], attempts to improve the ICA technique separation quality by incorporating higher order statistics in the form of second-order moments and Principal Component Analysis.

However, the modification still presents problems regarding amplitude and phase of the estimated signal, relative to the reference signal, being this behavior present in other ICA algorithms. In this context, this work objective is to insert an amplitude correction adjustment in the ICA methodology to improve convergence in the estimation of source signals, and its use as a technique for the decoupling of multivariate systems.

2 MULTIVARIATE PROCESS

Most applications with industrial process control involve a set of input variables (manipulated variables) and another set of output variables (controlled variables), and this type of application is called the Multiple Input - Multiple Output (MIMO) system. The MIMO system can be exemplified by considering a 2x2 system in Figure 1, where the process variables, y1 and y2 undergo the simultaneous influence of the two manipulated variables, u1 and u2, through the information transmitted by the transfer functions g12 and g21. In this case, the greater the interference described by the transfer functions g12 and g21, the greater the coupling level of the system in the process variables, y1 and y2, causing higher difficulty in the application of conventional control techniques.

Figure 1: Example of interaction between variables of the multivariate process



In general, the dynamics of a 2x2 process can be represented by the Eq (1) e Eq (2).

$$y_1(k) = g_{11}(z^{-1})u_1(k) + g_{12}(z^{-1})u_2(k) \quad (1)$$

$$y_2(k) = g_{21}(z^{-1})u_1(k) + g_{22}(z^{-1})u_2(k) \quad (2)$$

According to Eq (1) and Eq (2) any changes in signals u1 and u2 compromise both outputs. Reduction of influence can be achieved by applying mathematical techniques that cause the impact of transfer functions g12 and g21 to be eliminated or minimized. One of the alternatives for this is the application of decoupling techniques.

Some processes have structures that make them weak candidates for decoupling [8,9,10]. Consequently, one should perform a preliminary analysis of certain process characteristics such as controllability, the degree of interaction between control loops and degree of conditioning to decoupling.

Controllability is defined for a selected set of manipulated variables and controllable variables. Thus, for multivariate anyone process, controllability may vary according to the chosen subset of variables. Using such permanent regime relationships:

$$y_1(k) = K_{11}u_1(k) + K_{12}u_2(k) \quad (3)$$

$$y_2(k) = K_{21}u_1(k) + K_{22}u_2(k) \quad (4)$$

A system interaction indication can be obtained when the system behavior variation changes according to the manipulated variables settings. The inverse of the K-1 gain matrix allows us to determine whether the system is controllable or not. If the inverse exists, and its determinant is different from zero, the system is said controllable:

$u_i(k) = K^{-1}y_i(k)$	(5)

2.1 DEGREE OF INTERACTION IN PROCESS VARIABLES

The degree of interaction in the process variables can be indicated by obtaining the indicator: relative gain matrix (RGA). The RGA technique was proposed by [11] and is widely used in the selection of pairs of input and output variables, to select configurations with the minimum possible interaction.

From the relative dimensionless gain, we have that for values equal to 1 indicates that the other gains in closed mesh do not influence the gain in open mesh, so there is no interaction between the meshes and the more decoupled the system. Values smaller than 0 indicate the impossibility of control, for values between 0 and 1, suggests that the interaction between the meshes is low.

2.3 DECOMPOSITION BY SINGULAR VALUE (SVD)

Singular values are defined, $\sigma\iota$, as indicators of the proximity that has a matrix of the singularity, constituting as the limits of the possible gain of Gp. This method is beneficial for the analysis of multivariate systems, mainly because it is possible to determine the variables that influence the operation, as well as to determine if the system has interaction between the meshes [12]. SVD consists of expressing the static gain matrix of process K in the form:

$$K = USV^T \tag{6}$$

Where K is the static gain matrix, U is an orthogonal matrix whose columns contain the singular vectors of output from the left and V is an orthogonal matrix whose columns represent the singular input vectors by the right.

The conditioning number, gc, serves as a substantial degree of conditioning indicator for the process model, so that no other, such as an RGA, or the degree of sensitivity, provided by |K|, can determine [13,10]. This number was defined by, [14,15,16], as the relation of the magnitudes of the maximum and minimum singular value, according to Eq. (7).

$$g_c = \frac{S_{Max}}{S_{Min}} \tag{7}$$

3 UNCOUPLING

Due to the existence of the interaction between the control loops is responsible for hindering the application of conventional control techniques. According to [17], the most applied decoupling technique is the permanent decoupling technique. As for decoupling technique, this work proposes the use of the ICA methodology with a modification in the bleaching process; this method was named by MOD-ICA.

3.1 MOD-ICA

Independent component analysis (ICA) can be summarized as a statistical technique to search for independent components referring to a set of random variables, in the form $X = [X_1, X_2, \ldots X_n]^T$. The n elements are mixed signals from n statistically independent components, each other, a random vector in the form, $S = [S_1, S_2, \ldots S_n]^T$. Mathematically, the ICA model can be summarized by Eq (8).

$$\boldsymbol{X_i} = \sum_{j=1}^{n} \boldsymbol{a_{ij}\, S_j} \tag{8}$$

Where aij represents the coefficients of the mixture matrix A, responsible for representing the mean of the mixing of the unknown source signals.

Purpose of the ICA method is to estimate the independent components, assuming that the values of the mixing coefficients and the independent elements are not known. Mathematically, we have to determine an array W, such that the independent components are found according to Eq (9).

$$\boldsymbol{S} = \boldsymbol{WX} \tag{9}$$

However, since there is no knowledge about the mixture matrix A, we cannot find the matrix W that satisfies Eq (9). Thus, looking at a matrix W* such that Eq (10) is respected.

$$\boldsymbol{Y} = \boldsymbol{W^{*}X} \ \forall \ \ \boldsymbol{min} \ \| \boldsymbol{S} - \boldsymbol{Y} \| \tag{10}$$

In general, application of independent component analysis techniques can be summarized in the following topics: Centralization of X, Bleaching; of X, and Search for independent components.

The Bleaching stage is one of the most important steps, for the estimation of the independent components, by the ICA methodology. This action is responsible for causing a linear transformation in the observed variables, such that these vectors are uncorrelated and of unit variance [18]. The Bleaching process is represented in Eq (11). The vector z represents the bleached vector, V is the bleaching matrix, x the vector of the original data, and E and D are, respectively, the eigenvector matrices and eigenvalues of the original data vectors obtained by the eigenvalue decomposition.

$$\boldsymbol{z} = \boldsymbol{Vx} \quad \forall\, \boldsymbol{V} = \boldsymbol{ED}^{-1/2}\boldsymbol{E}^{T} \tag{11}$$

As a solution to the amplitude problem of the ICA technique, this work proposes a term $\mathbf{1}/\sqrt{\boldsymbol{n}}$ insertion, Eq(12), which is a weighting for the bleaching matrix V. This weighting term is used from the consideration of circulating matrices [19]

$$\boldsymbol{z} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{n}}}\boldsymbol{Vx} \tag{12}$$

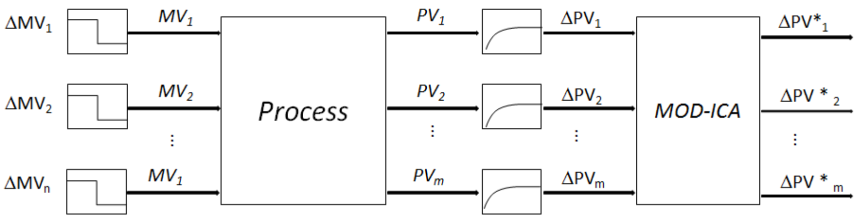
4 CASE STUDY

MOD-ICA technique proposed in this study was used in the process of obtaining anhydrous ethanol, via extractive distillation, in Aspen® platform, as a technique to reduce the control system degree of coupling.

Information about the process dynamics was collected using a step variation in the manipulated variables (ΔMVi). The gains of the output variables (ΔPVi) were used in the MOD-ICA, thus generating the processed gains (ΔPV*i), as shown in the diagram in Figure 2. The gain matrix, considering ΔPV* was generated from the application of the SVD technique to determine the pairs for the control system as well as the conditioning for indirect verification of the system degree of coupling.

Information obtained by calculating the conditional number (NC) and the general relative gain matrix (RGA) will be used to verify the degree of coupling of the system.

Figure 2 – Diagram of the application steps of MOD-ICA



4.1 PROCESS FOR OBTAINING ANHYDROUS ETHANOL

The model of the anhydrous ethanol extraction plant, via extractive distillation, was implemented in the Aspen® Dynamics platform and is presented in Figure 3. The RADFRAC models were used to represent the process, being the most indicated as a rigorous representation of extractive columns and Solvent recovery. The extractive column C101 has 23 equilibrium stages, and the solvent recovery column C102 presents nine stages.

5 RESULTS AND DISCUSSION

Using the process plant model, in Aspen Dynamics®, disturbances were 6 MV's ($Q_{cond,101}$, $Q_{cod,102}$, $Q_{reb,101}$, $Q_{reb,102}$, $R_{ref,101}$, $Q_{ref,102}$) selected in the range of 0.01% to 0.5%. 38 PV's variations ($T_{i,101}$, $T_{i,102}$, $x_{itop,101}$, $x_{itop,102}$) were obtained and used to calculate the static gain matrix, according to Eq (13). The static gain matrix was applied in the SVD method, in its classical form and using the MOD-ICA technique.

$$\boldsymbol{K} = \frac{\Delta \boldsymbol{PV_i}}{\Delta \boldsymbol{MV_i}} \tag{13}$$

From the decomposition of the gain matrix, using the classical SVD method, the pairings and the conditional number calculations presented in Table 1 were obtained. The same procedure of applying the gain matrix from the MOD-ICA method, shown in table 1.

The application of the MOD-ICA in the gain matrix has generated a different pairing when compared to the classic result. Also, there was a significant reduction in system conditioning. This modification improves the controllability of the control system using such pairs, as well as a system decoupling indicator.

5.1 CALCULATION OF THE RGA

The pairings found by classical SVD techniques and a using the MOD-SVD technique were evaluated for the system coupling condition. Table 2 presents, respectively, the RGA matrix for classical SVD and SVD with MOD-ICA. The values obtained by the RGA for the pairs obtained from the SVD with the MOD-ICA are mostly within the range 0 and 1.

Figure 3 - Ethylene glycol extraction process plant for anhydrous ethanol

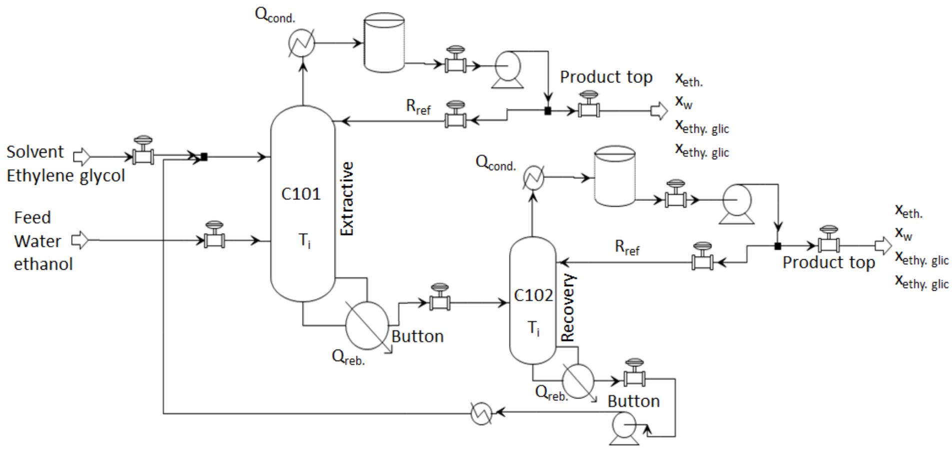


Table 1: Pairing proposed by the classical SVD method and SVD method with the MOD-ICA

Classical SVD			SVD MOD-ICA		
Process Variables	Manipulated variables	Conditional number	Process Variables	Manipulated variables	Conditional number
$x_{eth.}$, top C102	$Q_{Reb.}$ – C102	1	$x_{eth.}$, top – C102	$Q_{Reb.}$ – C102	1
T_7 – C102	$Q_{Cond.}$ – C101	140.88	$x_{wat.}$, top – C102	$R_{ref.}$ – C101	36.05
T_{22} – C101	$Q_{Reb.}$ – C101	470.95	T_8 – C102	$Q_{Reb.}$ – C101	75.119
$x_{eth.}$, top – C101	$Q_{cod.}$ – C102	4,360.85	T_7 – C102	$Q_{Cond.}$ – C102	697.67
T_{21} – C101	$R_{ref.}$ – C101	16,960.49	T_{22} – C101	$Q_{Cond.}$ – C101	768.00
T_6 – C102	$R_{ref.}$ – C102	120,686.40	T_{21} – C101	$R_{ref.}$ – C102	875.41

Table 2: RGA for classical SVD method and SVD method with the MOD-ICA

Classic SVD	MV4	MV1	MV3	MV2	MV5	MV6	SVD MOD-ICA	MV4	MV5	MV3	MV2	MV1	MV6
PV4	0.373	3.326	-0.209	-3.535	-0.020	1.066	PV4	3.509	-152.534	-1.432	0.148	153.923	-2.619
PV36	2.197	0.695	-1.310	-3.326	-0.473	3.216	PV6	-3.468	153.474	1.444	-0.161	-152.962	2.672
PV28	-2.087	-2.171	-0.161	1.613	4.542	-0.737	PV37	0.099	0.007	0.431	0.465	-0.004	0.003

PV1	-2.035	-0.743	0.638	3.880	-1.739	1.000	PV36	0.031	0.001	0.443	0.538	-0.012	-0.001
PV27	-0.518	0.395	2.533	-0.069	-1.739	0.398	PV28	0.125	0.052	0.033	0.005	0.004	0.780
PV34	3.070	-0.502	-0.491	2.436	0.429	-3.943	PV27	0.705	0.000	0.081	0.005	0.050	0.165

Due to negative values, one can reduce control structure for a 4x4 system for an RGA SVD Classic presented in Table 3. It is observed that removal of the loops 5 and 6 caused an improvement in values for the RGA system, however, due to the coupling system difficulty. The same pairs of reduction procedure were conducted similarly to that performed in the classic pairing. Pairings 1 (MV4 - PV4) and 2 (MV5 - PV6) were removed from the control system.

Table 3: RGA for 4x4 systems from the SVD Classic and SVD MOD-ICA

Classic SVD	MV4	MV1	MV3	MV2	SVD MOD-ICA	MV3	MV2	MV1	MV6
PV4	0.935	3.176	-0.266	-2.84	PV37	0.592	0.3483	0.0609	-0.0019
PV36	4.37	0.4330	-1.80	-2.00	PV36	0.512	0.5950	-0.1050	0.0020
PV28	-2.88	-0.825	3.22	1.482	PV28	-0.008	0.0194	0.2486	0.7405
PV1	-1.42	-1.784	-0.15	4.36	PV27	-0.09	0.037	0.7954	0.2634

It can be seen in Table 3 that for the RGA with the traditional SVD, with the control pairs that were more competition with each other removal, there was an adjustment in the values of relative gains. However, there was a reduction in the degree of coupling Still needed. For the reduction of the pair system from the MOD-ICA SVD, the significant decrease in the degree of coupling was achieved, since the obtained values are close to 0 (zero) and less than 1 (one).

6 CONCLUSION

The use of the MOD-ICA technique as a decoupling methodology, it enabled, in addition to a new pairing for the control system, reduction in the system's conditional number. This reduction may indicate greater controllability, lower uncertainty degree and greater decoupling for the system.

The application of the proposed technique in a widely used process model, such as the anhydrous ethanol dehydration process, via extractive distillation process, allowed a comparison with other works published in literature.

The analysis of the relative gain matrix was important for the identification of control meshes that were causing system instability, indicating pairings not identified by the SVD technique.

It is also observed that the application of the decoupling system, together with the elimination of unstable meshes, resulted in more satisfactory relative gain values and, consequently, more stable control system. This analysis also indicated the elimination of PVs, referring to composition variables, from the table of candidates for controlled variables.

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