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# Detection of control loop interactions and prioritization of control loop maintenance

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Chemical processes with multiloop control configurations have significant amount of control loop interactions due to tight mass and heat integration. Change in set point and/or controller parameters of one control loop may affect the variables of other loops. The presence of loop interactions in a process plant can cause significant quality and production losses of the plant. It is challenging to measure the degree of interaction between control loops and rank the loops according to the extent of interactions. This paper presents two data driven techniques to quantify control loop interactions and rank the loops according to their importance. In the first approach, a novel method based on canonical correlation analysis has been developed to calculate interaction among the loops and then normalization is done with respect to the maximum canonical correlation to determine the rank of the loops. In another approach, two indices have been developed using integral of absolute or squared error criteria to quantify loop interaction and determine rank of the loops. Both methods require step test data of the plant. Simulation and experimental results show the validity and efficacy of the proposed methods.


## 1. Introduction

The presence of loop interactions in a multiloop control configuration can cause several undesirable effects in chemical processes. Chemical processes may become unstable and show oscillatory responses due to the presence of significant loop interactions. Detection of the degree of interactions among the loops and finding the most interacting loop is a challenging task, because in a chemical process there are hundreds of automatic control loops connected in a MIMO control configuration. In recent times plant engineers or operators are overloaded and each of them needs to look after a couple of hundred of control loops. It is often difficult for them to start the maintenance work of the loops because they do not know where to start or which loops are more important than others from operational point of view. Therefore, it is important to have some diagnostic measures to rank the loops according to their relative importance. This can be done in many possible ways such as ranking the loops according to the standard deviation of the error signals, key performance indicators, economic indicators, oscillation index and interaction index. This paper presents two methods to rank the loops according to their interaction index.

Over the past few decades, several researchers presented different methods to determine the degree of loop interactions and prioritize the loops according to their importance from the interaction point of view. Bristol (1966) proposed a novel method in 1966 to determine control loop interaction using relative gain array (RGA) and recommended a method for best pairing of manipulated and controlled variables using steady state information of the process. Dynamic relative gain array is used in Witcher and McAvoy (1977) for dynamic interaction analysis of a process. Tung and Edgar (1981) proposed a method to determine dynamic interaction using open loop response of the process. Gagnepain and Seborg (1982) also used open loop response of the process expressing each transfer function as a first order plus time delay model. Shimizu and Matsubara (1985) calculated the loop interaction using singular perturbation technique. Hwang (1995) and Zhu, Lee, and Edgar (1997) used steady state information of the process to determine control loop interaction. Meeuse and Huesman (2002) proposed a graphical method which determines the loop interaction by considering the dynamic information of the process. Lee and Edgar (2004) analyzed loop interaction using sensitivity and complementary sensitivity functions. Vilanova (2008) used dynamic information of the process to measure loop interaction.

Since exact process models are almost never known, the model based interaction detection methods find limited applications. Data based interaction detection technique appeared in Rossi, Tangirala, Shah, and Scali (2006), Farenzena and Trierweiler

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(2009), Farenzena, Trierweiler, and Shah (2009). These methods require either step change or routine operating data of the process. Rossi et al. (2006) used plant set point change data to determine loop interaction. Farenzena and Trierweiler (2009) presented a new tool to determine loop interaction using partial correlation function and rank the loops according to their importance using the PageRank technique. Farenzena et al. (2009) calculated loop interaction by using the variability information of the controlled variables.

Simple statistical signal processing methods such as data correlation and integration of the absolute or squared data is used to find techniques for determination of control loop interaction. Different correlation methods such as partial correlation and cross correlation have been used for interaction detection. An auto-correlation value of 1 represents the data is correlated with itself. The cross-correlation value close to one for two variables indicates that they are highly correlated. Another statistical technique called canonical correlation can be used to quantify relation between multidimensional variables. On the other hand, if a variable in one control loop is highly disturbed by change in another control loop then that variable will have high value of integral of absolute error (IAE) or integral of squared error (ISE).

This paper proposes two new methods that can determine control loop interaction effectively and can also rank the loops according to their importance. One method is based on canonical correlation analysis and the other method is based on IAE or ISE. Both methods are data-driven and do not require explicit identification of process models. Only closed loop step test data suffices the calculation of interaction indices.

The paper is organized as follows. Section 2 describes about canonical correlation analysis. Section 3 describes the analysis using IAE or ISE. Application of the techniques to simulated and experimental data are presented in Sections 4 and 5 respectively. The paper ends with the concluding remarks in Section 6.

## 2. Interaction analysis using canonical correlation

### 2.1. Canonical correlation

Among the different correlation, canonical correlation analysis (CCA) is a way of measuring the linear relationship between two multidimensional variables (Hotelling, 1936; McKeon, 1964; Morrison, 1967). A multidimensional variable is a matrix containing $m$ observations and $n$ columns (variables), where $n \geq 2$. For example, if there are four variables such as $y1$, $y2$, $y3$ and $y4$ each having 5000 data samples, then a multidimensional variable, $y$, can be formed so that $y$ has the dimension of $5000 \times 4$. The canonical correlation finds two bases, one for each variable, that are optimal with respect to correlations and, at the same time, it finds the corresponding correlations. In other words, it finds the two bases in which the correlation matrix between the variables is diagonal and the correlations on the diagonal are maximized. The dimensionality of these new bases is equal to or less than the smallest dimensionality of the two variables. An important property of canonical correlations is that they are invariant with respect to affine transformations of the variables. This is the most important difference between CCA and ordinary correlation analysis (Weenink, 2003; Muller, 1982).

In canonical correlation analysis the correlations between objects that are to be maximized are represented with two data sets. Let these data sets be $\mathbf{A_x}$ and $\mathbf{A_y}$, of dimensions $m \times n$ and $m \times p$, respectively. Sometimes the data in $\mathbf{A_y}$ and $\mathbf{A_x}$ (where they are mean corrected) are called the dependent and independent data, respectively. The maximum number of correlations that can be found is then equal to the minimum of the column dimensions $n$ and $p$. Let the directions of optimal correlations for the $\mathbf{A_x}$ and $\mathbf{A_y}$ data sets be given by the vectors $\mathbf{x}$ and $\mathbf{y}$, respectively. When the data are projected on these direction vectors, two new vectors $\mathbf{z_x}$ and $\mathbf{z_y}$ is obtained and is defined as

$$\mathbf{z_x} = \mathbf{A_x x} \tag{1}$$

$$\mathbf{z_y} = \mathbf{A_y y} \tag{2}$$

The variables $\mathbf{z_y}$ and $\mathbf{z_x}$ are called the scores or the canonical variates. The correlation between the scores $\mathbf{z_y}$ and $\mathbf{z_x}$ is then given by (Montgomery & Runger, 2003)

$$\rho = \frac{\mathbf{z_y' \cdot z_x}}{\sqrt{\mathbf{z_y' \cdot z_y}}\sqrt{\mathbf{z_x' \cdot z_x}}} \tag{3}$$

Now the problem is to find the directions $\mathbf{y}$ and $\mathbf{x}$ that maximize Eq. (3) above. It should be noted that $\boldsymbol{\rho}$ is not affected by a rescaling of $\mathbf{z_y}$ or $\mathbf{z_x}$, i.e., a multiplication of $\mathbf{z_y}$ by the scalar $\alpha$ does not change the value of $\rho$ in Eq. (3). Since the choice of rescaling is arbitrary, therefore Eq. (3) is maximized subject to the constraints

$$\mathbf{z_x' \cdot z_x} = \mathbf{x' A_x' A_x x} = \mathbf{x' R_{xx} x} = 1 \tag{4}$$

$$\mathbf{z_y' \cdot z_y} = \mathbf{y' A_y' A_y y} = \mathbf{y' R_{yy} y} = 1 \tag{5}$$

Here, $\mathbf{R_{yy}} = \mathbf{A_y' A_y}$ and $\mathbf{R_{xx}} = \mathbf{A_x' A_x}$, where the $\mathbf{R}$'s are covariance matrices. When $\mathbf{R_{yx}}$ is also substituted by $\mathbf{A_y' A_x}$, the maximization problem along with the two constraints above can be written in Lagrangian form:

$$\mathbf{L}(\rho_\mathbf{x},\rho_\mathbf{y},\mathbf{x},\mathbf{y}) = \mathbf{y' R_{yx} x} - \frac{\rho_\mathbf{x}}{2}(\mathbf{x' R_{xx} x} - 1) - \frac{\rho_\mathbf{y}}{2}(\mathbf{y' R_{yy} y} - 1) \tag{6}$$

Eq. (6) can be solved by first taking derivatives with respect to $\mathbf{y}$ and $\mathbf{x}$:

$$\frac{\partial \mathbf{L}}{\partial \mathbf{x}} = \mathbf{R_{xy} y} - \rho_\mathbf{x} \mathbf{R_{xx} x} = 0 \tag{7}$$

$$\frac{\partial \mathbf{L}}{\partial \mathbf{y}} = \mathbf{R_{yx} x} - \rho_\mathbf{y} \mathbf{R_{yy} y} = 0 \tag{8}$$

Now subtracting $\mathbf{x}'$ times the first equation from $\mathbf{y}'$ times the second gives

$$0 = \mathbf{y' R_{yx} x} - \rho_\mathbf{y} \mathbf{y' R_{yy} y} - \mathbf{x' R_{xy} y} + \rho_\mathbf{x} \mathbf{x' R_{xx} x} = \rho_\mathbf{x} \mathbf{x' R_{xx} x} - \rho_\mathbf{y} \mathbf{y' R_{yy} y} \tag{9}$$

Together with the constraints of Eqs. (4) and (5) it can be concluded that $\boldsymbol{\rho_x} = \boldsymbol{\rho_y} = \boldsymbol{\rho}$. When $\mathbf{R_{xx}}$ is invertible Eq. (7) can be written as

$$\mathbf{x} = \frac{\mathbf{R_{xx}^{-1} R_{xy} y}}{\rho} \tag{10}$$

Substitution in Eq. (8) gives

$$(\mathbf{R_{yx} R_{xx}^{-1} R_{xy}} - \rho^2 \mathbf{R_{yy}})\mathbf{y} = 0 \tag{11}$$

In an analogous way the equation for the vectors $\mathbf{x}$ can also be written as

$$(\mathbf{R_{xy} R_{yy}^{-1} R_{yx}} - \rho^2 \mathbf{R_{xx}})\mathbf{x} = 0 \tag{12}$$

Because the matrices $\mathbf{R_{xy}}$ and $\mathbf{R_{yx}}$ are each other's transpose the canonical correlation analysis can be written as follows:

$$(\mathbf{R_{xy}' R_{xx}^{-1} R_{xy}} - \rho^2 \mathbf{R_{yy}})\mathbf{y} = 0 \tag{13}$$

$$(\mathbf{R_{xy} R_{yy}^{-1} R_{xy}'} - \rho^2 \mathbf{R_{xx}})\mathbf{x} = 0 \tag{14}$$

Eqs. (13) and (14) are known as generalized eigenvalue–eigenvector problems. The solution of these equations gives the value of canonical correlation.