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Variability Reduction Estimation for SISO Systems through Unmeasured Disturbance Estimation

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Abstract: The variability within a process can be seen as a limiting factor for its efficiency. Because this, the present paper provides a simple, fast and non-intrusive methodology, able to translate the part in total variability that can be changed through controller adjustment. These types of analyses are usually intrusive; however, this work presents an alternative to obtaining such information from non-intrusive manner, thus eliminating a need for system perturbation. It is proposed to estimate the variability reduction through a sequential method that uses unmeasured disturbance estimation and a representative model of the actual process. The method's quality was tested by analyzing the sensitivity of methodology against several initial conditions, since the procedure requires an optimization step. The case studies that involved pure time delay have showed high sensitivity to the initial condition, but even in this case the potential for variability reduction was correctly estimated.

Keywords: Performance Monitoring, Variability, Loop Maintenance, Unmeasured Disturbance, Variance.

1. INTRODUCTION

In the industrial scenario about 80% of controllers' performance have performed lesser their potential (Bialkowski, 1992). This behaviour can be attributed to several factors, in particular, four these main factors are:

a) Changes in raw material;

b) Faulty instrumentation (e.g. valve stiction and sensors degradation);

c) Presence of unmeasured disturbance throughout the process;

d) Poor controller tuning.

In many cases, the poorly performing control system can increases the process variability (Yan et al., 2015), reducing its efficiency. In practice it can be see that by improving the controller tuning it is possible to obtain a reduction in variability (Brand, 2009), increasing the confidence of the control system. This improvement allows operate close to the limits and specifications imposed to the process as illustrated in Fig. 1.

Given the relationship between variability, performance and efficiency, this paper proposes a methodology to estimate the variability reduction potential (VRE) in process output variable. The quantification of VRE will be made by the ratio of the future variance of output signal estimated ($\hat{\sigma}_2^2$), measured with a different controller's tuning, and the actual variance this in signal (σ_1^2), measured with the actual controller's tuning, minus one. That is:

$$VRE = \frac{\sigma_2^2}{\sigma_1^2} - 1 \tag{1}$$

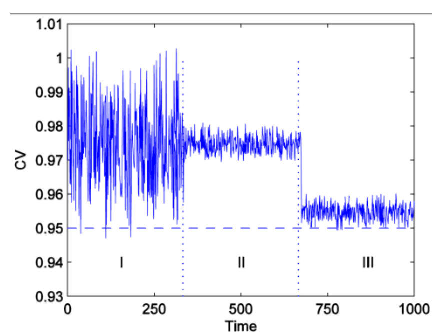

Fig. 1. Variability of a process before and after improving the controller tuning (Farenzena, 2008).

Negative values of VRE indicate that the control loop has potential to reduce variability. This potential is higher how much closer to 1 is its value.

Farenzena and Trierweiler (2007) introduced the concept of Variability Matrix (VM), that shows how the variance is transferred between the loops and the impact of a specific loop on the variance of each loops. Brand (2009) proposed the Model for Inference Variability (MIV) as a tool for determining the variability change, this method is based on two steps. The first step uses the Inference Model for Performance and Robustness (IM) proposed in Farenzena and Trierweiler (2006), to generate deterministic indexes (characteristic of closed loop) non-intrusively using as a benchmark the performance in open loop. The IM inputs are

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parameters easily quantified in real time, as Harris index, Integral Square Error (ISE), Integral Absolute Error (IAE), white noise influence index ($nosi$), time delay influence index ($deli$), controller performance influence index ($tuni$), etc. and process' parameters as time constant (τ) and time delay (θ). Through IM is possible to find parameters such as the ratio between ratio between open and closed loop rise time (Rt_R), ratio between the open and closed loop settling time (St_R), maximal sensitivity (MS), phase margin (PM), gain margin (GM), etc. These indices provide information about performance and robustness of control system. Once obtained, these indeces, are used as input for MIV which is defined as a nonlinear function that provides a predicting of the change variability from the change in controller performance expressed from indexes obtained by IM and model process characteristics, such as time delay and time constant**.**

The methodology used to determine VRE presented in this work was based on idea that is possible determining an initial model to represent the process model from controller parameters using restriction relations, obtained through tuning method IMC (Internal Model Control) proposed by (Garcia and Morari, 1982) for PI/PID controllers. Using this initial model it is possible to estimate the unmeasured disturbance (UD) which is occurring in process. With the estimated UD the potential reduction of variability can be easily estimated by closed loop simulation.

The proposed procedure for the determination of VRE is presented in section 2. In section 3 some case studies will be exposed, along with the main results. Finally, a brief conclusion about the work is disposed in section 4.

2. METHODOLOGY FOR DETERMINATION OF VRE

Aiming to determine VRE without any intrusive action on the system, it was used as a basis for formulation the methodology a scenario where only the following information is known:

i. The controller tuning (i.e., Kp, Ti and Td) and PID parametrization (i.e., series or parallel);

ii. Normal operating process data (the process output and control action);

iii. The UD is a output additive signal;

iv. Dynamic characteristic of the real process model (model order and whether exist or not pure time delay).

The control loop used on methodology developed this work is shows in Fig. 2, where $Gp(s)$ is the real model of process plant. $C(s)$ is the controller model, the real unmeasured disturbance is represented for d. $Gn(s)$ is an arbitrary model, that works like a filter with similar form of $Gp(s)$. The controller action is represented by u, the process output signal by y and the output signal of $Gp(s)$ by w. It is assumed that the setpoint y_{set}, is not changed along of analysing data. Of course, if there is change in set-point the procedure to estimate the UD is much simpler. We are assuming the worst situation, where there is normal operating plant data only.

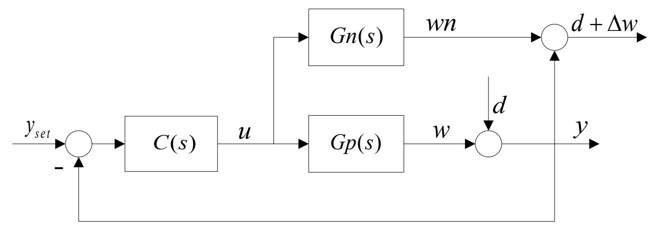

Fig. 2. Diagram representation of overall process.

As shown in Fig. 2, y can be represented as the sum of the signals (time series) d and w:

$$y = d + w \tag{2}$$

With the signal u and $Gn(s)$ it is possible to calculate wn (output signal of filter $Gn(s)$). Based on Fig. 2, the following relation can be written:

$$y - wn = d + (w - wn) \tag{3}$$

$$y - wn = \underbrace{d + \Delta w}_{dud} \tag{4}$$

To simplify, the right hand side of (4) is represented by dud. Note that the term Δw is the mismatch between the signals w and wn, this way the smaller the mismatch between they. This way bigger is the correlation between the signals dud and d how much closer is $Gn(s)$ than $Gp(s)$.

The attainment of $Gn(s)$ is done through the parameters of the PI/PID controller (Kp, Ti and Td) by IMC tuning method (the complete table that determines the adjustment controller can be found in Seborg (2004)), which is a very effective tuning method and provides the control system a good compromise between performance and robustness. This adjustment method establishes a direct relation between the controller tuning parameters and plant model parameters, and can be represented by the function below:

$$[Kp, Ti, Td] = f(x) \tag{5}$$

Where x represents the parameters which make up the plant model (as gain (K), poles ($-1/\tau_1$ and $-1/\tau_2$), zeros ($-1/\tau_3$) and time delay (θ)) plus the constant τ_{cl} (this constant is the desired speed for the response in closed loop and it is defined by operator). Therefore, the number of parameters is dependent of the model process.

The idea behind the determination of $Gn(s)$ is analogous to follow the other way of (5), i.e., from the controller tuning parameters to determine the parameters of model plant i.e.:

$$x = [K, \tau_1, \tau_2, \tau_3, \theta, \tau_{cl}] = g(Kp, Ti, Td) \tag{6}$$

For example, given a first order plant model, represented by $G_A(s)$:

$$G_A(s) = \frac{K}{\tau s + 1} \tag{7}$$