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VARIABILITY MATRIX: A NOVEL TOOL TO PRIORITIZE LOOP MAINTENANCE

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RESUMO – É de comum conhecimento tanto da indústria quanto da academia que cerca de 60% das malhas de controle da maioria dos processos industriais possui significativo potencial de melhora em seu desempenho. Devido ao grande número de malhas em uma planta industrial, tão importante quanto auditar seu desempenho é a hierarquização de sua manutenção. É sabido que reduzir a variabilidade em uma dada malha acarreta o aumento da variabilidade em outras. Este é o escopo deste trabalho: propor uma metodologia para quantificação do potencial econômico de cada malha, como ferramenta pra hierarquização de sua manutenção, considerando a transferência de variabilidade entre elas. O ponto central é a Matriz de Variabilidade (VM). Esta mostra o impacto da melhora de um dado controlador em toda a planta. Baseado na VM, uma metodologia para traduzir esta matriz no potencial econômico de cada loop também é proposta. A VM pode ser quantificada considerando que tanto o modelo da planta quanto do controlador estão disponíveis, ou quando um ou ambos estão ausentes. A eficácia da metodologia proposta é ilustrada pela aplicação em um caso de estudo.

PALAVRAS-CHAVE:

ABSTRACT – It is now common knowledge that as many as 60% of the control loops in most industrial processes have considerable performance potential of improvement. Because of the large number of control loops in an industrial plant, control loop monitoring is indispensable, but also equally important is how to prioritize their maintenance. It is well known that variance reduction in a loop occurs by transferring variability to other variables or loops. The focus of this study is to propose a methodology to prioritize loop maintenance based on the potential improvement of each loop and the variability transfer among them. The central point of this work is the Variability Matrix (VM), an array that shows the impact of performance improvement of a given loop on the whole plant. Based on VM, a methodology to translate the VM into a potential loop economic benefit metric is also introduced. The VM can be quantified in the ideal scenario where plant model and controller are available and also when they are not, thus allowing the application of these idea in industry. The efficacy of proposed methodology is illustrated by successful application to a case study.

1. INTRODUCTION

The main requirement for a control system is ensure the process stability and robustness. This is the key reason for the industrial interest in performance assessment methodologies and tools. Many good reviews on assessment of control loops are available in the literature (Jelali, 2006, Huang et al., 1997). However, in a typical plant there are hundreds or thousands of controllers and most of them have potential to improvement (Bialkowski, 1993). How can the control engineer prioritize the loop maintenance? The answer should not only be based on the performance potential, but also mainly on the economic benefits that can be realized in improving the performance of each loop.

The main motivation for improving the performance of the plant is simple: reduction in process variability allows to achieve a more profitable operating point, closer to the constrains, as shown in Figure 1. In scenario I, the process has large variability and therefore the setpoint or the target has to be significantly far away from the economically optimal operating point (in this case the restriction is 0.95). If the variability is reduced, due to a controller improvement or process improvement, elsewhere as in scenario II the process operating point can be moved to a more profitable setpoint (scenario III).

The literature is relatively sparse in terms of quantification of control improvement economic benefits. Muske (2003) proposes the idea of potential reduction in control loop variability. The economic benefit is quantified based on the mean shift in the mean operation toward a product specification or process constraint. The variance reduction is based on a fix benchmark, which is the minimum variance controller. Craig and Henning (2000) proposed another methodology to quantify the economic

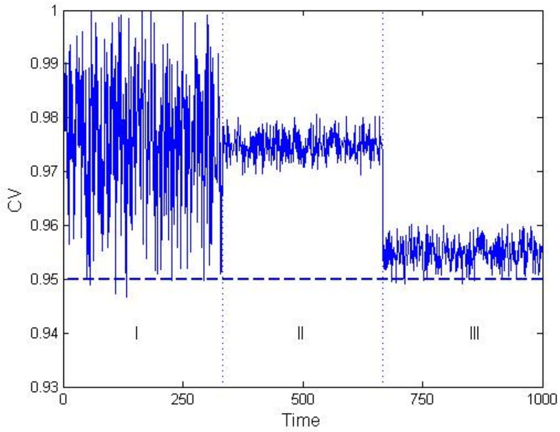

Figure 1: Variability reduction impact: (I) normal operating variability (II) variability reduction and (III) operating point shift.

benefit of Advanced Process Control (APC) projects. The authors mention that the whole part of the benefit comes from the steady-state optimization. They assume that the variance of the products can be reduced by 35% to 50%. Mascio and Barton (2001) propose a methodology to quantify the control quality in economic terms based on the Taguchi Framework.

All available methodologies agree that reduction in variability means shifting the operating point to a more profitable point. The main drawback is that they consider each loop as an isolated case, i.e. if performance of one loop is improved then the whole plant will not suffer its effect. This is clearly not a realistic scenario.

All modern industrial plants have significant interaction among loops due to tighter heat integration. Because of this, one cannot assume that the variance reduction in one loop will occur without impacting other loops adversely. Typically, variability is transferred from loops where it should be reduced to loops that have the room or the buffer to accommodate large fluctuations (e.g. level loops). In many cases, if one variable has its variability reduced and its operating point shifted, then it is likely that other interacting or complementary will have their variability increased, shifting the operating point away from the constraints. This implies that "part of the profit" realized by variability reduction in a given loop "will be offset" by the loops where the variability increases. This is why a control loop should not be considerate in isolation and the potential economic benefit should be computed by analyzing the whole plant, not only a specific loop.

The main contribution of this work is the introduction of the notation of the Variability Matrix (VM). This array shows how the variability transfers between the loops and the impact of one specific loop on the variances of all other interacting or complementary loops. The potential economic benefit of each loop can be quantified based on VM.

This paper is structured as follows: section 2 introduces the concept of Variability Matrix. In section 3, practical issues in computing the VM are discussed. The methodology to quantify the economic benefit of each control loop and prioritize loop maintenance is shown in section 4. The complete methodology is illustrated by the application in the Wood and Berry case study (section 5) showing fruitful results. The paper ends with concluding remarks.

2. VARIABILITY MATRIX: CONCEPTS AND DEFINITION

2.1 Preliminary Definitions

To quantify the economic impact, it is interesting to classify control loops into the following two categories:

Main Loops are the loops that directly control the products specification. Their performance improvement causes reduction in product variability, which can be directly translated into profitability.

Auxiliary Loops: Loops that do not directly control product quality, but can indirectly affect the product variability.

2.2 Variability Matrix Structure

The structure of the variability matrix consists of the following:

- **Rows:** The rows show the influence of each loop on the same final product. The number of rows is the same as the products or the number of main loops.

- **Columns**: Shows the influence of a specific loop on all other loops that may impact or influence the specification of the final product. The number of columns is the same as the number of control loops implemented in the plant. The first columns correspond to the main loops and the adjacent set of columns corresponds to the auxiliary loops as shown in Figure 2.

Main Loops | Auxiliary Loops

$$\begin{array}{c|cccc|ccc|}
 & Mn_1 & Mn_2 & \cdots & Mn_m & Aux_1 & \cdots & Aux_{l-m} \\
Mn_1 & VM_{1,1} & VM_{1,2} & \cdots & VM_{1,m} & VM_{1,m+1} & \cdots & VM_{1,l} \\
Mn_2 & VM_{2,1} & VM_{2,2} & \cdots & VM_{2,m} & VM_{2,m+1} & \cdots & VM_{2,l} \\
\vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\
Mn_m & VM_{m,1} & VM_{m,2} & \cdots & VM_{m,m} & VM_{m,m+1} & \cdots & VM_{m,l}
\end{array}$$

Main

Figure 2: Schematic representation of Variability Matrix

In Figure 2 Mn_i is the main loop i and Aux_j is the auxiliary loop j. The total number of loops in the plant is l and it has m main loops. For example, column 1 (Mn_1) shows the impact of variability reduction in main controller 1 on all other main loops. The row 1 shows the impact on the variability of Mn_1 when the performance of all other loops is changed.

This section discusses the methodology for computing each element VM(i,j) of the Variability Matrix. In the first scenario, the following assumptions are taken: (I) the plant model (G) is available; (II) the controller model (C) is also available; and (III) the controlled variables (y) and control outputs (u) are available. For the sake of simplicity, we consider that the setpoint is fixed and set to zero.

Based on the previous assumptions, the procedure to quantify the VM is described below:

1. Read process data y_j ($j = 1\ldots l$) and u_j ($j = 1\ldots l$) with all loops closed (with actual performance);
2. Select main and auxiliary loops;
3. Compute the actual variance for each main loop ($\text{var}_{\text{act,i}}$, $i = 1\ldots m$);
4. For each loop j ($j = 1\ldots l$)
    a. Calculate the best performance achievable (see section 3.2) for loop j;
    b. Apply the controller;
    c. Calculate the new variance for each main loop i ($var_{best,i,,j}$, $i = 1\ldots m$)
    d. Compute the elements of VM j^{th} column using equation (1).

$$VM(i,j) = \frac{\text{var}_{act,i} - \text{var}_{best,i,j}}{\text{var}_{act,i}} \qquad (1)$$

This structure for VM elements was chosen because of two reasons: 1) it provides directly the variability impact potential for each loop; and 2) it is dimensionless, fact that allows comparing the impact of two or more loops in the plant.

Each element of the VM shows the potential improvement in the variability of each product, when a given loop has its performance improved. For example, consider the VM of:

$$\begin{bmatrix} 0.3 & 0 & -1.2 \\ -0.7 & 0.9 & -1.5 \end{bmatrix} \qquad (2)$$

Initially, we can verify that this plant has 2 main loops and one auxiliary loop. From this VM we can conclude that: 1) if the performance of main controller 1 is improved, its variance will decrease 30%; 2) it has a negative and strong impact on another loop: its variance will increase by 70%. Is this healthy for the process? Clearly the answer to this question depends on the economic impact of each main loop. In the second case, the main loop 2 has potential reduction in variability of 90%. This controller has no influence on the main loop 1 variance; 3) improving the performance in the auxiliary loop (3rd column) will increase the variability in all main loops.

In complement with the VM, the concept of the complementary VM arises (CVM). It is not necessary for all controllers to have fast performance, many loops have to play the role of accommodating or buffer disturbances. Based on this assumption, we define the Complementary Variability Matrix (*CVM*). The values are computed with actual loop variance ($var_{actual,i}$) and the variance of the loop with the worst performance acceptable ($var_{worst,i,j}$). The structure is the same as shown before, and the elements are computed as follows:

$$CVM(i,j) = \frac{\mathrm{var}_{wor,i,j} - \mathrm{var}_{act,i}}{\mathrm{var}_{act,i}} \qquad (3)$$

The same procedure as considered earlier can be used to evaluate the Complementary Variability Matrix (*CVM*). Only step 4.1 is replaced by the slowest accepted performance (see Smith, 2002) and the worst accepted performance (var_{wor}) should be quantified.

The proposed computational steps may not be easily applicable in an industrial setting, because the required information (controller and process model) is generally unavailable. The algorithm to compute VM where the controller and plant model are not available is shown in section 3.

3. PRACTICAL ISSUES IN COMPUTING VM

3.1Computing the VM

This section presents the methodology to evaluate VM in industrial setting where process and/or controller models may not be available.

The first analyzed scenario is where a Model Predictive Controller is implemented. In this case, the controller model is not available, because most of industrial MPCs are "closed box solutions". However, the plant model is available. In this case, setpoint variations in MPC controllers are quite common, because of the optimization layer. In this scenario, the controller model can be extracted (identified) using the Asymptotic Method (Zhu, 1998) or Subspace Identification (Overschee and Moor, 1996).

A second scenario contemplates the case where only low order controllers (PI and PID) are present and setpoint activity is available all loops. For this case, the following steps are contemplated:

- Identify the controller order and parameters (C) using structured target factor analysis (STFA) (Fotopoulos et al., 1994);
- Estimate the time delay (Tuch et al., 1994);
- Identify the process model (G) using Subspace Identification (Overschee and Moor, 1996);
- Identify the disturbance model (d) using Subspace Identification.
- With *G*, *C*, and *d* available, the VM can be estimated applying the methodology shown in section 2.3.

Based on our limited experience, we can affirm that the VM is not extremely dependent on both model and controller models accuracy. Even for visible mismatch, the obtained results are fairly good, comparing with the case where controller and plant model are available.

3.2 Best and worst controller performances

A natural question that arises is: how can the best and worst performance be computed for a given system? The answer clearly depends on the controller that is implemented on the process.

For MPC controllers, the best achievable performance can be computed using the methodology proposed by Trierweiler and Farina (2003). If the desired performance is attainable, this methodology provides the tuning parameters for the chosen performance. Otherwise, if it's not achievable, the best achievable performance is quantified. In this work, we assume that the "best performance" is based on the open and closed loop rise time ratio, and a convenient value for this ratio is 3.

For low order (PI and PID) decentralized controllers, the best performance can be estimated using the methodology proposed by Faccin and Trierweiler (2004). The worst performance can be evaluated based on the methodology to tune buffer tanks (Smith, 2002). Classical methodologies for PI/PID tuning (e.g. Ziegler-Nichols) can also be used as benchmark.

4. QUANTIFYING THE ECONOMIC BENEFITS BASED ON VM

The economic benefits of improving control performance each loop can be computed in two ways. The first method considers that the best performance can be achieved. In this case the VM can be used as follows. We represent the column j of the VM as VM_j. The economic benefit can be easily quantified using the relationship:

$$CLEB = D \cdot VM \tag{4}$$

where *CLEB* is the *Control Loop Economic Benefit* vector. It has the same number of elements as the number of main loops.

$$CLEB = \begin{bmatrix} D \cdot VM_1 & D \cdot VM_2 & \cdots & D \cdot VM_l \end{bmatrix}^T \tag{5}$$

Where D is the vector that translates variability reduction into \$ per unit time.

$$D = \begin{bmatrix} D_1 & D_2 & \cdots & D_m \end{bmatrix}^T \tag{6}$$

where m is the number of main loops in the plant. This vector can be quantified as a function of plant throughput increase, utilities reduction, among others factors. This value can be provided by the commercial department of the plant or the optimization layer weights used in MPC design.

However, as previously mentioned, not all controllers need to have high or tight tuning and the economic benefit, considering the worst performance of each one, can also be quantified. This vector is defined as *Complementary Control Loop Economic Benefit:*

$$CCLEB = \begin{bmatrix} D \cdot CVM_1 & D \cdot CVM_2 & \cdots & D \cdot CVM_m \end{bmatrix}^T \tag{7}$$

For example, suppose a plant where the VM and D are:

$$VM = \begin{bmatrix} 0.7 & -0.6 \\ -0.3 & 0.8 \end{bmatrix} \tag{8}$$

$$D = \begin{bmatrix} 100 & 50 \end{bmatrix}^T \tag{9}$$

the *CLEB* is then be computed as:

$$CLEB = \begin{bmatrix} 55 & -20 \end{bmatrix} \tag{10}$$

The CLEB indicates that improvement loop 1 performance means an increasing the plant profitability. However, the opposite behavior is expected when loop 2 performance is improved.

5. CASE STUDY - WOOD AND BERRY DISTILLATION COLUMN

The pilot-scale distillation column proposed by Wood and Berry (1973) will be studied in this case study. The plant model is given by:

$$\begin{bmatrix} x_D(s) \\ x_B(s) \end{bmatrix} = \begin{bmatrix} \dfrac{12.8}{16.7s+1}e^{-1s} & \dfrac{-18.9}{21s+1}e^{-3s} \\ \dfrac{6.6}{10.9s+1}e^{-7s} & \dfrac{-19.4}{14.4s+1}e^{-3s} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{11}$$

where xD and xB are the overhead and bottom products composition, and R and S are the reflux and steam flow rates, respectively. The time constants and time delays are expressed in minutes.

Two decentralized PI type controllers were applied in this case study. The disturbance was generated by passing a random signal through a first order transfer function with unitary gain and 50 minute time constant. The VM analysis of this case study is next presented under 3 scenarios: 1) controller and plant models are assumed to be available; 2) only plant model is available; 3) neither the plant model nor controller models are available. However active setpoint activity is assumed. This serves as good excitation for closed loop identification.

The PI controllers were tuned to have a performance where the closed loop rise time is twice faster than the open loop case. We consider here the best achievable performance when the rise time is 6 times faster than open loop.

The D vector for this case is hypothetically set as:

$$D = \begin{bmatrix} 100 & 30 \end{bmatrix} \qquad (12)$$

In the first scenario, the controller and plant model were available. The VM was computed using the methodology shown in section 2.3.

$$VM = \begin{bmatrix} 0.57 & -0.17 \\ -0.18 & 0.41 \end{bmatrix} \qquad (13)$$

The CLEB for this case is:

$$CLEB = \begin{bmatrix} 52 & -5 \end{bmatrix} \qquad (14)$$

Based on CLEB, loop 1 should have its performance improved (top composition), increasing the plant profitability. Loop 2 shows the opposite behavior, improvement in its performance is likely to result in decreased plant profitability.

In the second scenario, the controller model is assumed to be unavailable. Initially, using a scenario where two setpoint variations in each variable are available, the controller model was identified (see section 3.1). In this scenario, the VM was estimated to be:

$$VM = \begin{bmatrix} 0.60 & -0.19 \\ -0.19 & 0.46 \end{bmatrix} \qquad (15)$$

Notice that the estimated VM closely matches the true VM shown in (17). In the third scenario, both controller and plant model were identified using closed loop data. The estimated VM for this scenario is:

$$VM = \begin{bmatrix} 0.60 & -0.19 \\ -0.18 & 0.46 \end{bmatrix} \qquad (16)$$

Even for this case, where controller and plant model were first identified using subspace identification, a good estimative of VM was obtained.

6. CONCLUDING REMARKS

The main conclusions of the proposed work can be summarized as:

- industrial plants have many loops with considerable potential for performance improvement and therefore methodology to prioritize loop maintenance is required;
- the concept of Variability Matrix was introduced in this work and has been shown to highlight the potential improvement in each loop and its impact on the whole plant;
- the methodologies to compute VM where neither the controller nor plant model are available has also been presented; in this

scenario Subspace Identification can be used; even for this case the methodology has been shown to yield very good results for closed loop identification;

- the proposed methodology was applied to two case studies providing good results;

- the proposed scenarios where the VM can be computed allows the application in an its industrial setting.

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