UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ENGENHARIA
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PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA QUÍMICA

Novel Methodologies for Assessment and Diagnostics in Control Loop Management

DOCTORAL THESIS

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Novel methodologies for assessment and diagnostics in Control Loop Management

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Abstract

Many works available in the literature support the importance of control loop performance assessment (CLPA) tools. Industrially, there is an increasing interest in this area and the reason is trivial: ensuring the exact performance for each loop means allowing it to operate in a high profitable operating point. However, the available methodologies in commercial tools and literature do not provide clear and conclusive metrics of the actual loop performance. Consequently, the diagnostics is not easy, making the analysis sometimes difficult and confusing. The aim of this thesis is to reduce the gap between assessment and diagnostics by proposing a set of metrics to help the engineer in control loop performance management. The thesis is divided into two sections: Assessment and Diagnostic.

The first contribution of this work is the proposition of a new methodology to decompose the impact of control loop performance, time delay, and white noise in the total control loop variance, helping the engineer to diagnose the loop performance problem and take the right action to achieve the desired product variability (by changing tuning parameters, changing controller type, replacing instrument, or changing the process, among others). The proposed method does not require any invasive tests, only control loop routine operating data and process time delay, allowing the industrial application of the proposed indices in real time. The methodology was applied in three case studies, providing very good results.

The second contribution is propose a methodology to estimate conclusive indices (also called deterministic indices) to evaluate loop performance and robustness (maximal sensitivity, ratio between open and closed loop rise time, settling time, among others), based on stochastic indices (i.e. indices that can be computed using only normal operating data) and process parameters (time delay and time constant). A performance and robustness inferential model (PRIM) for loop assessment will be shown. The PRIM provides a clear picture of loop performance and robustness, making the analysis easier and the diagnostics straightforward. Moreover, this section highlights the limitation and drawbacks of stochastic metrics for CLPA.

The last contribution of the Assessment section proposes a method to prioritize loop maintenance, based on the economic impact of each loop. Assuming that a typical process plant has hundreds or thousands of loops and most of them have significant impact over loop variability, prioritizing loop maintenance is essential. The economic impact is based on the concept of Variability Matrix (VM), which is an array that shows the impact of performance improvement of a given loop on the whole plant.

The second section of this work is the Diagnostics of some controller problems. The first methodology aims to quantify the stickband in a sticky valve, using only normal operating data of controller output and process variable. An analogous inference model, called Stiction Inference Model (SIM), is proposed to estimate the stickband.

In the final contribution, it is proposed a simple method to evaluate the Model Plant Mismatch (MPM) based on Independent Component Analysis (ICA). This analysis is very useful to point out the poor channels models in Model Predictive Controllers.

The work ends with concluding remarks and further work.

KEYWORDS: Asset management; Control loop assessment; Economical evaluation; Economic Assessment; Valve stiction.

RESUMO

Na literatura há vários trabalhos elucidando a importância de ferramentas para auditar malhas de controle. Na indústria, o interesse por esse tipo de software é crescente, devido ao benefício trazido: garantir o exato desempenho para cada controlador significa atingir pontos de operação mais lucrativos. Todavia, as metodologias disponíveis na literatura e nas ferramentas comerciais não provêm medidas conclusivas das características da malha. Conseqüentemente, a análise muitas vezes é confusa e difícil, acarretando um diagnóstico difícil. Reduzir a distância entre a auditoria e o diagnóstico, propondo novas métricas para ajudar o engenheiro no gerenciamento de malhas é o foco central deste trabalho.

A presente tese é segmentada em duas partes: auditoria e diagnóstico, dentro das quais se inserem as principais contribuições deste trabalho.

A primeira contribuição deste trabalho é a proposição de uma metodologia para decompor o impacto da velocidade do controlador, tempo morto e ruído branco sobre a variância total da malha, auxiliando o engenheiro de processos a tomar uma ação: trocar os parâmetros de ajuste, aumentar a ordem do controlador, substituir o medidor, reduzir o tempo morto, entre outros. O método proposto requer apenas dados de operação normal e o tempo morto da malha, não sendo necessários testes intrusivos, sendo possível a aplicação industrial. O conjunto de métricas propostas foi aplicado em três casos de estudo, fornecendo resultados promissores.

Dentro do campo de auditoria, se insere a segunda contribuição: a proposição de uma metodologia para estimação de parâmetros conclusivos (ou determinísticos) para avaliação da performance e robustez de controladores (Máxima Sensibilidade, razão entre o tempo de subida de malha aberta e fechada, razão entre o tempo de assentamento de malha aberta e fechada, entre outros), baseado em índices estocásticos (i.e. métricas que podem ser computadas em tempo real, sem testes intrusivos) e parâmetros da malha (tempo morto, constante de tempo). O modelo de inferência para desempenho e robustez, chamado PRIM, é proposto. Este modelo fornece uma clara indicação do real desempenho e robustez da malha, facilitando a análise e tornando o diagnóstico direto. Além disso, visando elucidar a vantagem dos

índices determinísticos sobre os estocásticos, ambos serão aplicados a um conjunto de casos de estudo.

A última contribuição no campo de auditoria está na estimação do potencial impacto econômico de cada malha, como ferramenta para hierarquizar sua manutenção. Considerando que uma típica planta química possui centenas ou milhares de malhas e que a maioria delas possui significativo potencial de melhora, a priorização da manutenção é essencial. O impacto econômico é baseado no conceito de Matriz de Variabilidade (VM), que é uma matriz que mostra o impacto da melhora da performance de um controlador sobre a variabilidade de toda a planta.

A segunda parte deste trabalho aborda o diagnóstico de algumas avarias comuns em controladores. A primeira metodologia visa quantificar a banda de agarramento em válvulas de controle, que apresentam este fenômeno, através de um modelo de inferência chamado SIM. A metodologia proposta requer apenas dados de operação normal do controlador e planta.

A contribuição final deste trabalho é um método simples para avaliação do modelo em controladores preditivos MPCs, baseado na Análise de Componentes Independentes (ICA). Esta análise é bastante útil para indicar os canais que possuem modelo pobre em relação à planta.

O trabalho finaliza com as conclusões finais e os trabalhos futuros relativos a esta tese.

Palavras-Chave: Gerenciamento de Ativos; Auditoria de controladores; Avaliação econômica; Avaliação da válvula de controle.

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Abbreviations

APC, advanced process control;

AR, autoregressive model;

ARMA, autoregressive moving average model;

CCLEB, complementary control loop economic benefit;

CLEB, control loop economic benefit;

CLP, control loop performance;

CLPA, control loop performance analysis;

CLPR, control loop performance and robustness;

CVM, Complementary Variability Matrix;

DB, deadband;

DCS, digital control system;

DELI, time delay influence;

EPI, Economic Performance Indicator;

FCOR, filtering and correlation algorithm;

GA, genetic algorithm;

GM, gain margin;

GMV, Generalized Minimum Variance;

IAE, integral of absolute error;

IAE_{OPT}, optimal integral of absolute error;

ICA, independent components analysis;

IM, inference model;

ISE, integral of square error;

LQG, Linear Quadratic Gaussian;

MIMO, multi-input, multi-output;

MP, moving phase;

MPC, model predictive control;

MPM, model-plant mismatch;

MS, maximal sensitivity;

MV, minimum variance benchmark;

MV, manipulated variable;

MVC, minimum variance controller;

MVI, minimum variance index;

NN, neural network;

NOSI, white noise influence;

OP, controller output;

O_S, overshoot;

PI, proportional integral controller;

PID, proportional, integral, derivative controller;

PM, phase margin;

POPC, potential operating point change;

PRIM, performance and robustness inference model;

PV, process variable;

Rt, rise time;

Rt_R, ratio between open loop and closed loop rise time;

RVI, relative variance index;

R_{xx}, autocorrelation function;

SB, stickband;

SIM, stiction inference model;

SISO, single-input, single-output;

SJ, slip jump;

SP, process variable setpoint;

St, settling time;

St_R, ratio between open loop and closed loop settling time;

TUNI, controller performance influence;

$TUNI_{PID}$, controller performance influence when a PID controller is applied;

VM, Variability Matrix;

$\sqrt{VM}$, root square of the variability matrix;

Variables List

a_t, random input in AR model;

Aux_j, auxiliary loop j;

C, controller model;

d, time delay;

D, monetary gain per unit time for a unit change in operating point

e_t, feedback invariant portion of the signal;

$E[]$, expectation;

E_T, integral of square error of error between PV and the best triangular curve interpolation;

E_W, integral of square error of error between PV and the best wave-shape curve interpolation;

f_i, AR model parameters;

f_t , signal portion unreachable to feedback controller due to the time delay;

G, plant model;

$\hat{G}$, plant model approximation (used by controller);

G_d, disturbance model;

g_t, signal portion that can be removed by feedback controller;

$g_{PID,t}$, signal portion that can be removed by a PID type controller;

$h_{j,i}$, parameter that gives the influence of independent output i into output j;

$\hat{h}_{j,i}$, parameter that gives the influence of independent output i into predicted output j;

K_D, derivative constant of the PID controller;

K_I, integral constant of the PID controller;

K_P, proportional constant of the PID controller;

L, loss function;

m, AR model order;

Mn_i, main loop i;

N, disturbance model;

n, size of the dataset (generally size of y_t);

$POPC_{i,j}$, potential operating point change for the main variable i when controller j has its performance improved;

r, reference (setpoint);

$r_{ya}(k)$, covariance of y_t dataset shifted k samples;

s, independent component;

u_t, process input;

$\mathrm{var}_{\mathrm{act,i}}$, actual variance for each main loop i;

$var_{best,i,,j}$, new variance for each main loop i when controller j has its performance improved;

$var_{wor,i,j}$, variance for each main loop i when controller j has the worst acceptable performance;

x, measured variable (mixture of independent components);

w_t, white noise component of output signal (y_t);

y, process output;

$\hat{y}$, predicted process output;

y_t, process output dataset;

$y_{t,d}$, deterministic portion of the signal;

$y_{t,d}$, indeterministic portion of the signal;

y_∞, steady steate value of y_t;

z, actual product quality;

z^0, nominal value (product specification);

ZC, Number of zero-crossings in the zero-mean data;

ZC_{ACV}, number of zero-crossings in the autocovariance function;

$\eta(d)$, complementary Harris Index;

η^{level}, performance index for level loops;

$\kappa(d)$, Harris Index;

${\sigma_{MV}}^2$, process minimum variance;

σ_{OL}^2, process open loop variance;

σ_{OT}^2, optimal variance for buffer tank level loops;

${\sigma_y}^2$, process output variance;

$\mu_{present}$, present process mean;

$\mu_{optimal}$, optimal process mean;

τ, process time constant;

τ_I, controller integrating constant;

Δ_{PV}, Difference between the maximum and minimum value in PV;

Chapter 1

Introduction

In this chapter the scope of this thesis will be defined, and the structure and motivation for this work will be presented. Subsequently, a brief description of each chapter is shown. The list of publications that arise from this thesis is found in the end of this chapter.

1.1– Why assess control loop performance

Maintenance is the keyword to achieve a highly efficient operating point. Evaluate in real time each asset is essential to ensure the plant profitability. Watching the controllers in a typical process plant, we will see that 80% performs poorly (Bialkowski 1992). Many surveys show similar scenarios, confirming these numbers. Paulonis and Cox (2003) gives a good example of the industry situation. In a set of 8500 control loops:

- 20% have the adequate performance;
- 30% are oscillatory because of instrumentation problems, increasing process variability;
- 30% have poor performance, increasing process variability;
- 15% have wrong project (wrong pairing);
- 5% only changing the process can reduce its variability.

Because of the large number of controllers in a typical process plant, assess the performance of all controllers manually in real time is not possible. This fact explains the increasing interest in the academia in automatic methodologies to assess controllers, as well as the widespread of these tools in the industry. Good reviews in control loop performance assessment are given in Huang and Shah (1999), Jelali (2006), and Qin (1998).

1.2 – The meaning of performance assessment

Assess control loop performance initially (90’s) meant compare one actual loop indicator with its ”golden period”, i.e. a period where the loop has good performance or the best possible controller (Jelali 2006). The most used benchmark is the minimum variance controller (MVC) proposed by Åström (1970). This metric compare the actual loop variance with MVC, and it is called Harris index (Harris 1989). This index only aimed to evaluate the performance of SISO controllers and it only requires time delay and normal operating data. This work (Desborough and Harris 1992) started the issue of “on-line control loop performance assessment” in the academia and industry.

Today, control loop performance assessment has a wider meaning:

- evaluate loop performance;
- evaluate loop economic benefit;
- diagnose plant-wide (single and multiple) oscillations;
- diagnose the root cause of plant-wide oscillations;
- evaluate valve behavior.

Subsequently, many researchers proposed new methods to evaluate MVC (Jelali 2006), as well as methodologies to apply this concept in specific controllers. Many researches extended this concept to multivariable controllers (Harris et al. 1996; Huang et al. 1997). Nevertheless, MVC benchmark has scale problems, which makes the analysis difficult and the diagnostics is not straightforward, as shown in this work. Besides, no information about robustness is provided, only performance is analyzed.

As important as assess loop performance is to diagnose poor valve behavior. Extensive work can be found in this area. Gerry and Ruel (2001) propose an intrusive technique to diagnose and compute the stiction. Choudhury et al. (2004) use high-order statistics to assess the valve health. Horch (1999) propose a simple method based on PV and OP correlation. Singhal and Salsbury (2005) propose a measurement based on the area before and after the peak of PV data. Rossi and Scali (2005) extended the Horch’s method where the stiction is detected based on the interpolation of triangular, sinusoidal, and wave-shape curves. Yamashita (2006) proposed a method based on valve movements patterns. The main drawback of the methodologies to quantify stiction is that intrusive tests are required or the position of the stem must be available. Using only normal operating data and considering that only OP and PV are available, there is no methodology to compute the stiction.

Another important issue in control loop performance assessment (CLPA) is to diagnose plant wide oscillations. Many authors proposed methodologies to identify plant wide oscillations (e.g., Thornhill et al. 2003a; Thornhill and Hagglund 1997; Thornhill et al. 2003b; Hagglund 1995, among others).

Besides pointing out plant wide oscillations, diagnosing the root cause of them is also important. Recently, Thornhill and Horch (2007) wrote a survey about this subject. All methodologies listed in this work require only normal operating data, no other information is required. Xia and Howell (2005) proposed a method based on independent component analysis (ICA) which requires also time delays. Xia et al. (2005) proposed another methodology based on spectral ICA, where no information about loop delay is required. Jiang et al. (2007) suggested using the spectral envelope to achieve the diagnostics. Thornhill (2005) proposed a method based on loop nonlinearity to diagnose the root cause of the oscillation.

Considering that in a typical plant hundreds or thousands of loops are found, a methodology to prioritize loop maintenance based on the economic impact of each loop is required. Mascio and Barton (2001) proposed a methodology to quantify the control quality in economic terms based on the Taguchi Framework. Muske (2003) proposed the idea of potential reduction in control loop variability. The economic benefit is quantified based on the shift in the mean operation toward a product specification or process constraint. Craig and Henning (2000) proposed to use a fixed variability reduction, based on a rule of thumb, to evaluate control loop economic benefit. 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. Considering that modern plants have strong interaction, this assumption can lead to wrong diagnostics.

Thus, many drawbacks and limitations still remains, which sometimes make the analysis difficult, confusing and the diagnostic is not straightforward.

1.3– Our proposal: control loop management

The current tools to assess loop performance are far away from the desired tool by industry. Today, there is an extensive effort to design an effective tool not only to assess loop performance, but also to manage them achieving a more efficient and profitable process operation.

The attribution of the Control Loop Management Tool can be compared with the work of a physician, which evaluates the “health of the loop”. Figure 1.1 illustrates this analogy.

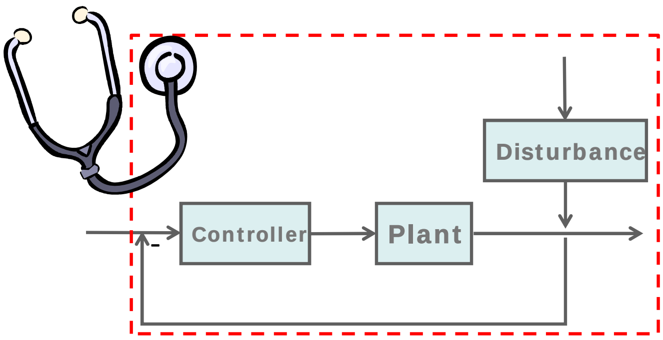

Figure 1.1: Illustration of the analogy between a physician and the Closed Loop Performance Assessment (CLPA) tools

Similarly to diagnosing the patient's health, the procedures to evaluate the "controller's health" has the following three steps:

1. **Assessment:** measure conclusive metrics to evaluate some loop characteristics.
2. **Diagnostics:** based on the metrics computed in the assessment procedure, the "loop disease" is diagnosed.
3. **Treatment:** the procedure to "heal the loop disease" is prescribed.

The assessment step has been divided in this thesis as follows:

- Performance;
- Robustness;
- Economic Impact;
- Instrumentation;
- Plant-wide oscillations.

In the second step, the illness of the control loop is diagnosed. Some of the problems that can be diagnosed are:

- Poor / high / adequate loop performance;
- Poor / fast / adequate loop robustness;
- Poor / fast / adequate MPC performance:
    - Tuning

  - Model
  - Disturbance
  - Regulatory control.
- Plant-wide oscillations:
  - Cause (tuning or stiction);
  - Root cause (i.e. which loop is the source of disturbance).
- Sticky valve;
- Data useless to analysis because of compression or quantization.

Moreover, assuming that a high number of loops has an expressive potential of improvement, the control loop monitoring (CLM) tool should provide a ranking of the loops that should be fixed. The list should be based on the economical potential of each loop. Thus, a methodology to compute the economic benefit of each loop is extremely required.

These assessment indices should provide a clear idea about the actual loop health. Moreover, they should help to diagnose the source of the illness, when it is detected. Today, this link between assessment and diagnostic is open, because the loop exams do not provide conclusive metrics.

Furthermore, the treatment is prescribed. Here, the tool should have a knowledge base, where each procedure to heal the controller is described. Moreover, only senior engineers can update this base. Some tools should be integrated to the loop management tool, e.g.:

- SISO control loop tuning;
- MPC tuning;
- Workflow integration;
- Valve problems compensation (e.g. stiction, see Rossi and Scali 2005);
- Control structure design (feedback and feedforward).

This thesis focus on the first and second steps (assessment and diagnose). The aim is to propose metrics to evaluate the loop, helping the engineer achieve an easy and effective diagnostics. This is the reason why the thesis will be divided into two parts: Assessment and Diagnosis.

Moreover, this work highlights some drawbacks of the classical (or stochastic) indices (minimum variance index, integral of square error, among others).

We believe that our contributions will help engineers to achieve a better and more effective analysis and diagnostics.

1.4– Thesis outline

Chapter 2 describes the main indices to evaluate control loop performance showing their advantages and drawbacks. They are divided into two groups

- stochastic: indices that can be quantified using only normal operating data and minimal knowledge of the process. They provide metrics that are not conclusive and the diagnostic based on them is sometimes difficult.

- deterministic: indices that provide a conclusive metrics about the process performance and robustness (e.g. maximal sensitivity, rise time ratio between open and closed loop, among others). However, they need intrusive tests to be quantified.

Part 1 - Assessment

Chapter 3 – Performance and Robustness assessment I

In this chapter, a new set of indices that helps the engineer decompose the impact of white noise, time delay, and control loop performance in the final variability is introduced. Three new indices were presented, nosi, deli, and tuni, which gives respectively the white noise, time delay and tuning impacts over the total loop variability. Moreover, we propose a new method to compute the achievable minimum variance considering a low order controller, in this case PID. A new index, called $tuni_{PID}$, is proposed and it gives the ratio between the percentage of the variance that can theoretically be removed by a low order controller and the total loop variance.

Chapter 4 – Performance and Robustness assessment II

The Performance and Robustness Inference Model (PRIM), which provides conclusive (or deterministic indices) to evaluate control loop performance and robustness will be introduced and defined. The PRIM inputs are plant parameters (time delay and time constant) and some loops metrics that only need normal operating data to be computed (e.g. correlation slope, autocovariance zero crossings). The procedure to build PRIM is also described in this chapter: variables selection procedure and neural network training and test. Moreover, this Chapter shows the main drawbacks of minimum variance index and other stochastic indices widely used to assess loop performance. PRIM allows computing conclusive indices to assess loop performance and robustness, making this analysis straightforward. The PRIM is applied in a set of case studies where minimum variance index (MVI) and other stochastic indices do not provide conclusive information.

Chapter 5 – Economic assessment

A new methodology to evaluate the control loop economic benefits as a tool to prioritize loop maintenance is proposed. The concept of Variability Matrix (VM) is introduced. VM is an array that shows the impact of performance improvement of a given loop on the whole plant. Based on the VM, a methodology to translate this array into a potential loop economic benefit metric is also shown. In this chapter, the methodology to evaluate VM in the ideal scenario where plant model and controller are available will be presented as well as when they are not, thus allowing the application of these ideas in industry. The efficacy of proposed methodology is illustrated by successful application to two case studies.

Part 2 - Diagnostics

Chapter 6 – Stiction diagnosis

The concept of Inference Model, described in Chapter 4, will be extended to compute valve stiction, using only normal operating data. This chapter describes the procedure to construct the Stiction Inference Model (SIM): candidate inputs, variable selection, inputs selection, neural network training. The SIM is applied in simulated and industrial case studies, providing effective results.

Chapter 7 – MPC model-plant mismatch evaluation

A methodology to evaluate the Model-Plant Mismatch (MPM), based on Independent Component Analysis (ICA) is proposed. The main application for this work is to evaluate the quality of the model used by Model Predictive Controllers (MPC). The methodology can deal with two scenarios: the first where setpoint variations are available and other when no external excitation is shown. Besides, a discussion about what industry understands about MPC performance assessment and what are the restrictions and frontiers for this field are also presented. The proposed work is applied in the Wood and Berry and Shell control problem benchmark showing fruitful results.

Chapter 8 summarizes the main conclusions of the thesis and indicates some directions for future works.

1.5– List of publications that compose this thesis

Chapter 3

1. FARENZENA, M. & TRIERWEILER, J. O. (2008) Decomposing the Impact of Control Loop Performance, Time Delay, and White Noise in the Final Product Variability. *Submitted to Journal of Process Control.*

Chapter 4

1. FARENZENA, M. & TRIERWEILER, J. O. (2008) A Novel Approach for Control Loop Performance and Robustness Assessment. *Submitted to Control Engineering Practice.*

Chapter 5

1. FARENZENA, M., SHAH, S. L. & TRIERWEILER, J. O. (2008). Variability Matrix: A Novel Tool to Prioritize Loop Maintenance. *Submitted to Journal of Process Control.*

Chapter 6

1. FARENZENA, M. & TRIERWEILER, J. O. (2008) A Novel Technique to Estimate the Stickband in a Sticky Valve. To be s*ubmitted to Control Engineering Practice.*

Chapter 7

1. FARENZENA, M., TRIERWEILER, J. O. (2008). Model Plant Mismatch Evaluation Using Independent Component Analysis. *To be presented in Advanced Control in Chemical Processes Conference (ADCONIP)*. Jasper, Canada.

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Chapter 2

Performance assessment

This chapter gives an overview of the available methodologies to assess control loop performance and robustness (CLPR). Initially this issue will be defined and the available metrics will be divided in two groups and the main indices of each group will be described.

2.1– Definitions

Assess control loop performance means evaluating one specific property of the controller that reflects its performance, which in most cases is a statistic property, with a benchmark that provides a clear metric of this property (Jelali 2006). One synonym of assessment in the literature is *monitoring*.

All loops of the plant should be assessed (or monitored) to maintain the plant in a highly efficient operating point. Malfunction in control loops are very frequent and it is a common knowledge that it has a strong impact in plant profits. In the introduction of this thesis, some numbers are provided to corroborate this statement. Even a controller which is performing well today can have its performance deteriorated. Several studies show that the half-life of a good performance is about 6 months (Paulonis and Cox 2003). Several factors can deteriorate controller performance (Jelali 2006), e.g.:

- modification in operating points;
- changes in the raw materials;
- plant modifications;
- disturbance pattern changes.

Several control loops have roughly been tuned or even are still using the default tuning parameters, which is responsible for bad performance. Engineers and operators “accept” the actual performance because of some factors (see Paulonis and Cox 2003):

- few people responsible for controllers maintenance;
- controllers tuned conservatively to ensure plant stability in non-linear plants, when operating conditions change;
- controllers are tuned only to work properly; its performance usually is not optimized;
- operators and engineers often do not have proper knowledge to understand that the performance of each controller deteriorates and each one has potential to be optimized.

Finally, some controllers will never have a good performance because of (see Trierweiler 1997):

- inappropriate control structure;
    - wrong pairing;
    - wrong variable selection;
    - linear controllers applied in highly non-linear plants;
    - decentralized controllers applied in a highly coupled plants;
    - scenarios where the disturbance has strong impact in the loop performance without feedforward compensation;
- poor actuator design.

The first set of indices to assess control loop performance use only normal operating data and requires only small knowledge of the process (Harris 1989). This set is called stochastic indices and the main one is called *Harris Index*. It compares the actual loop variance with the minimum variance controller proposed by Åström (1970). Minimum Variance Indices (MVI) and other stochastic indices are described in section 2.2, and its potentialities and drawbacks highlighted in chapter 4.

Stochastic indices allow the assessment of all controllers in the whole plant because of their simple requirements. Many works show procedures to CLPA in process plants (Hagglund 2005; Paulonis and Cox 2003; Thornhill et al. 1999). The procedure often used in the industry to assess control loop performance can be summarized as proposed by Thornhill et al. (1999), illustrated in Figure 2.1:

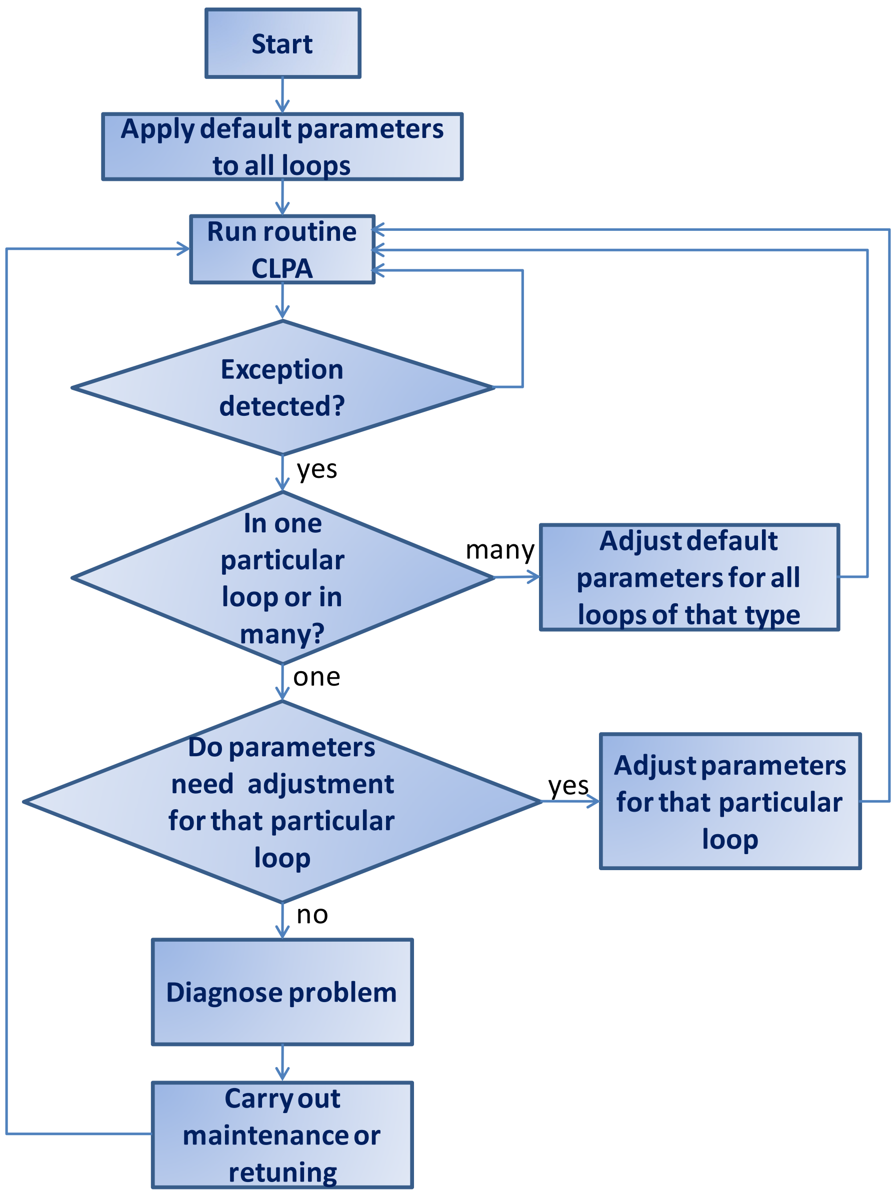

Figure 2.1: Procedure to assess control loop performance

In the procedure shown in Figure 2.1, when the CLPA procedure starts, all loops of the same type receive the same parameters. Only the loops where the performance is bad will have their parameters checked, to verify if they are not the source of the problem. If not, the loop problem should be diagnosed (tuning, valve, among others). The problem is then fixed and the procedure starts again.

Besides the stochastic indices, there are the deterministic indices. They provide a clear picture of the process performance and robustness. In section 2.3, these indices will be described, as well as their advantages and limitations.

2.2– Stochastic Indices

2.2.1 – Minimum Variance Index

The pioneer work that has opened a vast field called *performance assessment* has been proposed by Harris (1989). As it has been stated earlier, the Harris Index compares the actual loop variance with the minimum variance controller proposed by Åström (1970). In Harris (1989), the author has shown the first methodology to compute the minimum variance, based on time delay and routine operating data.

The index proposed by Harris (1989) allowed the on-line evaluation of the control loop performance of all controllers in a given plant because of its simplicity and minimal requirements. Both on literature and academia, the most applied and discussed index is the *Harris Index*. This is the main index of a set called stochastic indices (Bezergianni and Georgakis 2000). They allow evaluating on-line the control loop performance, using minimal knowledge of the process. But, is it the best metric to evaluate CLP? In the following, this question will be discussed, highlighting its drawbacks and potentialities.

The *Harris Index* is widely used and it was the basis of many tools to assess the control loop performance. In the academia, *control loop performance assessment* becomes an issue with large interest. Many good reviews (Harris et al. 1999; Huang and Shah 1999; Jelali 2006; Kozub 1997; Qin 1998) highlight the developments in the last 20 years in this field.

The Harris index $\eta(d)$ is defined as the ratio between the minimum variance (${\sigma_{MV}}^2$) and the actual controlled variable variance (${\sigma_y}^2$).

$$\eta(d) = 1 - \frac{{\sigma_{MV}}^2}{{\sigma_y}^2} \tag{2.1}$$

The index is always between 0 and 1. The best possible controller, i.e. the controller that performs equal to minimum variance has grade equal to 0. Increasing values of $\eta(d)$ means deterioration of controller performance.

The complementary value $\kappa(d)$ is also used to evaluate CLP.

$$MVI = \kappa(d) = \frac{{\sigma_{MV}}^2}{{\sigma_y}^2} \tag{2.2}$$

This last equation is more widespread in the literature (Huang and Shah 1999; Huang et al. 1997; Kozub 1997), because it gives a more intuitive metric, i.e. increasing values mean increasing performance. In this thesis, we apply the Eq. 2.2 definition and it will be often mentioned as MVI (minimum variance index).

To compute the actual process variance $\sigma_y^{\,2}$ and to estimate the minimum variance $\sigma_{MV}^{\,2}$ only routine operating data is required.

2.2.2 – Minimum variance controller (MVC)

The idea behind the MV is very simple: assuming that the process time delay is *d*, the control actions are effective only after *d*. Thus, a portion of the total process variance is unreachable to the feedback controller. All feedback controllers have higher variance comparing with MV, which is one reason why MV can be a good benchmark to CLPA.

We should emphasize here that MVC is only a theoretical controller, its implementation in a real plant is not feasible, because of robustness limitations. Besides, the concept here presented assumes that both controller and plant are linear. The MVC is specific for one plant model and disturbance pattern. Small changes on any plant or disturbance parameter can lead the process to instability (Huang and Shah 1999).

Based on routine operating data of the process output, the signal can be divided in two portions. Initially, the process output (y_t) is modeled using an Moving Average Model (MA).

$$y_t = \underbrace{f_0 a_t + f_1 a_{t-1} + \cdots + f_{d-1} a_{t-(d-1)}}_{e_t} + f_d a_{t-d} + f_{d+1} a_{t-(d+1)} + \cdots \tag{2.3}$$

Where a_t is the random input (white-noise), d is the time delay, f_i are the model parameters, and e_t is the feedback invariant portion of the signal. Stated in another way, the feedback controller can remove only a certain part of the signal, and the remaining part is called minimum variance.

In the following, the expression for MVC will be derived. Assume a SISO feedback controller whose schematic representation is subsequently showed (see Figure 2.2).

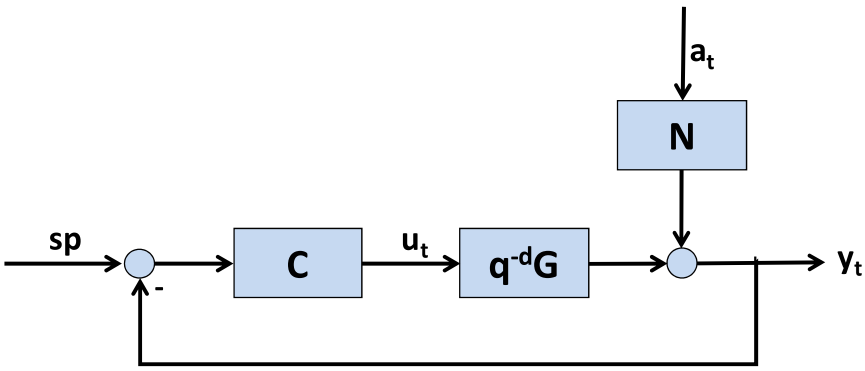

Figure 2.2: Schematic representation of a SISO controller

Where C is the controller, G is the plant, d is the time delay, N is the disturbance model, a_t is the white noise input, u_t the controller output (manipulated variable) and y_t is the process output (controlled variable).

The transfer function of $\frac{y_t}{a_t}$ is

$$y_t = \frac{N}{1+q^{-d}GC}a_t \tag{2.4}$$

Using the Diophantine identity:

$$N = \underbrace{f_0 + f_1 q^{-1} + \cdots + f_{d-1}q^{-d+1}}_{\text{F}} + Rq^{-d} \tag{2.5}$$

Where f_i are the impulse response parameters of the disturbance model (N), F is the polynomial of the feedback invariant terms and Rq^{-d} are the remaining terms of N.

Eq. 2.4 can be rewritten as

$$\begin{aligned} y_t &= \frac{F+q^{-d}R}{1+q^{-d}GC}a_t \\ &= \left[F + \frac{R-FGC}{1+q^{-d}GC}q^{-d}\right]a_t \\ y_t &= Fa_t + La_{t-d} \end{aligned} \tag{2.6}$$

Where $L = \frac{R-FGC}{1+q^{-d}GC}$ is a proper function.

The two terms of Eq. 2.6 are independent. Therefore

$$Var(y_t) = Var(Fa_t) + Var(La_{t-d}) \tag{2.7}$$

The first term is only affected by the process and the controller C does not have influence over it. The controller can affect only the second term. Based on Eq. 2.7 we can write:

$$Var(y_t) \geq Var(Fa_t) \tag{2.8}$$

The inequality in Eq. 2.8 can become an equality if L is equal to zero. It is achievable if the numerator of L is equal to zero,

$$R - FGC = 0 \tag{2.9}$$

This yields to the Minimum Variance Controller:

$$C = \frac{R}{GF} \tag{2.10}$$

Since F is independent of the controller (C), the term Fa_t , which is the process under the minimum variance control, is invariant to the feedback control.

The original conception of MVC cannot be applied in a tool to assess controller performance, because plant model, disturbance model and disturbance input a_t should be known. In the next section, some methodologies to estimate MV will be described.

2.2.3 – Indices based on Minimum Variance

The ground-breaking study by Harris (1989) proposes the use of MVC as benchmark to evaluate loop performance. The first work that allows computing the MV using only normal operating data and time delay was proposed by Desborough and Harris (1992). The MV was estimated by a linear regression to process data.

Later, many researchers (Huang and Shah 1999; Kempf 2003; Tyler and Morari 1996) have proposed methodologies to estimate the MV for SISO controllers. All methodologies need only routine operating data and time delay.

One of the main difficulties is to compute the time delay for each loop. This is one source of misleading results, because often default values are used, depending on loop type (Thornhill and Hägglund 1997). Many works available in the literature aim to estimate this loop parameter using only normal operating data (Ahmed et al. 2006; Elnaggar et al. 1991; Tuch et al. 1994).

Industrially, the Harris index has stimulated the development of tools to evaluate in real time the control loop performance. Many works proposed to systematize the plant-wide performance assessment based on Harris index (Desborough and Harris 1992; Olaleye et al. 2004; Thornhill et al. 1999).

The MVC benchmark has also many limitations and drawbacks, which sometimes make the analysis difficult and the diagnostic not straightforward. Many works mention that MVC has some limitations; however, few of them discuss these limitations. Bezergianni and Georgakis (2000) mention that it has some limitations and sometimes MVI is difficult to understand, but they do not show the limitations. Eriksson and Isaksson (1994) say that classical indices are better metrics to closed loop performance.

Many authors, after the initial work of Harris, have proposed some methodologies to compute MVC for specific types of controllers:

- The Harris index assumes a fixed setpoint. Some authors have studied this fact using different approaches:

- Thornhill et al. (2003b) have studied the reasons why Harris index is different when setpoint changes constantly and when it is fixed;
- Seppala et al. (2002) have shown a methodology to CLPA when a given control loop has occasional setpoint changes;
- some works have aimed to estimate MV when frequent setpoint activity is shown (Perrier and Roche 1992; Seppala et al. 2002; Thornhill et al. 2003a);
- the performance of cascade controllers has been studied by Ko and Edgar (2000).

- The performance of feedforward (and feedback-feedforward) controllers has been studied by Stanfelj et al. (1993);

Some methodologies have been proposed to compensate some of MVC limitations:

- Tyler and Morari (1996) have proposed a methodology called *Generalized Likelihood Method* to estimate MV for plant with nonminimum phase factors;
- Huang and Shah (1999) and Li and Evans (1997) have published works to evaluate MVC when the disturbance is time varying.

The impact of some parameters over MVI has also been studied:

- Controller order (Kendra and Cinar 1997);
- Plant order (Basseville 1998; Kumar et al. 2002);
- Data compression (Thornhill et al. 2004);
- The dataset selection (Olaleye et al. 2004);
- The disturbance pattern (Salsbury 2005; Xia and Howell 2005).

Some authors proposed alternative formulations to evaluate CLP using MVC:

- Bezergianni and Georgakis (2000) proposed the Relative Variance Index, based on MVC and open loop variance. The RVI is given by

$$RVI = \frac{\sigma_{OL}^2 - \sigma_y^2}{\sigma_{OL}^2 - \sigma_{MV}^2} \tag{2.11}$$

Where σ_{OL}^2 is the open loop variance. The main advantage of RVI is that it shows both the distance to the best controller (MVC) and the worst (open loop). However, this index requires the plant and controller model estimation, as well as the disturbance pattern.

- To use MVI to evaluate the performance of some groups of controllers is not advisable. Level loops are one example. Generally, they buffer disturbances, thus having a slow performance. In this case, a fast performance will imply increasing the products variability, because the disturbances will not be accommodated. Some works have been proposed to evaluate the performance of level loops. In the work of Hugo (2001), the performance of level loops can be evaluated comparing its variance with the variance of "an optimal" controller which always keeps the tank level between the desired constrains. This variance is called optimal variance (σ_{OT}^2).

$$\eta^{level}(d) = 1 - \frac{\sigma_{OT}^2}{\sigma_y^2} \tag{2.12}$$

2.2.3.1 – The FCOR algorithm

One of the most widespread algorithm to compute MV is called Filter and Correlation (FCOR), proposed by Huang and Shah (1999). It requires only one normal operating dataset and time delay.

A stable closed-loop system can be characterized as an infinite moving average model.

$$y_t = \left(f_0 + f_1 q^{-1} + \cdots + f_{d-1} q^{-d+1} + f_d q^{-d} + \cdots\right) a_t \tag{2.13}$$

Considering that y_t and a_t have zero mean and multiplying Eq. 2.13 by $a_t, a_{t-1}, \cdots, a_{t-d+1}$ and taking the expectation in both sides, the equation becomes

$$\begin{aligned}
r_{ya}(0) &= E[y_t a_t] = f_0 \sigma_a^2 \\
r_{ya}(1) &= E[y_t a_{t-1}] = f_1 \sigma_a^2 \\
r_{ya}(2) &= E[y_t a_{t-2}] = f_2 \sigma_a^2 \\
&\vdots \\
r_{ya}(d-1) &= E[y_t a_{t-d+1}] = f_{d-1} \sigma_a^2
\end{aligned} \tag{2.14}$$

Where:

- $E[\cdot]$ is the expectation operator
- $r_{ya}(k)$ is the covariance of y_t dataset shifted k samples
- σ_a^2 is the signal variance.

The minimum variance or the controller invariant part of output variance is

$$\begin{aligned}\sigma_{MV}^2 &= \left(f_0^2 + f_1^2 + f_2^2 + \cdots + f_{d-1}^2\right)\sigma_a^2 \\ &= \left[\left(\frac{r_{ya}(0)}{\sigma_a^2}\right)^2 + \left(\frac{r_{ya}(1)}{\sigma_a^2}\right)^2 + \left(\frac{r_{ya}(2)}{\sigma_a^2}\right)^2 + \cdots + \left(\frac{r_{ya}(d-1)}{\sigma_a^2}\right)^2\right]\sigma_a^2 \\ &= \frac{\left[r_{ya}(0) + r_{ya}(1) + r_{ya}(2) + \cdots + r_{ya}(d-1)\right]}{\sigma_a^2}\end{aligned} \tag{2.15}$$

The controller performance index is defined by Eq. 2.2 ($\kappa(d) = \frac{\sigma_{MV}{}^2}{\sigma_y{}^2}$), then the Eq. 2.15 is inserted in 2.2.

$$\begin{aligned}\kappa(d) &= \frac{\left[r_{ya}(0) + r_{ya}(1) + r_{ya}(2) + \cdots + r_{ya}(d-1)\right]}{\sigma_a^2 \sigma_y^2} \\ &= \rho_{ya}^2(0) + \rho_{ya}^2(1) + \rho_{ya}^2(2) + \cdots + \rho_{ya}^2(d-1)\end{aligned} \tag{2.16}$$

where $\rho_{ya}(k)$ can be computed using the following relation:

$$\rho_{ya}(k) = \frac{\frac{1}{M}\sum_{t=1}^{M} y_t a_{t-k}}{\sqrt{\frac{1}{M}\sum_{t=1}^{M} y^2{}_t \frac{1}{M}\sum_{t=1}^{M} a_t}} \tag{2.17}$$

Where M is the size of the data vector y_t.

Although a_t is unknown, it can be estimated ($\hat{a}_t$) by pre-whitening the process output y_t, via time series analysis. This algorithm is called FCOR (Filtering and Correlation) (Huang and Shah 1999) and it is schematically shown in Figure 2.3.

The white-noise can be estimated ($\hat{a}_t$) as the difference between the original process output and its predicted value (Chatfield 1989). The process output can be modeled using an autoregressive model (AR), whose order should be provided by the user. The minimum variance is dependent on the model order and a methodology to compute this value can be found in Chatfield (1989).

2.2.4 – Indices based on Integral of Error

Another common and simple possibility to evaluate loop performance is to use the integral of error, i.e. the integral of the difference between the setpoint and the process variable. Figure 2.4 illustrates the integral of error of a setpoint change.

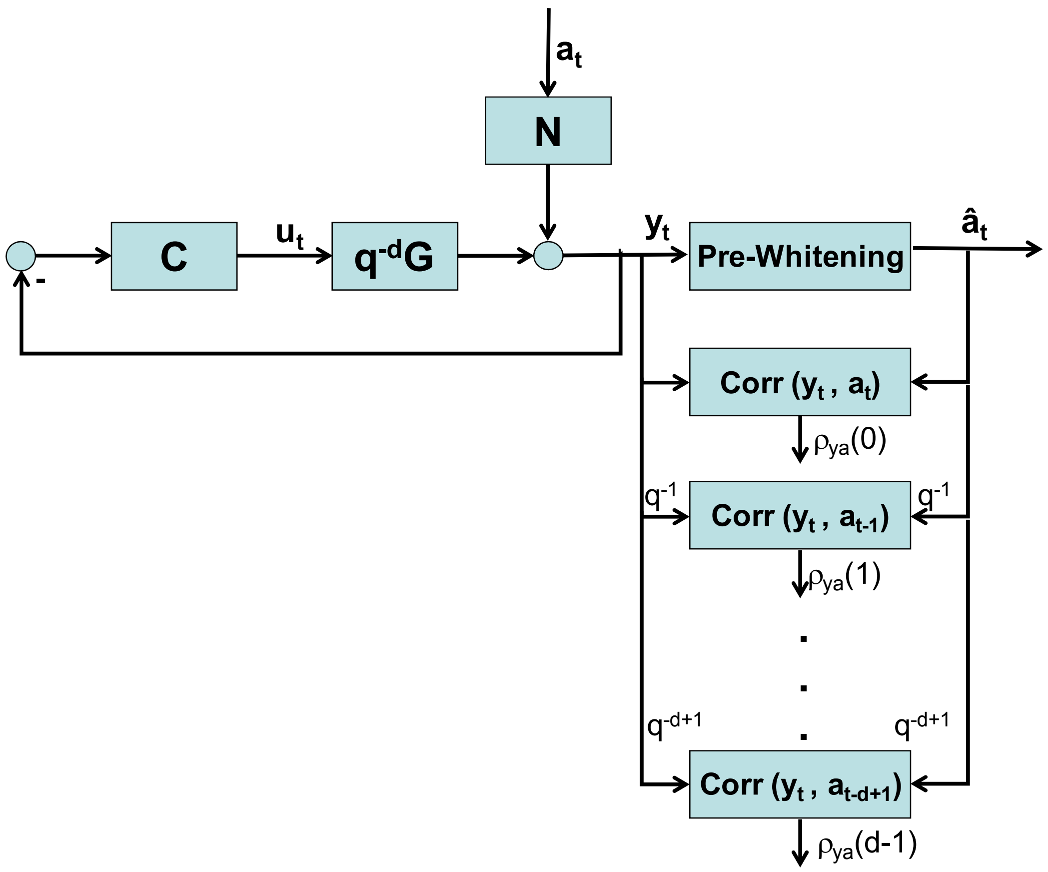

Figure 2.3: Schematic representation of FCOR algorithm

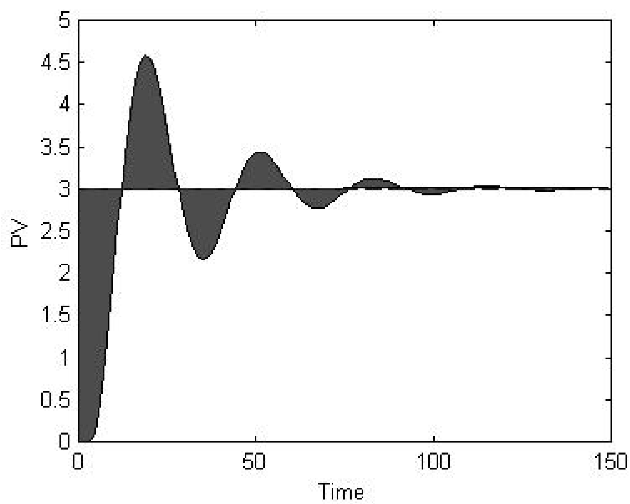

Figure 2.4: Integral of error for a system with a fixed setpoint

Some of the most used indices are:

- Integral of square error

$$ISE = \int_{ti}^{tf} (PV - SP)^2 \, dt \qquad (2.18)$$

- Integral of absolute error

$$IAE = \int_{ti}^{tf} |PV - SP| \, dt \qquad (2.19)$$

Where PV is the process variable data and SP is the setpoint.

The main potentiality of integral of error based indices is that only routine operating data is needed to evaluate loop performance. On the other hand, the benchmark should be imposed by the user for each loop to assess loop performance, because these indices are dependent on the plant model, disturbance pattern and controller performance.

An index derived from IAE was proposed by Gerry (2004) and it compares the actual IAE with the optimum IAE (IAE_{OPT}). It is also called ExpertTune Index, because it is applied in the commercial tool with the same name.

$$ETI = \frac{IAE - IAE_{OPT}}{IAE} \qquad (2.20)$$

The IAE_{OPT} is obtained when the controller is commissioned, where the engineer set this performance as the desired.

2.2.5 – Other benchmarks

Because of the Minimum Variance Controller limitations, some works using alternative benchmarks have been proposed to evaluate CLP.

Huang and Shah (1999) have proposed to use the LQG (*Linear Quadratic Gaussian*) to evaluate CLP. Grimble (2002) has suggested the Generalized Minimum Variance (GMV), whose score of each controller is a function of both the controller error and the manipulated variable effort. The main drawback is to set adequate weights for each contribution.

Another proposition that has been accepted mainly in commercial tools is to set an imposed benchmark for the loop. One property (which in most cases is variance or integral of error) is on-line monitored and compared with the “golden value” for each controller, obtained from a period where the controller performed well. Some works in this area are Gerry (2004) and Li et al. (2003).

Assuming that most of industrial controllers have poor performance, Hägglund (1999) proposed that initially the controllers with sluggish performance should be detected and its performance improved. A methodology based on the process variable autocorrelation slope was proposed.

2.2.6 – Multivariable controllers

The methodologies previously shown exclusively evaluate SISO controllers in real time. Recently, multivariable controllers (mainly MPCs) have started to widespread in the industry, with more than 4000 applications until 2003 (Qin and BADGWELL 2003).

Despite the MPC popularity in the industry, to evaluate MPC performance and diagnose the cause of its bad performance is still a challenge to the academia. Recently, many researchers have started to develop methodologies to evaluate MPCs. Many good reviews on multivariable controllers performance assessment are available in the literature (Harris et al. 1996; Huang et al. 1997; Qin 1998). Patwardhan and Shah (2002) have published a work that shows the impact of some MPC parameters over its performance.

Evaluating MPC performance is not as simple as evaluating the performance of SISO controllers. The source of poor performance can be:

- Tuning
- Model-Plant mismatch
- Disturbances
- Regulatory control
- Non-linearity; among others.

Some researchers tried to extend MV benchmark to MIMO controllers (Huang and Shah 1999). The main difficulty is that not only the time delay for each channel is required, but also the interactor matrix (Huang and Shah 1999) and the actual plant model are required to proceed the computation. Thus, the industrial application of this methodology is restricted.

Huang et al. (1997), Schäfera and Cinar (2004), and Kadali and Huang (2002) proposed to compare the MPC actual cost function value with the LQG benchmark. Ghraizi et al. (2007) proposed a methodology to address the MPC performance based on the predictability of the controller behavior. Kamrunnahar et al. (2002) proposed a method to evaluate multivariable control performance based on ARMarkov approach. DeVries and Wu (1978) proposed a methodology based on one-step ahead prediction.

2.3– Deterministic Indices

Classic indices (also called deterministic indices) are alternative metrics to quantify closed-loop performance and robustness (e.g. closed and open loop rise time ratio, gain margin, phase margin, among others). They provide conclusive marks for these loop characteristics (Goodwin et al. 2001). Their quantification in real time is prohibitive, because intrusive tests are necessary. However a clear metrics of loop performance and robustness is provided (Seborg et al. 2004), making the assessment easy and the diagnostics straightforward. Below, some of these indices are described.

2.3.1 – Deterministic indices to quantify loop performance

For stable systems, the loop performance can be measured using the classical set of parameters that describe the system dynamics. For both open loop and closed loop step responses, the following properties can be quantified (Goodwin et al. 2001):

- Rise time (Rt, $t_{i,95\%}$-$t_{5\%}$) – the time elapsed between the moment at which the step response reaches for the first time $0.05y_\infty$ and $0.95y_\infty$. This definition varies from author to author.
- Settling time (St, $t_{f,95\%}$-$t_{5\%}$) – the time required between the moment at which the step response reaches for the first time $0.05y_\infty$ and the time that the process enters and remains inside a band whose width is $0.05y_\infty$ (Seborg et al. 2004).
- Overshoot (Os) – the ratio between the maximum amount that the step response exceeds its final value (Os) and the final value (y_∞).

Figure 2.5 illustrates these parameters.

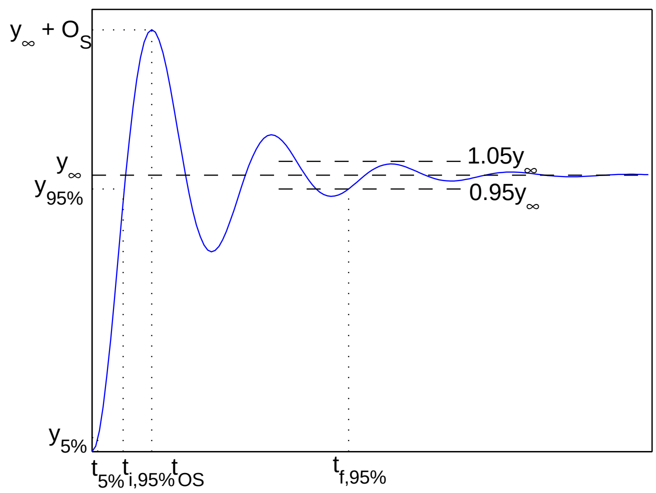

Figure 2.5: Deterministic metrics for performance

2.3.2 – Deterministic indices to quantify loop robustness

In the literature, another set of indices was derived to evaluate loop robustness, i.e. measure how far is the current loop from the marginal stability.

Figure 2.6 shows the representation of phase and gain margins, in the Bode Diagrams (Goodwin et al. 2001). The gain margin (GM) can be defined as the maximal additional gain that would take the closed loop to reach the critical condition. The phase margin (PM) quantifies the pure phase delay that could be added in the loop to achieve the critical point.

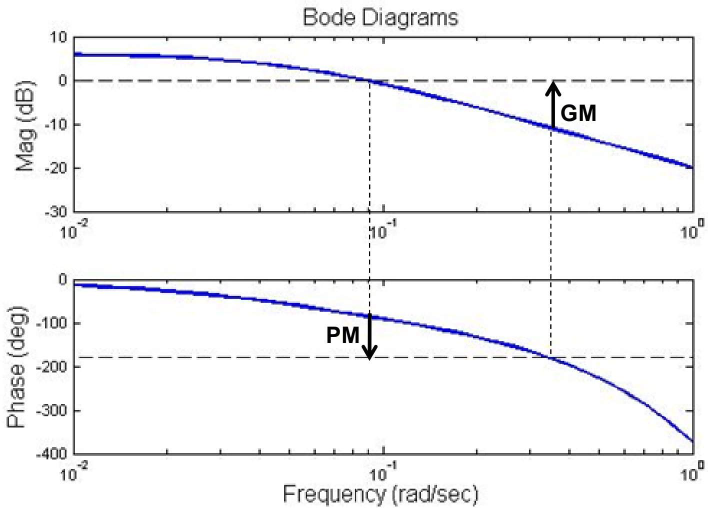

Figure 2.6: Definition of phase and gain margins based on Bode Diagrams

An alternative metric for loop robustness is the Maximal Sensitivity (*MS*). Consider the plot of $C(j\omega)G(j\omega)$ (Nyquist Diagram), and then the distance from -1 is computed (*r*), as shown in Figure 2.7. The *MS* is defined based on the inverse of *r*. The larger the *MS* value is, more instable the loop will be.

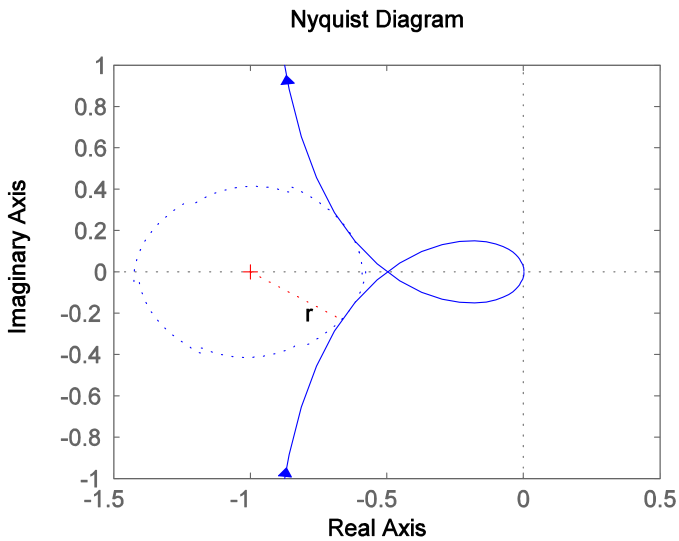

Figure 2.7: Maximal Sensitivity definition using Nyquist Diagram

Few works address the use of deterministic indices to CLPA. In the work of (Kozub 1997), the benchmark for MPC controllers should be specified by the engineer, based on intuitive measurements, like rise time or settling time.

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Chapter 3

Decomposing the Impact of Control Loop Performance, Time Delay, and White Noise in the Final Product Variability

Abstract:🕮 *This work proposes a new methodology to decompose the impact of control loop performance, time delay, and white noise in the total control loop variance, helping the engineer to diagnose the loop performance problem and take the right action to achieve the desired product variability (changing tuning parameters, changing controller type, replacing instrument, or changing the process, among others). The proposed method does not require any invasive tests, only control loop routine operating data and process time delay, allowing the industrial application of the proposed indices in real time. The methodology was applied in three case studies, providing very good results.*

3.1– Introduction

Control performance assessment tools are important to achieve and maintain the process in a high-efficiency operating point. Even if one controller has a good initial performance, several factors contribute to the gradual performance deterioration (e.g. operating point changes, sensor/actuators failure, process non-linearity, and seasonal influences, among others). Several studies support the importance of control loop performance assessment, where as many as 60% of total industrial controllers have some kind of problem (Bialkowski 1993).

The minimum variance index (MVI) (Harris 1989) is widely used to assess control loop performance. The Harris index (η) can be defined as:

🕮 *This chapter is based on the paper submitted by M. Farenzena and J. O. Trierweiler to the Journal of Process Control*

$$\eta(d) = 1 - \frac{\sigma_{MV}^2}{\sigma_y^2} \tag{3.1}$$

where σ_{MV}^2 is the process minimum variance and σ_y^2 is the actual process variance. The best controller is achieved when the value is close to zero, i.e. the control loop variance is close to the minimum variance. The worst occurs when the ratio is equal to one (i.e. $\sigma_y^2 \rightarrow \infty$). The estimation of σ_{MV}^2 requires only routine operating data, without additional experiments, and the process time delay.

There is a large amount of literature about control loop performance assessment and applications, including some recent survey papers (Jelali 2006; Qin 1998; Harris et al. 1999; Kozub 2002; Harris and Seppala 2001; Hoo et al. 2003; and Huang and Shah 1998).

The MVI allows to answer the following question (Huang et al. 1997): *"Does my controller perform close to or far from the best achievable?*". In this case, the best achievable is the minimum variance controller (MVC) (Harris 1989). It is important to mention that MVI cannot answer the question: "*Does my controller have a good closed-loop performance?*", i.e. two controllers with the same MVI can have completely different closed loop rise times or settling times.

This work proposes a methodology to decompose the impact of white noise, time delay, and control performance in the total variance for SISO controllers, answering the five following questions. Only process output signal and loop time delay should be available, which allows applying the proposed methodology in industrial scenario, where scarce information is available.

1. What is the total impact of white noise over total signal variability?

2. What is the impact of time delay over total signal variability?

3. What is the impact of control performance over total signal variability?

4. Suppose that a given controller has a MVI close to 0, i.e. its variance is equivalent to minimum variance. However, the total variance is higher than the minimum value accepted. What action should be taken: compensate the time delay (using feedforward techniques or Smith predictor (Weidong et al. 1998), or decrease the white noise (e.g. replacing the sensor)?

5. MVI assumes that a high order controller is available. However, in most DCS only PI and PID are available. What is the percentage of variance that could be removed using a low order controller?

The chapter is segmented as follows. Section 3.2 introduces the signal decomposition which is the base for the proposed methodology. Section 3.3 shows the new set of indices to evaluate the impact of time delay, white noise, and controller performance. In the next section (3.4), the procedure to quantify each index is shown. In section 3.5, the proposed methodology is applied in three case studies. The chapter ends with concluding remarks in section 3.6.

3.2– Signal decomposition

This section shows the signal decomposition that will be the base for the proposed method. The process output signal can be decomposed in three different parts, as shown in Figure 3.1:

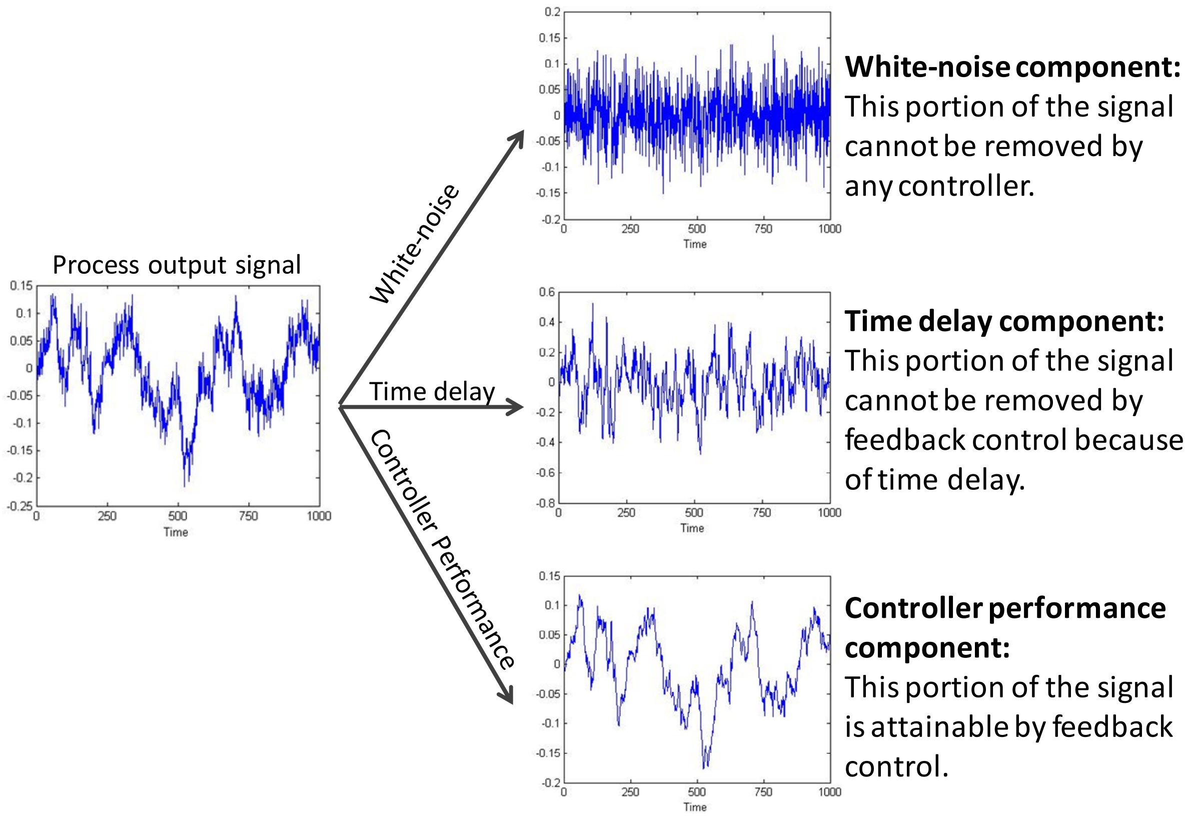


Figure 3.1: Schematic representation for the signal decomposition proposed in this work

- *White noise:* this is the random part of the signal and there is no controller that can remove it. The source of the problem can be the process or the instrument.

- *Achievable by feedback control:* the second part is achievable by feedback control and a high order controller can theoretically remove it.

- *Time delay influence:* this portion of the signal is accessible to the controller; however it cannot be removed because of time delay.

3.3– Influences of control performance, time delay, and white noise

This section introduces the new set of indices to quantify the influence of control performance, time delay, white noise, and controller order over total output variance. The procedure to compute each one will be shown in the next section. In this work, we assume that the process is locally linear and work around with only one operating point.

Initially, the control loop output signal (y_t) of a given controller is decomposed as a sum of three influences:

- w_t is the white noise component of output signal (y_t);
- f_t is the signal portion unreachable to feedback controller due to the time delay;
- g_t is the signal portion that can be removed by feedback controller.

$$y_t = f_t + g_t + w_t \tag{3.2}$$

Initially, we define the total signal variance (TSV) as:

$$TSV = \sigma^2(f_t) + \sigma^2(g_t) + \sigma^2(w_t) \tag{3.3}$$

where σ^2 is the signal variance.

The first index, called *nosi*, quantifies the white noise influence in the control loop. It is defined as the ratio between white noise component variance and total signal variance.

$$nosi = \frac{\sigma^2(w_t)}{TSV} \tag{3.4}$$

No controller can eliminate this portion of process variability. Only a modification in the process or instrument can attenuate this component.

The second index, called *deli*, quantifies the time delay influence in the control loop. It is defined as the ratio between time delay component variance and total signal variance.

$$deli = \frac{\sigma^2(f_t)}{TSV} \tag{3.5}$$

If the time delay causes a big impact in product variability, a control structure that compensate the time delay should be used. In this case, a Smith Predictor (Weidong et al. 1998) or FeedForward techniques (Adam and Marchetti 2004) can be used to attenuate the strong time delay influence.

The third index, called *tuni*, quantifies the feedback control performance impact over the total variability. It is defined as the ratio between control performance component variance and total signal variance.

$$tuni = \frac{\sigma^2(g_t)}{TSV} \tag{3.6}$$

If the controller performance causes a strong impact in product variability, the tuning parameters should be changed or the order of the controller should be increased. The *tuni* index is analogous to Harris index (Harris 1989) and it provides the same information about the portion of the signal that a feedback controller can remove.

The controller attainable portion of the signal considers that a high order controller is available. However, in the industrial scenario high order controllers are not available or are more expensive than low order (e.g., PI and PID type controllers). The Internal Model Principle (Goodwin et al. 2001) says that the controller can perfectly track the setpoint if the pair plant and disturbance models are inside the controller: if one of them has high order, low order controllers could not remove part of the variance, even if this portion is theoretically removable. In this case, only a high order controller can remove a certain part of the variance.

Consequently, it is also convenient to quantify the signal portion that can be removed by a PID type controller ($g_{PID,t}$). The tuning index can be extended to the case where a PID type controller is available ($tuni_{PID}$).

$$tuni_{PID} = \frac{\sigma^2(g_{PID,t})}{TSV} \tag{3.7}$$

In the case where $tuni \approx tuni_{PID}$, the portion achievable by feedback controller can be potentially removed by a PID controller. In this case, a high order controller will not bring visible gain. On the other hand, if $tuni \gg tuni_{PID}$, then only a minor part of the variance that can be removed by a high order controller will be removed by a PID controller.

3.4– Computation of nosi, deli, and tuni

This section shows the procedures to quantify the indices previously defined.

3.4.1 - Quantifying the white noise influence

The Wold decomposition theorem (Chatfield 1989) says that any linear stationary process can be expressed as a sum of two uncorrelated processes, one purely deterministic and other purely nondeterministic, i.e.,

$$y_t = y_{t,d} + y_{t,i}. \tag{3.8}$$

Where $y_{t,d}$ and $y_{t,i}$ are the deterministic and nondeterministic portion of the signal, respectively.

The signal y_t is purely deterministic if their values can be forecasted exactly, using past data. On the other hand, if the past data of the process is useless to predict future behavior, we can say that the process behavior is purely nondeterministic.

The nondeterministic portion or, as previously called white noise component (w_t) of the signal, can be quantified by the difference between the original signal and the deterministic portion of the signal $y_{t,d}$.

$$w_t = y_t - y_{t,d} \tag{3.9}$$

The values of y_t can be forecasted using an autoregressive (AR) model (Oppenheim et al. 1999), resulting in $y_{t,d}$. The AR model order can be determined using the methodology shown in (Chatfield 1989).

3.4.2 – Quantifying control performance processes and time delay influences

This section describes the method to quantify the signal portion which can be removed by feedback controller. The methodology proposed by Harris (1989) and Seppala et al. (2002) can be used to evaluate this portion.

Suppose that the output signal (y_t) has zero mean. Based on a simple linear regression, the feedback-accessible portion of the signal (g_t) can be quantified.

$$g_t = X\alpha \tag{3.10}$$

where X is

$$X = \begin{bmatrix} y_{n-d} & y_{n-d-1} & \cdots & y_{n-d-m+1} \\ y_{n-d-1} & y_{n-d-2} & \cdots & y_{n-d-m} \\ \vdots & \vdots & \ddots & \vdots \\ y_m & y_{m-1} & \cdots & y_1 \end{bmatrix} \tag{3.11}$$

and n is the length of data vector (y), m is the auto-regressive polynomial order, and d the process time delay. α is the parameters vector:

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_m \end{bmatrix} \tag{3.12}$$

It can be computed solving the linear regression problem:

$$\alpha = (X^T X)^{-1} X^T \dot{y} \tag{3.13}$$

Where $\dot{y}$ is:

$$\dot{y} = \begin{bmatrix} y_n \\ y_{n-1} \\ \vdots \\ y_{m+d} \end{bmatrix} \tag{3.14}$$

The last contribution, which is inaccessible to the feedback controller (f_t), can be estimated assuming that the predictable part of y_t ($y_{t,d}$) is composed by the sum of g_t and f_t, i.e.

$$\begin{gathered} y_{t,d} = g_t + f_t \\ f_t = y_{t,d} - g_t. \end{gathered} \tag{3.15}$$

3.4.3 – Controller order influence evaluation

The minimum variance controller computes feedback-accessible portion of the signal using a high order controller. However, in industrial DCS, most of SISO controllers are PI and PID type. Thus, the minimum variance for low order controllers provides a more reliable information for most of industrial controllers.

This section evaluates the impact of the controller order, showing the variability portion that can be removed by changing tuning parameters ($g_{t,PID}$), considering a low order controller (PID type), and the part that can be removed only if a high order controller is applied (e.g. MPC).

The simplified discretized equation for a PID type controller output (u_t) is:

$$u_t = K_p\left(y_{sp} - y_t\right) + K_I \sum_{i=1}^{m-1} \left(y_{sp} - y_{t-i}\right) + K_D\left(y_t - y_{t-1}\right) \tag{3.16}$$

Based on Eq. 3.16, the new X matrix and α vector can be rewritten for PID type controller:

$$X = \begin{bmatrix} y_{n-d} & y_{n-d-1} & \sum_{i=2}^{m-1} y_{n-d-i} \\ y_{n-d-1} & y_{n-d-2} & \sum_{i=2}^{m-1} y_{n-d-i+1} \\ \vdots & \vdots & \vdots \\ y_m & y_{m-1} & \sum_{i=2}^{m-1} y_{m-i} \end{bmatrix} \tag{3.17}$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} \tag{3.18}$$

The details about this conversion can be found in appendix A. The parameters vector (α) can be computed using Eq. 3.13.

3.4.4 – Procedure to compute the indices

This section summarizes the methodology to estimate the proposed indices: *nosi*, *deli*, *tuni, and tuni$_{PID}$*. The scheme shown in Figure 3.2 summarizes the procedure to decompose the signal which is the base of the four proposed indices.

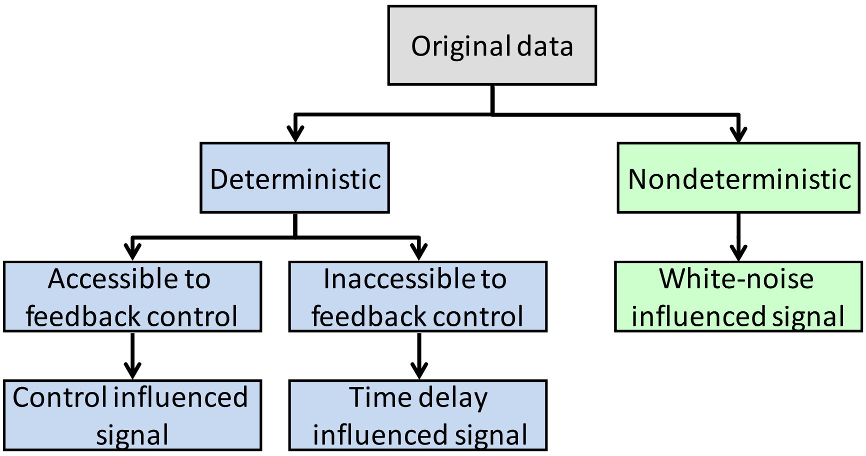


Figure 3.2: Schematic representation for the signal decomposition

The procedure to quantify each index is summarized below, using only process output signal (y_t) and time delay (d):

1. Decompose the signal y_t in the deterministic and nondeterministic parts using an autoregressive model (AR). The AR model order should be adequately chosen (Chatfield, 1989).

2. Determine the white-noise portion of the signal (w_t), given by the difference between the deterministic part ($y_{t,d}$) and the original signal (y_t).

3. Evaluate the feedback-accessible portion of the signal (Eq. 3.10).

4. Determine the portion of the signal inaccessible to the feedback controller (Eq. 3.15).

5. Compute TSV (Eq. 3.3).

6. Compute the *nosi* index (Eq. 3.4).

7. Compute the *tuni* index (Eq. 3.6).

8. Compute the *deli* index (Eq. 3.5)

9. Evaluate the signal portion accessible to PID type feedback controller.

10. Compute the $tuni_{PID}$ index (Eq. 3.7)

3.5– Case studies

Values for the proposed indices have been exhaustively examined using several first and second order simulation models. To elucidate the indices potentialities, we will apply them to a first order plus time delay system with a first order disturbance, as shown in the subsequent scheme (Figure 3.3). The sensitivity analysis of the three indices applied to first and second order model can be found in Appendix B.

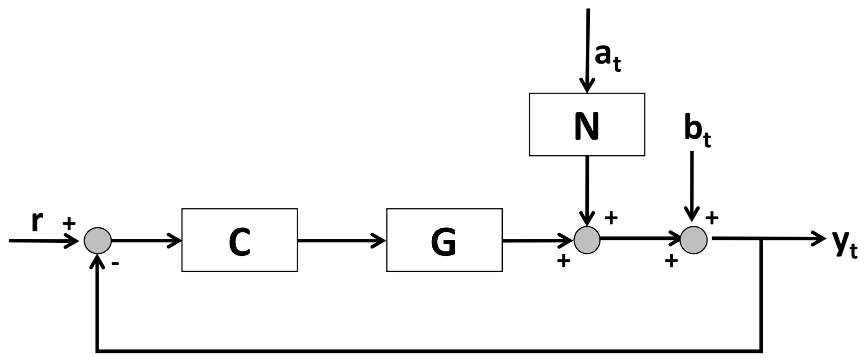


Figure 3.3: Schematic representation of the system

Where a_t and b_t are random signals with zero mean and variance A and B, respectively. C is the feedback PI type controller, G the plant, and N the disturbance model, and r is the reference, which in this case is zero. Table 3.1 shows the parameters used in this case study.

Table 3.1: Plant parameters of case study.

Parameter	Value
C	Kp = 1.5, Ti = 55
G	$\frac{1}{50s+1}e^{-5s}$
N	$\frac{1}{30s+1}$

The sample time used in the simulation is one time unit.

3.5.1 – Case-study I – Random signal

In the first case study, only random noise is fed into the system, i.e. the parameter A is set to zero and B to 10^{-4}. Then, each proposed influence is evaluated, as shown in Table 3.2.

Table 3.2: white noise influence

nosi	*deli*	*tuni*
0.93	0.01	0.06

Table 3.2 shows that less than 10% of the output variance can be removed by the "perfect controller", while more than 90% is caused by white noise. In this case, only a modification in the process or sensor can have a strong impact in the loop variability.

3.5.2 – Case-study II – Variable white-noise magnitude, time delay, and control loop performance

The current case study computes the three indices for scenarios with variable time delay, white-noise magnitude, and control performance.

The default values for A and B parameters are 1 and 10^{-4}, respectively. In the first scenario, the influence of white noise will be quantified. Table 3.3 shows the influence between noise amplitude (B) and each one of the proposed indices.

Table 3.3: noise amplitude (B) influence over each one of three the indices

B	*nosi*	*deli*	*tuni*
10^{-6}	0.08	0.32	0.60
10^{-5}	0.09	0.32	0.59
10^{-4}	0.17	0.30	0.53
10^{-3}	0.57	0.17	0.26
10^{-2}	0.94	0.03	0.03

Based on Table 3.3, we can verify that the white noise amplitude increase was captured by the index that quantifies this influence: *nosi*. The importance of the two other indices decreased as the influence of *nosi* increased.

In the second test, the time delay influence is quantified. Table 3.4 shows the relation between the time delay and the three proposed indices.

Table 3.4: time delay (d) influence over each one of the three indices

d	*nosi*	*deli*	*tuni*
3	0.18	0.17	0.65
5	0.17	0.30	0.53
8	0.15	0.47	0.38
10	0.14	0.54	0.32
20	0.11	0.70	0.19

Table 3.4 shows that *deli* index captured the time delay increase influence in the total output variance.

The influence of control performance is analyzed in Table 3.5. This table shows the influence of controller gain (K_P) in each index.

Table 3.5: controller gain (K_P) influence over each one of the proposed indices

K_P	*nosi*	*deli*	*tuni*	$tuni_{PID}$
0.1	0.11	0.19	0.70	0.70
0.5	0.13	0.23	0.64	0.64
1	0.15	0.27	0.58	0.58
3	0.22	0.39	0.39	0.38
5	0.25	0.44	0.31	0.27
8.5	0.25	0.44	0.31	0.20
12	0.18	0.32	0.50	0.31

Table 3.5 shows that initially, increasing the control loop performance decreased the influence of tuning parameters in total variability. Only when the loop had very fast tuning ($K_p = 12$), the performance influence increased due to closed-loop underdamped behavior and closeness to the stability boundary. In the case where a PID controller was applied, similar results than a high order controller can be obtained if $K_P \leq 3$. A high order controller can have a better performance than a PID controller only if $K_P \geq 5$.

3.5.3 – Case-study III – Controller order influence

In this case study, the impact of controller order will be exploited. Depending on the plant order or disturbance behavior, PID controller cannot remove the complete portion of the signal which is potentially removable by the feedback controller. In this case, a higher order controller should be applied.

To highlight the controller order importance, the disturbance b_t is generated using two different functions as shown below:

$$\begin{aligned} b1_t &= d_t + 5d_{t-1} - 3d_{t-2} \\ b2_t &= d_t + 5d_{t-1} - 3d_{t-2} + 1.5d_{t-4} - 7d_{t-7} \end{aligned} \tag{3.19}$$

where d_t is a random signal with zero mean and unitary variance. The parameter A is set to zero.

The system with the first disturbance pattern ($b1_t$) has low order and the PID can completely track the plant and the disturbance models. In this case, a high order controller will have insignificant impact in the process variability. On the other hand, the low order controller cannot compensate the second disturbance pattern ($b2_t$), because its order is higher than the order that PID controller can model. Our objective here is show that $tuni_{PID}$ can capture this behavior. Table 3.6 shows the influence of controller in the final variability.

Table 3.6: *tuni* and $tuni_{PID}$ using two different disturbance patterns

b	*tuni*	$tuni_{PID}$
$b1_t$	0.24	0.22
$b2_t$	0.73	0.59

Based on Table 3.6, the following conclusions arise:

- In the first scenario, where $b1_t$ is the disturbance function, both indices provide almost the same result. In this case, a high order controller will not bring visible impact in the loop variability.

- In the second scenario, where $b2_t$ is the disturbance function, 73% of the output variance could be removed by the feedback control, however only 59% can be removed by a low order controller. In this case, a high order controller can bring better performance than a PID controller.

3.6– Conclusions

In this work, a new set of indices was proposed to decompose the influence of white noise, time delay, and control loop performance in the total loop variance. The proposed method also allows evaluating the impact of the controller order, i.e. if the feedback-attainable portion of the signal that can be removed by a PID type controller. These indices help the minimum variance index diagnose the impact of each component in the total process output variance.

The computation of the given indices requires only routine operating data and plant time delay. Thus, their application in the industrial field is possible.

The proposed methodology was applied in three case studies showing reliable results in all of them. The proposed indices allowed quantifying the desired influence under several scenarios providing very good results.

Appendix A

In the minimum variance controller computation, a high order controller is used. However, in most of DCS only low order controllers are available. That is the reason why MV for PID controllers provides more reliable information about the "portion of the variance" that can be removed by feedback controller.

Based on the typical discretized PID equation (Eq. 3.16),

$$u_t = K_p(y_{sp} - y_t) + K_I \sum_{i=1}^{m-1} (y_{sp} - y_{t-i}) + K_D(y_t - y_{t-1}) \tag{3.16}$$

the procedure to estimate MV for PID controllers (MV_{PID}) will be derived in this appendix.

The output value for t+1 (y_{t+1}) is predicted by the controller using the same PID equation. Assuming that reference value is zero, i.e. $y_{sp} = 0$, then the equation becomes:

$$y_{t+1} = K_1 y_t + K_2 \sum_{i=1}^{m-1} (y_{t-i}) + K_3(y_t - y_{t-1}) \tag{3.20}$$

where K_1, K_2, and K_3 are the controller constants. Our objective here is to derive an equation where these constants can be analytically computed through a least squares problem. Initially, the terms are grouped based on their index.

$$y_{t+1} = (K_1 + K_3)y_t + (K_2 - K_3)y_{t-1} + K_2 \sum_{i=2}^{m-1} (y_{t-i}) \tag{3.21}$$

Renaming the constants, the equation becomes:

$$y_{t+1} = \alpha_1 y_t + \alpha_2 y_{t-1} + \alpha_3 \sum_{i=2}^{m-1} (y_{t-i}) \tag{3.22}$$

Where α_1, α_2, and α_3 are the constants that should be computed by least squares. The procedure now is simple and they can be calculated analytically:

$$\alpha = (X^T X)^{-1} X^T \dot{y} \tag{3.23}$$

Where:

$$X = \begin{bmatrix} y_{n-d} & y_{n-d-1} & \sum_{i=2}^{m-1} y_{n-d-i} \\ y_{n-d-1} & y_{n-d-2} & \sum_{i=2}^{m-1} y_{n-d-i+1} \\ \vdots & \vdots & \vdots \\ y_m & y_{m-1} & \sum_{i=2}^{m-1} y_{m-i} \end{bmatrix} \tag{3.24}$$

$$\dot{y} = \begin{bmatrix} y_n \\ y_{n-1} \\ \vdots \\ y_{m+d} \end{bmatrix} \tag{3.25}$$

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} \tag{3.26}$$

The minimum variance for PID controllers (MV_{PID}) is given by:

$$MV_{PID} = \sigma^2(X\alpha) \tag{3.27}$$

Appendix B – Sensitivity Analysis

3.B.1 – Introduction and scope

The scope of appendix B is to make a sensitivity analysis over each one of the proposed indices. This appendix has two main objectives:

- Show the impact of time-delay mismatch, i.e. if the time-delay is not correctly estimated, what its impact over each index.

- Show the impact of each model and controller parameter over each index, for 1st and 2nd order models.

3.B.2 – Impact of time-delay mismatch

Most of times in industrial plants, the model parameters (e.g. time delay, gain, time constant, among others) are unknown. To apply the proposed methodologies and tools, this value is estimated based on plant tests or even based on engineer knowledge. Thus, mismatch between plant and estimated value is expected and its impact should be quantified. This is the scope of this section. Only first order plus time delay models with first order disturbance model will be analyzed. The system structure and parameters are shown in Figure 3.3 and Table 3.1, respectively and the parameters that will be analyzed are shown in Table 3.7.

In the first scenario, the impact of time delay mismatch with variable gain will be shown. Table 3.8 shows the intervals for these parameters. In this analysis, only the DELI and TUNI plots will be shown, because the time-delay mismatch and controller gain will have strong impact only in these indices.

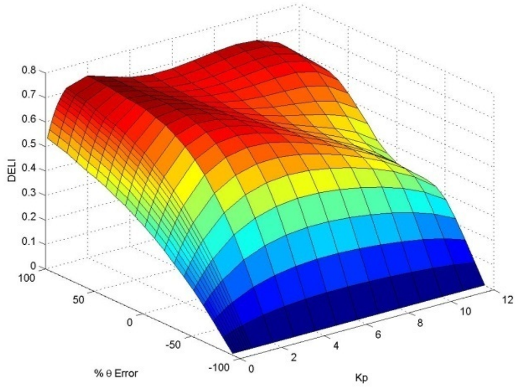
Table 3.7: Sensitivity analysis parameters

Parameter	Description
Kp	Controller Gain
τ	Process time constant
B	White-noise amplitude
τ_D	Disturbance transfer function time constant

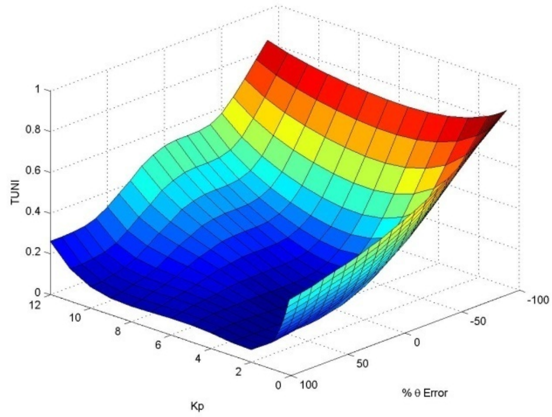
Table 3.8: Kp and % θ error intervals for sensitivity analysis

Parameter	Interval
Kp	0.1:0.1:1 1:1:12
$\%\ \theta\ Error$	-100%:10%:100%

The sensitivity analysis is shown in Figure 3.4.



(A) DELI



(B) TUNI

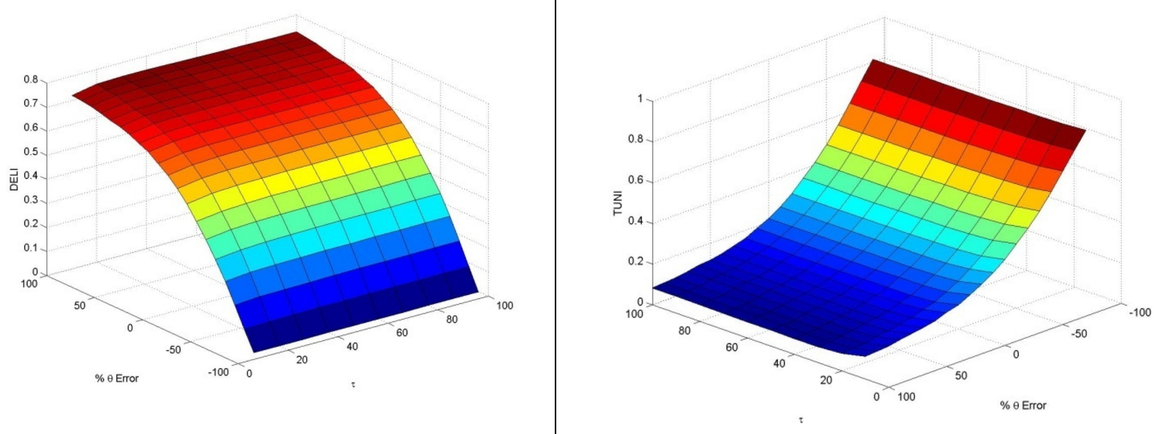
Figure 3.4: Sensitivity analysis for time delay mismatch and controller gain (*Kp*)

Figure 3.4 clearly shows visible impact of both time delay mismatch and controller gain over each index. The wrong quantification of time delay can clearly lead to wrong results. Depending on loop gain, the effect can be increased or decreased.

In the second analysis, the impact of process time constant (τ) as well as time delay mismatch will be evaluated. Table 3.9 shows the parameters intervals and Figure 3.5 the sensitivity analysis plots.

Table 3.9: τ and % θ error intervals for sensitivity analysis

Parameter	Interval
τ	10:10:100
% θ Error	-100%:10%:100%



(A) DELI

(B) TUNI

Figure 3.5: Sensitivity analysis for time delay mismatch and process time constant

Again, as shown in Figure 3.5, the impact of wrong evaluation of time delay has visible impact in both DELI and TUNI. This impact is expected, because the DELI index is responsible for quantify the time delay impact and, as it is wrongly computed, DELI results should be also affected.

In the third analysis, the impact of white-noise magnitude (B) will be analyzed. Table 3.10 shows the intervals for the parameters and Figure 3.6 shows the sensitivity analysis plots.

Table 3.10: B and % θ error intervals for sensitivity analysis

Parameter	Interval
% θ Error	-100%:10%:100%
log10(B)	-6:1:-2

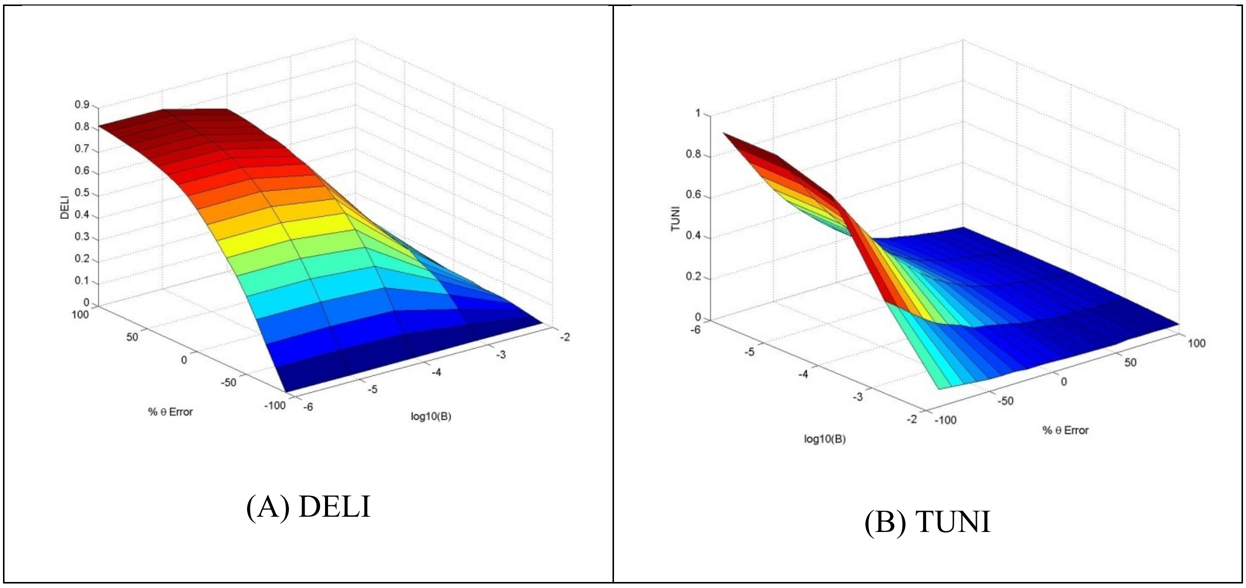


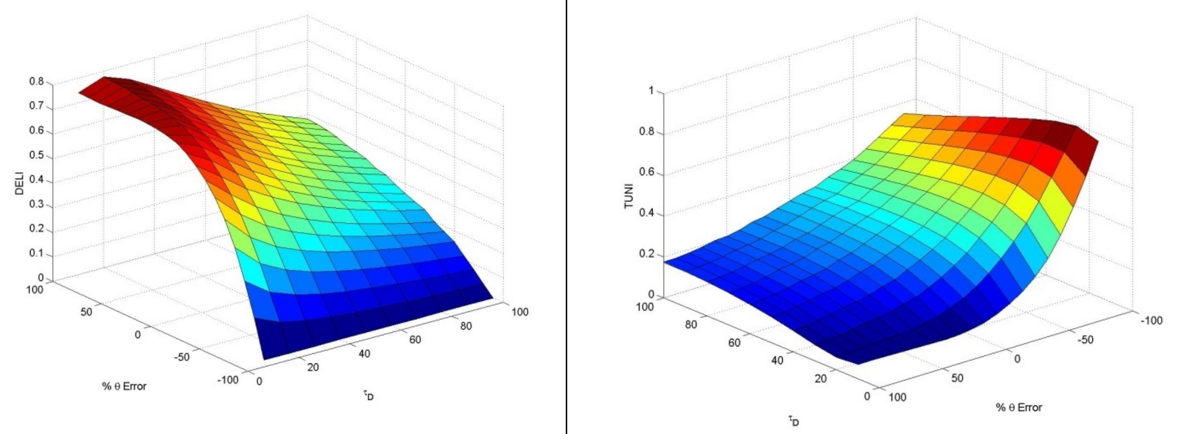
Figure 3.6: Sensitivity analysis for time delay mismatch and white-noise magnitude

Figure 3.6 shows that the impact of time delay mismatch decreases when white-noise magnitude increases, because the NOSI index increases, decreasing DELI and TUNI magnitudes.

In the last analysis, the impact of disturbance time constant (τ_D) will be exploited. Table 3.11 shows the intervals for the parameters, while Figure 3.7 shows the sensitivity analysis with time delay mismatch.

Table 3.11: τ_D and % θ error intervals for sensitivity analysis

Parameter	Interval
τ_D	10:10:100
% θ Error	-100%:10%:100%



(A) DELI

(B) TUNI

Figure 3.7: Sensitivity analysis for time delay mismatch and disturbance time constant

Figure 3.7 confirms the previous results, where time delay mismatch has visible impact over DELI and TUNI indices.

3.B.3 – Sensitivity analysis for 1st order models

In this section, the influence of some loop parameters will be analyzed for 1st order models. The system structure and parameters are shown in Figure 3.3 and Table 3.1, respectively. The parameters that will be analyzed are shown in Table 3.12.

Here, using the methodology described in the previous appendix, we compute the three indices in different scenarios, with variable parameters. In all cases, we ensure stability for the closed loop system.

In the first sensitivity analysis, the impact of *K*p and *T*i will be analyzed. Table 3.13 shows the intervals for these variables.

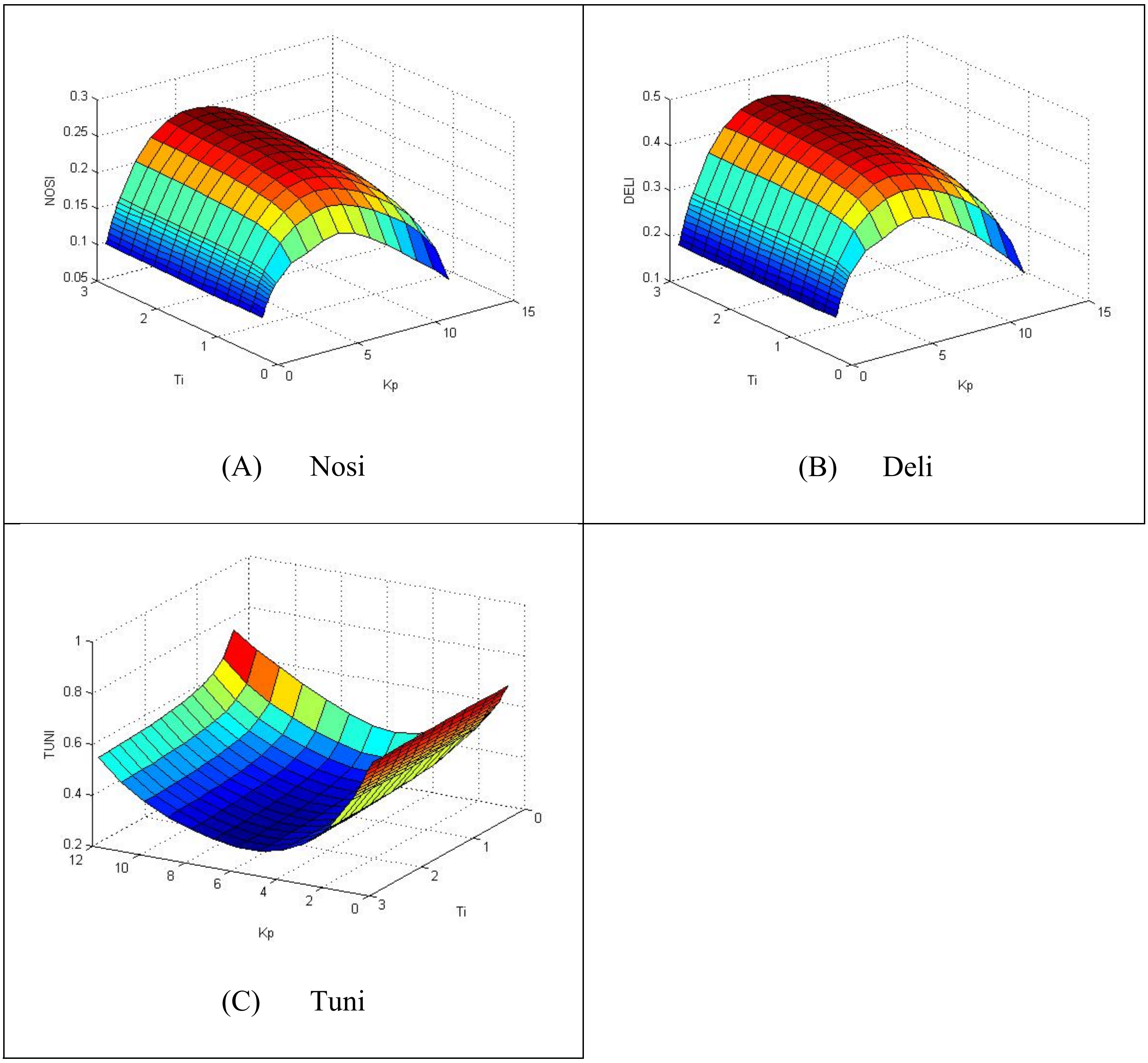
Table 3.12: Sensitivity analysis parameters

Parameter	Description
Kp	Controller Gain
Ti	PID integral constant
Td	PID derivative time
τ	Process time constant
θ	Time delay
B	White-noise amplitude
τ_D	Disturbance transfer function time constant

Table 3.13: Kp and Ti intervals for sensitivity analysis

Parameter	Interval
Kp	0.1:0.1:1 1:1:12
Ti	$0.3\tau : 0.1\tau : 3\tau$

Figure 3.8 shows the behavior of the three indices for Kp and Ti.



(A) Nosi

(B) Deli

(C) Tuni

Figure 3.8: Impact of *K*p and *T*i over the three indices

Figure 3.8 shows that Kp has a strong impact over the three indices. Initially, a faster controller implies in a variability reduction. Then, the controller becomes underdamped and its variability increases.

In the second sensitivity analysis, the impact of Kp and Td will be analyzed. Table 3.14 shows the intervals for these variables.

Table 3.14: Kp and Td intervals for sensitivity analysis

Parameter	Interval
Kp	0.1:0.1:1 1:1:12
Td	$0.1\tau : 0.1\tau : \tau$

Figure 3.9 shows the behavior of the three indices for Kp and Td.

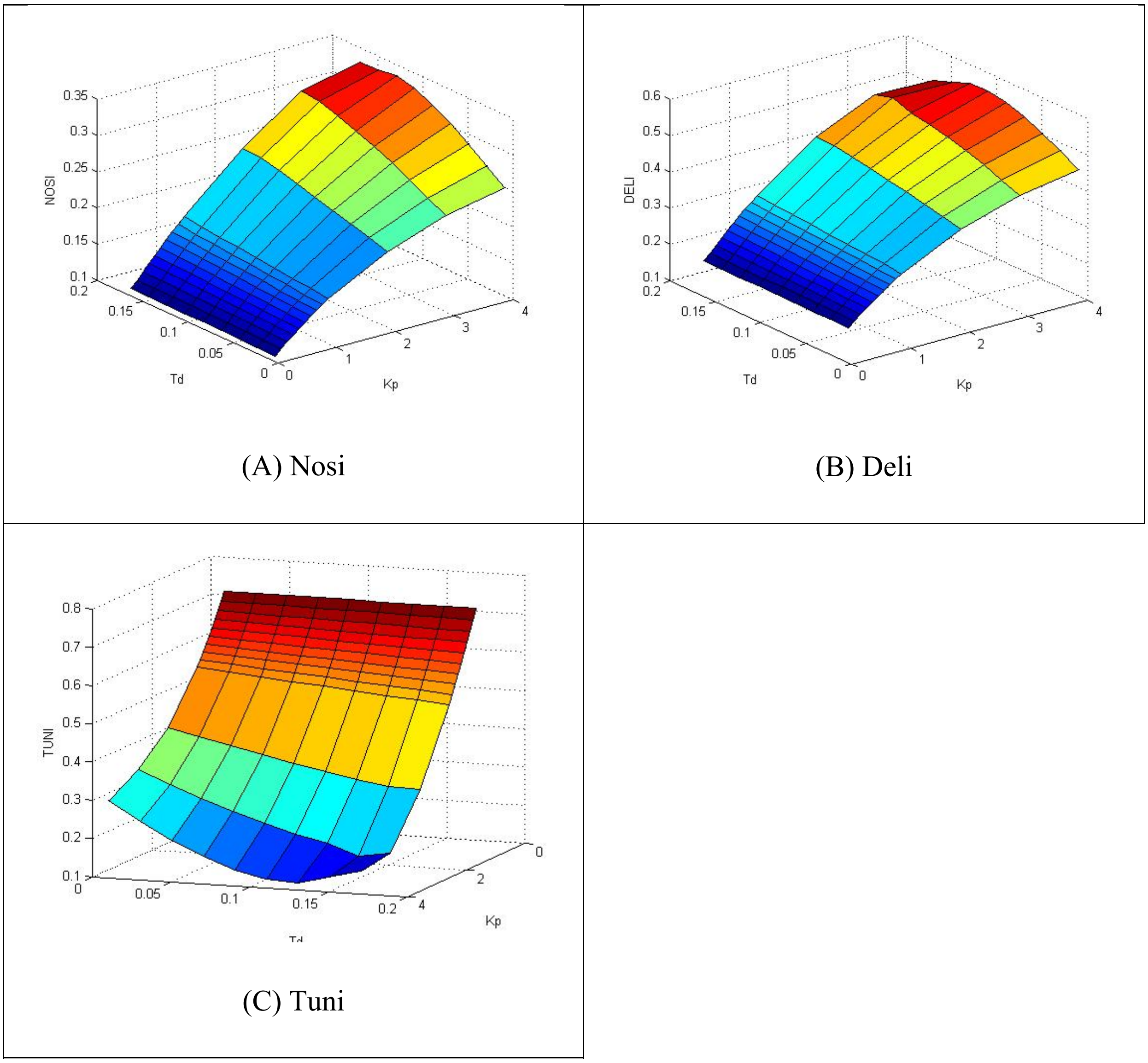


Figure 3.9: Impact of Kp and Td over the three indices

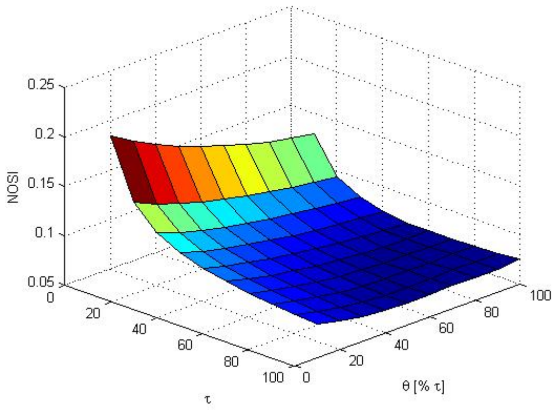
Based on Figure 3.9 we can see that increasing Td the white noise impact over the total variability, captured by Nosi index, also increases.

The third analysis for first order model will focus on model parameters impact – τ and θ. Table 3.15 shows the intervals for these variables.

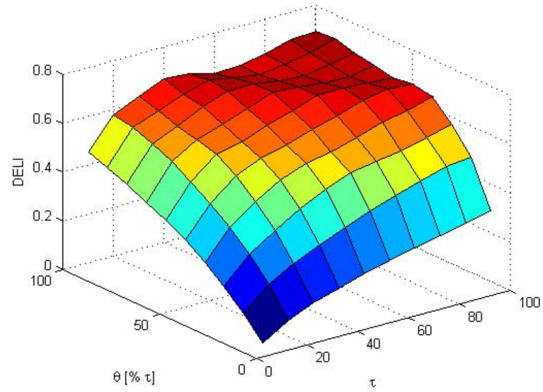
Table 3.15: τ and θ intervals for sensitivity analysis

Parameter	Interval
τ	10:10:100
θ	$0.1\tau : 0.1\tau : \tau$

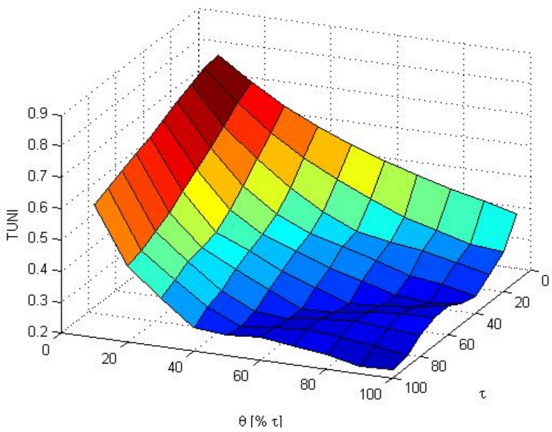
Figure 3.10 shows the behavior of the three indices for τ and θ.



(A) Nosi



(B) Deli

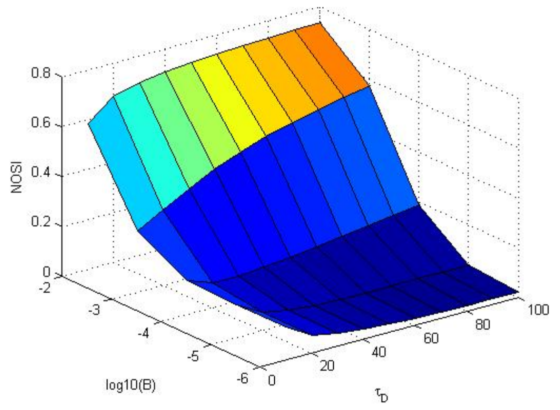


(C) Tuni

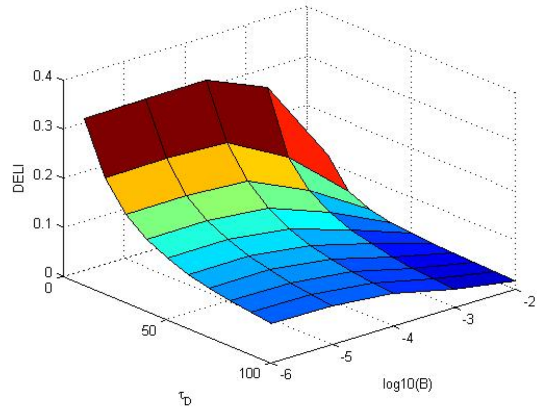
Figure 3.10: Impact of τ and θ over the three indices

Figure 3.10 corroborates the previous results, where both Nosi and Deli captures the impact of white-noise and time delay, respectively. Increase time constant with a fixed time delay means decrease noise impact and time delay, increasing the impact of the tuning. One important point to highlight is that increasing the time constant or time delay, the white-noise impact decreases, because the process "acts as a filter".

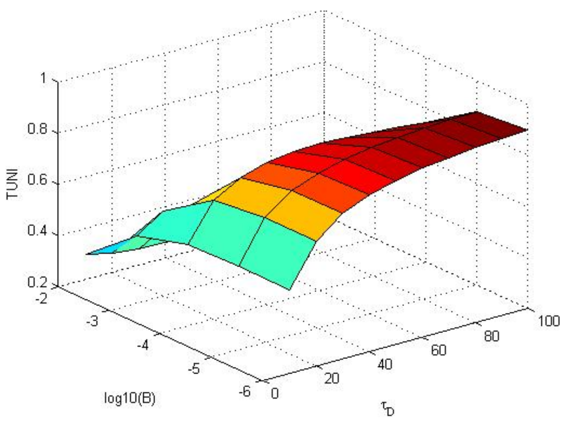
The last sensitivity analysis for first order models focuses the impact of white-noise impact (B) and disturbance model time constant (τ_D). Table 3.16 shows the intervals for each variable and Figure 3.11 shows the impact of these parameters over each index.



(A) Nosi



(B) Deli



(C) Tuni

Figure 3.11: Impact of τ_D and B over the three indices

Table 3.16: τ_D and B intervals for sensitivity analysis

Parameter	Interval
τ_D	10:10:100
log10(B)	-6:1:-2

Figure 3.11 provides straightforward conclusions: increasing the white-noise magnitude, the respective index increased. Increasing the disturbance dynamics, the impact of Tuni increases, because low order frequencies are feed in the system. Again, the proposed methodology provided reliable results for all analysis with first order models.

3.B.2 – Sensitivity analysis for 2nd order models

In this section, the impact of the second order models parameters, whose structure are following shown, will be exploited.

$$G(s) = \frac{K(\beta s + 1)}{\tau^2 + 2\tau\zeta s + 1} e^{-\theta s} \qquad (3.28)$$

Table 3.17 shows the model parameters that will be analyzed.

Table 3.17: Second order transfer function parameters that will be analyzed

Parameter	Description
Kp	Controller gain
Ti	Controller integral time
τ	Process time constant
θ	Time delay
β	Zero parameter
ζ	Damping coefficient

The default parameters used in this section are shown in Table 3.18.

Table 3.18: Plant parameters of sensitivity analysis

Parameter	Value
C	Kp = 0.5, Ti = 55
N	$\frac{1}{30s+1}$

In the first analysis, the impact of Kp and Ti will be exploited over the three indices. Four plants will be used, as shown in Table 3.19.

Table 3.19: Set of plants used to analyze Kp and Ti impact over the three indices

Plant	Model
G_1	$\frac{1}{400s^2+40s+1}e^{-15s}$
G_2	$\frac{1(-10s+1)}{400s^2+40s+1}$
G_3	$\frac{1(100s+1)}{2500s^2+100s+1}e^{-15s}$
G_4	$\frac{1(0.1s+1)}{400s^2+17s+1}e^{-15s}$

The step response for the models is shown in Figure 3.12.

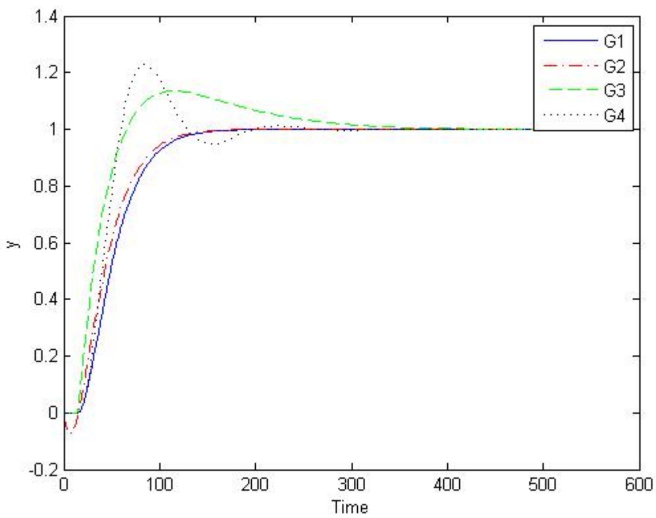


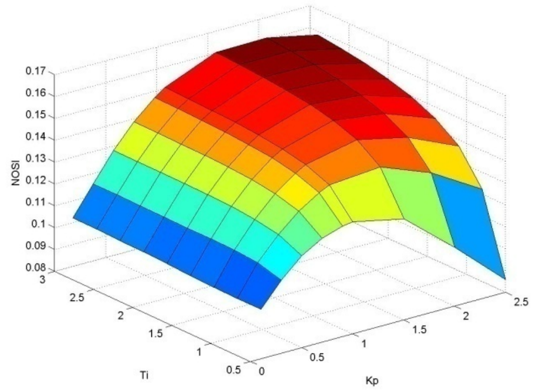
Figure 3.12: Step response for the second order models used in the sensitivity analysis

Table 3.20 shows the intervals for Kp and Ti used in the sensitivity analysis.

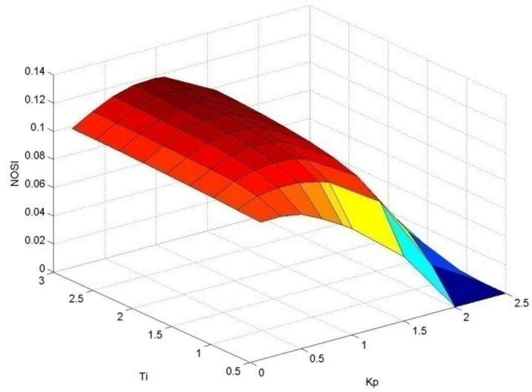
Table 3.20: Kp and Ti intervals for sensitivity analysis for the second order models

Parameter	Interval
Kp	0.1:0.1:1 1:0.5:2.5
Ti	0.5τ : 0.1τ : 3τ

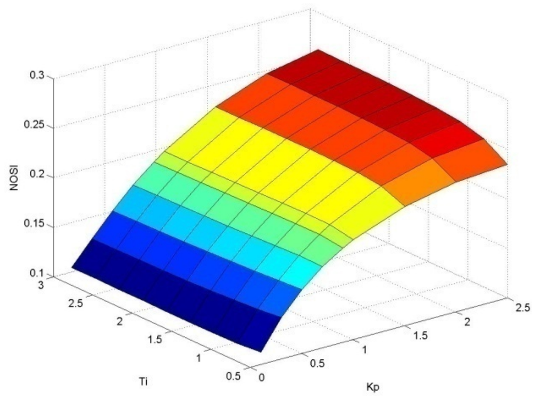
Figure 3.13 shows the impact of Kp and Ti in each index.



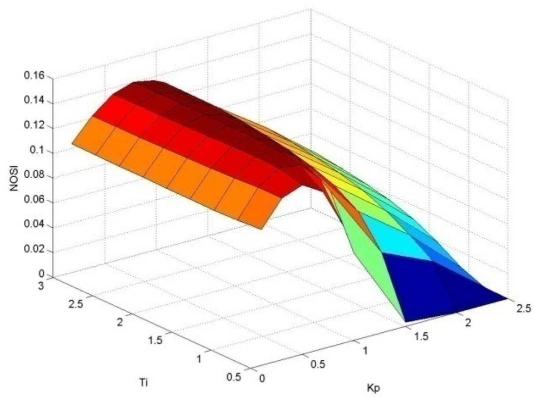
Plant 1 - Nosi



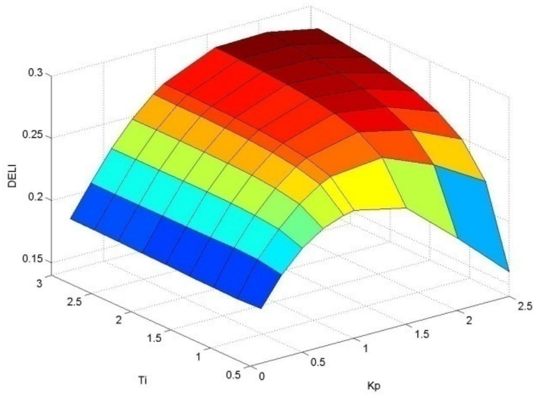
Plant 2 - Nosi



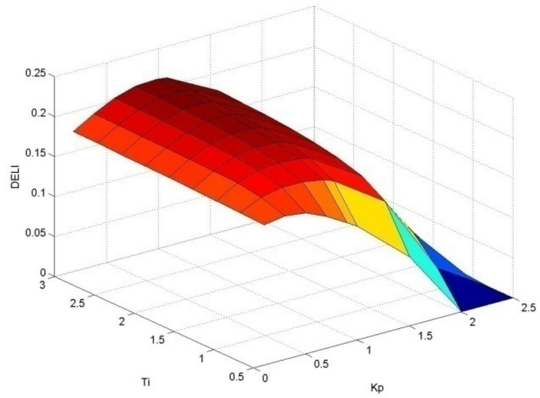
Plant 3 - Nosi



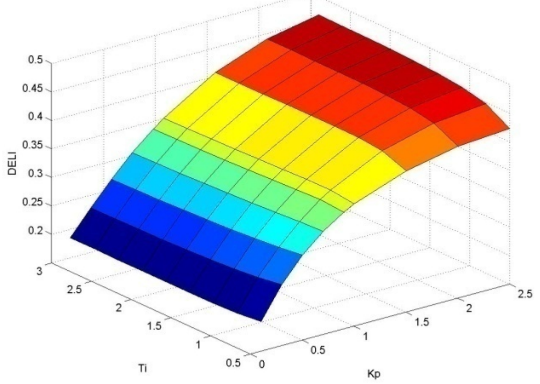
Plant 4 - Nosi



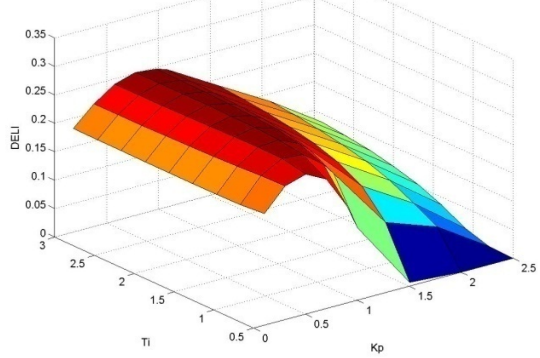
Plant 1 - Deli



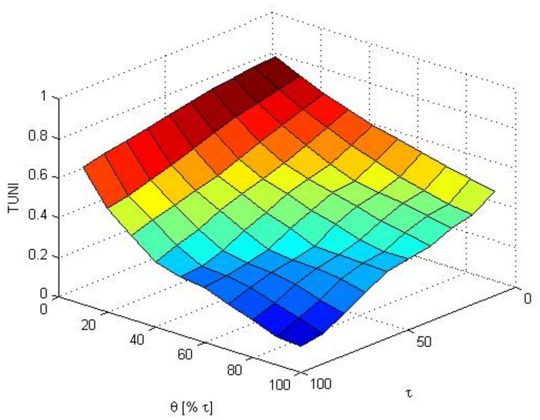
Plant 2 - Deli



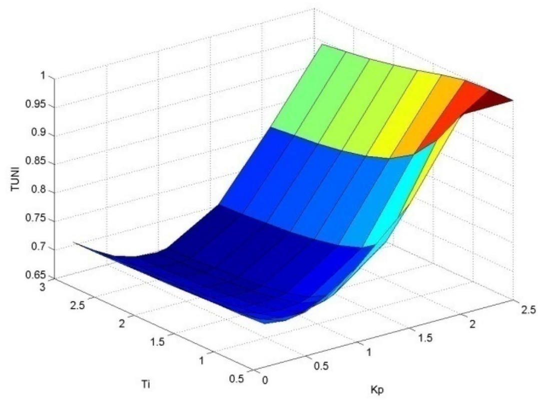
Plant 3 - Deli



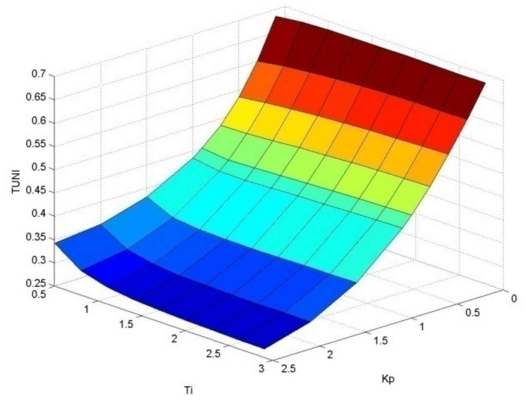
Plant 4 - Deli



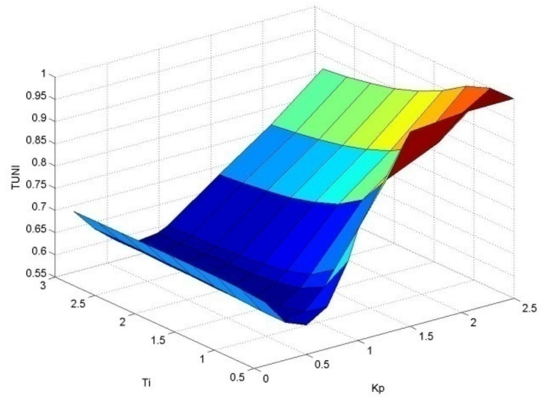
Plant 1 - Tuni



Plant 2 - Tuni



Plant 3 - Tuni



Plant 4 - Tuni

Figure 3.13: Nosi, Deli, and Tuni responses for each one of the three indices, for each plant with Kp and Ti as variables

Figure 3.13 shows coherent results when the three indices were applied. Increase the controller gain means initially decreases the impact of the tuning parameters and then its impact increases again, because of underdamped behavior. Moreover, the Deli index captures properly the time delay impact.

In the second analysis of this section the impact of time constant (τ) and time delay (θ) will be studied. Table 3.21 shows the intervals for these parameters.

Table 3.21: τ and θ intervals for sensitivity analysis

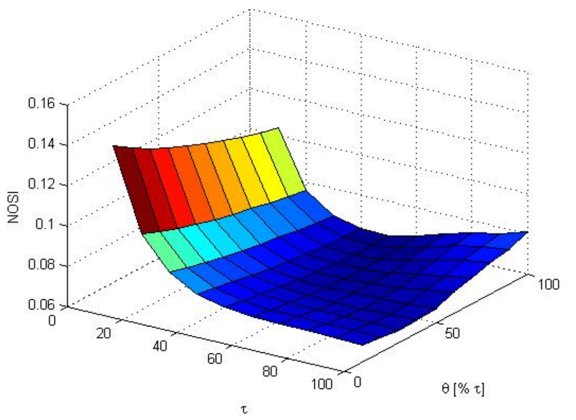
Parameter	Interval
τ	10:10:100
θ	$0.1\tau : 0.1\tau : \tau$

In this case, 4 scenarios will be used, i.e. 4 different pairs of β and ζ will be tested with the variable and τ and θ. Table 3.22 shows the values for each pair.

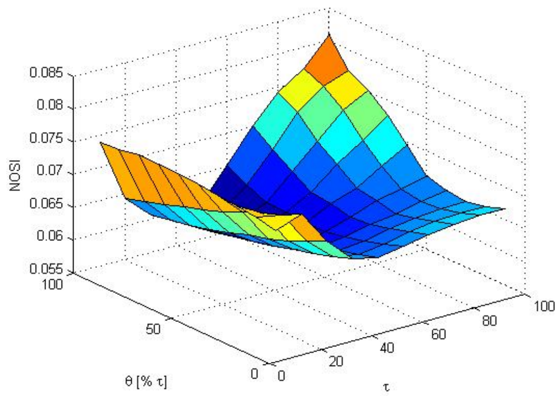
Table 3.22: Pairs of β and ζ used in the sensitivity analysis of τ and θ.

Scenario	Value [β and ζ]
1	[0 1]
2	[-10 1]
3	[100 1]
4	[0 0.43]

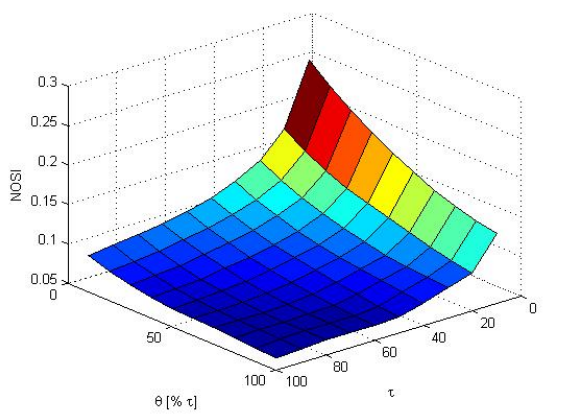
Figure 3.14 shows the responses for each one of the three indices, for each scenario.



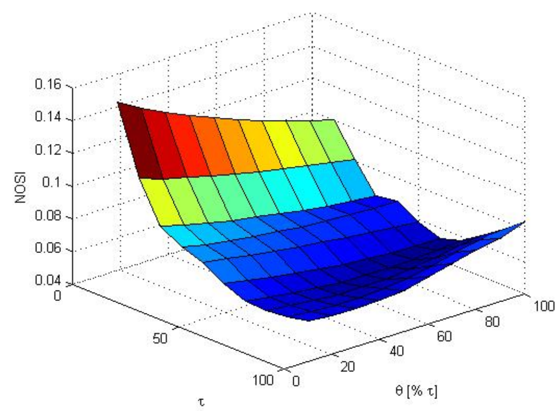
Scenario 1 - Nosi



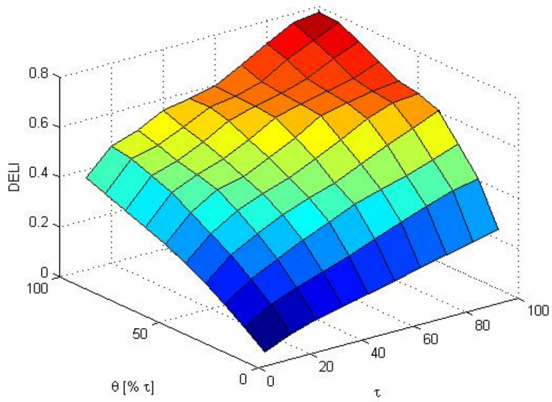
Scenario 2 - Nosi



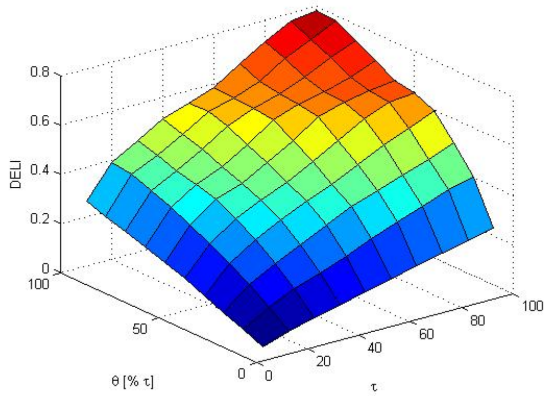
Scenario 3 - Nosi



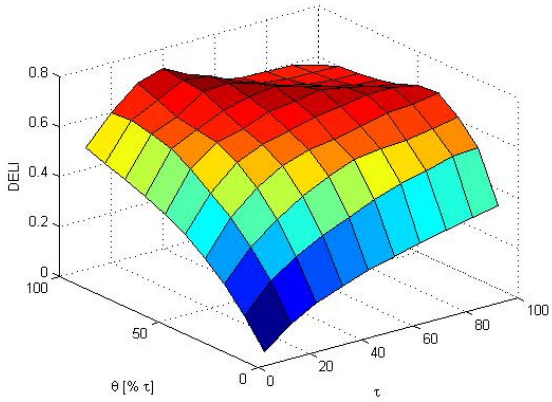
Scenario 4 - Nosi



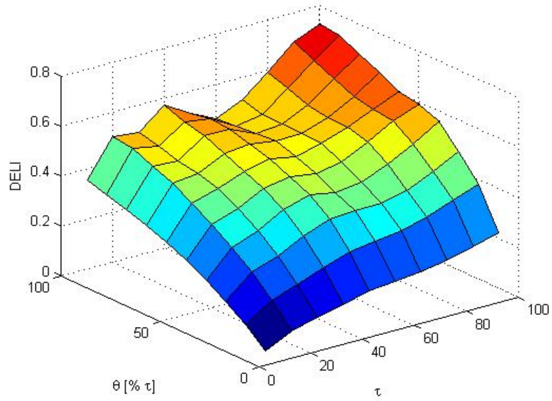
Scenario 1 - Deli



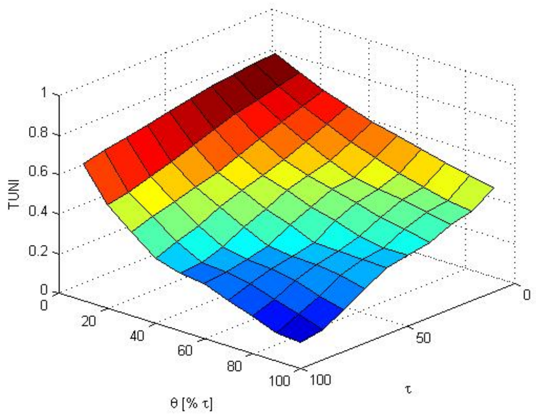
Scenario 2 - Deli



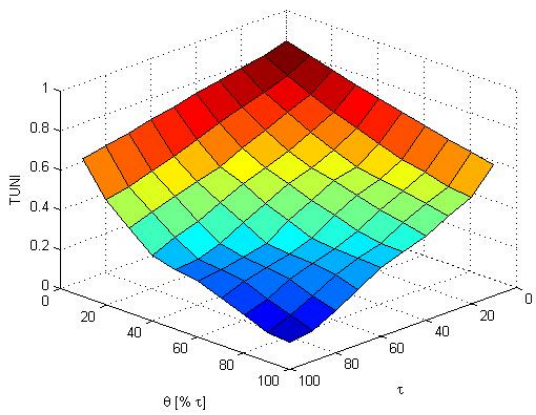
Scenario 3 - Deli



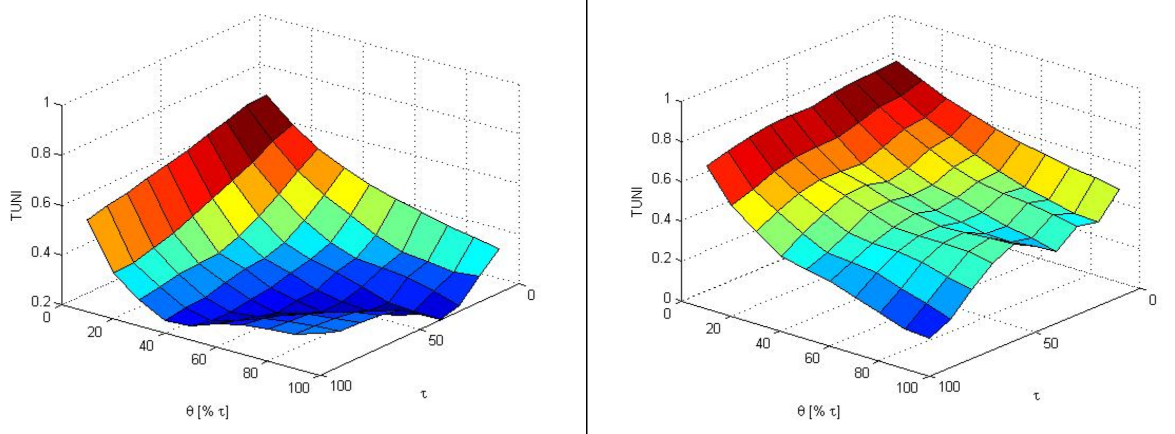
Scenario 4 - Deli



Scenario 1 - Tuni



Scenario 2 - Tuni



Scenario 3 - Tuni

Scenario 4 - Tuni

Figure 3.14: Nosi, Deli, and Tuni responses for each one of the three indices, for each scenario

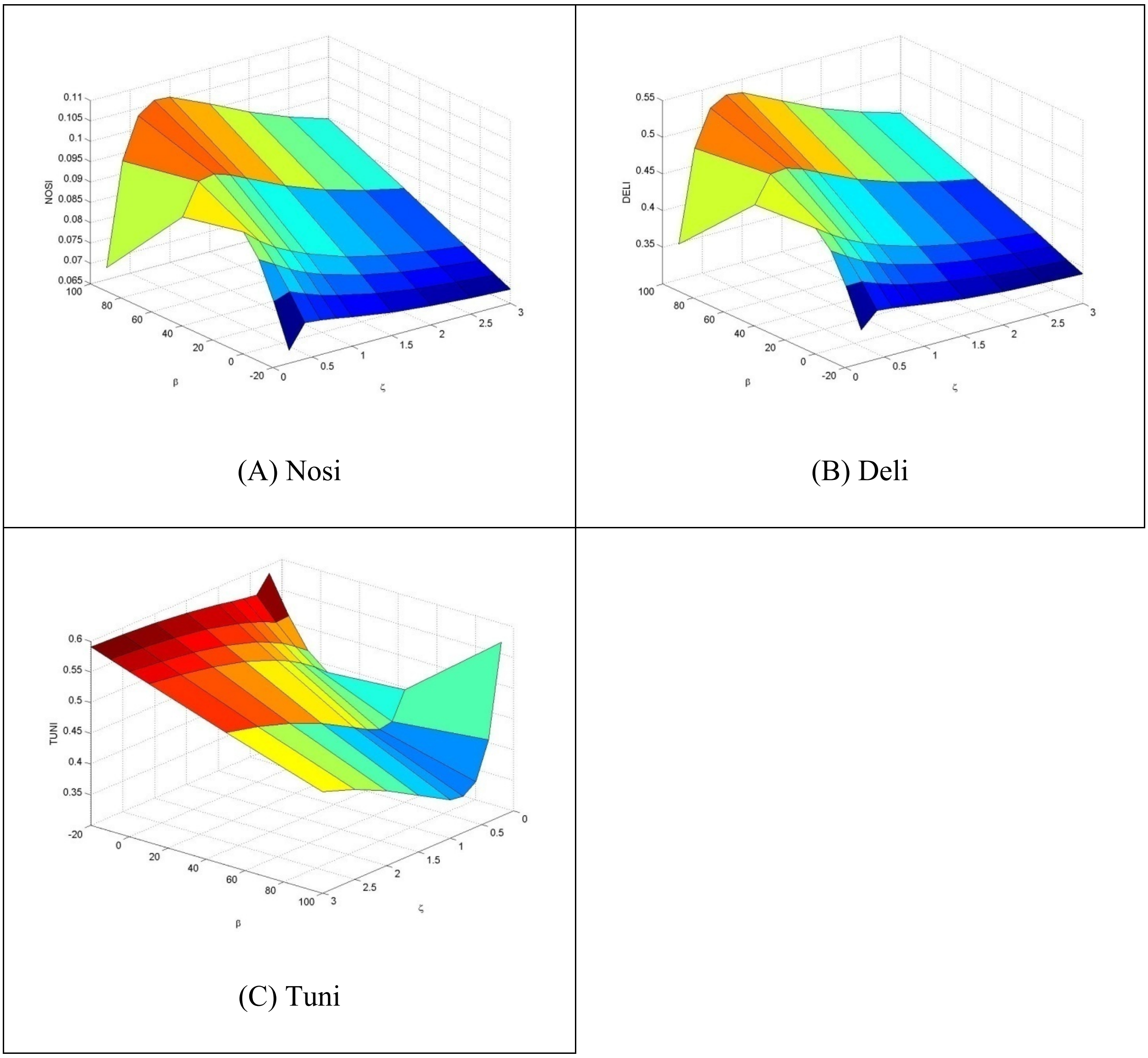
Figure 3.14 corroborates the previous results, where increasing time constant means decrease the impact of the white-noise. Moreover, decreasing the τ/θ ratio, the impact of the tuning parameters decrease. Again, the Deli index correctly captures the impact of the time delay in all scenarios.

In the last analysis, the impact of β and ζ will be exploited. Table 3.23 shows the intervals for these parameters.

Table 3.23: β and ζ intervals for sensitivity analysis

Parameter	Interval
β	[-20 -10 0 10 50 100]
ζ	[0.2:0.2:1 1.5:0.5:3]

Figure 3.15 shows the curves for each index.



(A) Nosi (B) Deli

(C) Tuni

Figure 3.15: Impact of β and ζ over each of the three indices

Based on Figure 3.15, we can see that ζ has a strong impact over the curve pattern, for all indices. For low values of ζ, Tuni has a linear behavior as function of β. For larger values of ζ, the behavior depends on β. The same is seen in Nosi and Deli.

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Chapter 4

A Novel Approach for Control Loop Performance and Robustness Assessment

Abstract:[📖] *The metrics to evaluate control loop performance (CLP) can be divided in two distinct groups. The first, called stochastic, allows evaluating CLP in real time, because they only require normal operating data and minimum knowledge of the process. The most known is de minimum variance index. On the other hand, this family of indices has some drawbacks like span and scale problems, that imposes barriers in CLP analysis. The second set is based on deterministic indices (e.g. closed and open loop rise time ratio, gain margin, phase margin, among others). Though they need intrusive plant tests to be computed, they provide measurements that make the analysis straightforward. Is it not possible join both worlds? This is the aim of this work: build an inferential model to compute deterministic metrics to assess performance and robustness of SISO controllers, where the inputs are stochastic indices and some information about the plant. This paper shows the procedure to build the Performance and Robustness Inferential Model (PRIM), its inputs and outputs, the variable selection using genetic algorithms, and the design of inference models using neural networks. The PRIM was applied in some case studies providing fruitful results.*

4.1– Introduction

"Assess control loop performance" is a term that was recently added to the process engineer's vocabulary. The reason for this "new expression" is based on the actual reality of the plants and consequent benefits that these tools can bring.

[📖] *This chapter is based on the paper submitted by M. Farenzena and J. O. Trierweiler to Control Engineering Practice*

Actual scenario: many works present the status of the industrial field, showing that 80% of the control loops have space for performance improvement (Bialkowski 1993). Besides, most of these loops have strong impact in the products variability, i.e. reducing their variability means achieving a more profitable operating point.

Benefits: Bialkowski (1993) shows the (positive) impact of CLPA tools in industrial plants and has reported the following typical results for industrial applications of these tools:

- variability reduction between 30% and 50%;
- reduce the energy consumption in 5%;
- plant throughput increase between 2 and 5%.

The precursor work that allowed to quantify the performance of hundreds to thousands of loops in real-time was proposed by Harris (1989), where the actual controller variance is compared with the minimum variance controller, proposed by Åström (1970). In the literature several reviews address CLPA (Huang et al. 1997; Jelali 2006; Qin 1998). However, few works address the limitations and drawbacks of MV benchmark (see definition in section 4.2.1). Eriksson and Isaksson (1994) say that MVI was difficult to interpret and affirm that it is inadequate to assess deterministic changes in loop performance. Bezergianni and Georgakis (2000) mention that classic (or deterministic) indices provide a better estimative of loop performance than stochastic methods.

The first objective of this work is to highlight some limitations of MVI for CLPA of SISO controllers. They can be summarized as follows:

- Strong dependence of disturbance pattern;
- The MVC is a high order controller, however in industrial DCS only low-order SISO controllers are available.
- Only performance is assessed, no information about robustness is provided.
- The scale is not absolute (i.e. there is no guaranty that a loop with MVI = 0.6 has a better performance than a loop with MVI = 0.4).
- The span of the scale is deficient. In some cases, the difference between a poor and a good tuning is very small.

These limitations make the analysis many times difficult and the diagnostic is not straightforward. The main stochastic indices for on-line CLPA and their limitations will be exploited in section 4.2.

Besides stochastic indices, there are the classical performance indices (also called deterministic indices), such as closed and open-loop rise time ratio (Rt_R), gain margin (GM), and phase margin (PM). They provide conclusive marks to quantify closed-loop performance and robustness (Goodwin et al. 2001). Their quantification in real time is expensive, because intrusive tests are necessary, however a clear picture of loop performance and robustness is provided. Section 4.3 describes some deterministic indices to evaluate CLP.

Many authors propose the use of deterministic indices to evaluate closed loop performance when setpoint activity is available (Åström 1991). Hägglund (1999) proposes an automatic method to detect sluggish loops based on output step variations. Jämsä-Jounela et al. (2003) propose to use both deterministic and stochastic methods to evaluate CLP in a flotation plant. All mentioned works "wait for" setpoint variations to evaluate performance metrics.

Is it not possible to join both worlds (deterministic and stochastic)? One where conclusive indices are provided to assess loop performance and robustness without any intrusive tests or with minimum excitation of the process, i.e. only setpoint variations. This is the aim of this work: propose an inferential model that provides deterministic and conclusive indices for CLPR assessment where the inputs are parameters that can be quantified in real time, using only normal operating data (without excitation and/or setpoint activity) for SISO controllers. In this work, the inference model is a Multilayer Feedforward Neural Network (Haykin 1999). Section 4.4 describes the main stochastic indices to evaluate loop performance, used as IM inputs. Section 4.5 shows the procedure to construct the inferential model for performance and robustness. First, the variables which are candidate to be PRIM inputs are listed and then a set of them are selected using genetic algorithms (Goldberg 1989). The inference model will be designed for two scenarios:

- only normal operating data – no intrusive excitation; and
- frequent setpoint activity.

In section 4.6, some issues on industrial application of PRIM will be discussed. In section 4.7, the proposed methodology was applied in a set of case studies, providing very good results. The chapter ends with the concluding remarks.

4.2– Stochastic indices: definitions, advantages and drawbacks

This section describes three of the most used stochastic indices to assess control loop performance: MVI, ISE, and IAE. Moreover, their limitations will be exploited.

4.2.1 – Minimum variance controller (MVC)

Assess CLP means comparing the output process variance to that which would be obtained if the "perfect controller" had been applied. The most used optimum controller is the MVC. The MVI also called Harris Index (Harris 1989) is expressed by

$$MVI(d) = \frac{\sigma_{MV}^2}{\sigma_y^2} \tag{4.1}$$

Where σ_{MV}^2 is the process minimum variance and σ_y^2 is the actual process variance.

The values of MVI are always between 0 and 1. Increasing values of MVI indicates the performance becomes better. The actual variance is easy to determine with a window of closed loop data. However, the minimal variance for a given control loop is more difficult to obtain. It depends both on the plant model and the disturbance pattern. Several methodologies to estimate the minimum variance are described in Huang and Shah (1999).

The main positive characteristic of MVI is that only routine operating data is required to assess the performance and process time delay.

4.2.2 – Indices related to Controlled Variables (CV)

Another simple alternative is to use indices based on the error of the controlled variable. The most used are Integral of Square Error (ISE) and Integral of Absolute Error (IAE).

$$\begin{aligned} ISE &= \int_{ti}^{tf} (PV - SP)^2 dt \\ IAE &= \int_{ti}^{tf} |PV - SP| dt \end{aligned} \tag{4.2}$$

Another set of indices is defined by the user. Any property of the loop (standard deviation, variance, among others) with the actual loop performance is compared with a "golden" period, where the controller performs well.

4.2.3 – Limitations concerning stochastic indices

It is well-known that MVI and other stochastic metrics have limitations and fail in many scenarios. Many authors have exposed their ideas to overcome some of them.

- Tyler and Morari (1996) proposed a method to evaluate CLP where the plant has non-minimum phase elements or unstable poles.

- Many authors proposed modifications in MVI to include setpoint variations (Ko and Edgar 2000; Perrier and Roche 1992).

- Desborough and Harris (1993) showed a method to evaluate CLP of feedforward controllers.

- Horton et al. (2003) proposed a method to assess level controllers performance.

Many limitations have been eliminated by the studies previously mentioned. However, many of them still remain. This section aims only to highlight some of these limitations, as a motivation and basis to justify the proposed methodology. To make this analysis clearer and easier to understand, these limitations will be exploited in five case studies.

In all subsequent case studies, the blocks diagram for the SISO system is represented in Figure 4.1 and the respective parameters are shown in Table 4.1.

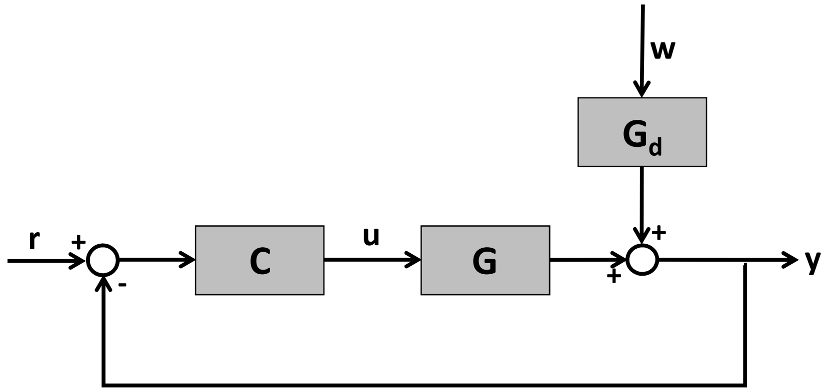


Figure 4.1: Case studies block diagram

Table 4.1: Parameters for the case studies

Parameter	Value
C	PI type $C(s) = K_P \frac{20s+1}{20s}$
G	$G(s) = \frac{1}{20s+1} e^{-3s}$
G_d	$G_d(s) = \frac{1}{30s+1}$
$\sigma^2(w)$	1

Where C is the PI controller, K_P is the (variable) controller gain, G is the linear plant, G_d is the disturbance model, and w is the disturbance input (random signal with zero mean). In this case, there is no setpoint activity.

In these case studies, we will compare two stochastic indices (MVI and ISE) with two deterministic indices (Rt_R and MS), and all conclusions will be drawn based on these indicators. Analogically, similar conclusions can be drawn using different pairs of deterministic measurements (Rt_R and St_R, Rt_R and MG, among others).

The first case study highlights one scenario where MVI and ISE agree with Rt_R. Considering that only control loop performance changes, MVI, ISE, and Rt_R are quantified, as shown in Table 4.2. This Table also shows the controller gain (K_P) for each case.

Table 4.2: K_P, MVI, ISE, and Rt_R for case study 1

Controller	K_P	MVI	ISE	Rt_R
I	0.3	0.23	2.3	0.32
II	0.8	0.30	1.8	0.95
III	1	0.33	1.6	1.2
IV	2	0.45	1.2	3.2
V	3	0.55	0.98	7.4

Based on Table 4.2, we can see that MVI and ISE agree with Rt_R, reflecting the performance improvement. However, some questions arise:

1. *Controller V has significant (45%) potential of improvement on its performance. Is it prudent to improve the performance of a controller 7 times faster than open loop to reduce this potential?*

2. *What are MVI or ISE default values for good, bad, and fair controllers?*

The CLPA needs one more benchmark (than MVC) to make the analysis straightforward: this value can be a heuristic value, as proposed by Thornhill et al. (2004) or an imposed benchmark based on each controller history, from a period where the controller performs well. Case study 1 elucidates this scenario: initially the controller has very slow performance (Controller I), then its performance is increased (Controller IV and V), even though MVI says that it is a fair controller (MVI = 0.55). In this case increasing the controller performance can make the controller unstable. Thus, the engineer computes MVI in this "golden period" and sets MVI = 0.55 as the new benchmark, instead of 1.

In the second case, the only modification from the previous scenario was the time delay, which in case study 2 is 7. The other plant parameters and controller type remained the same. The controller performance varies from a very poor controller (3 times slower than open loop) to a fast performance (5 times faster), as shown in Table 4.3. This Table also shows MVI and ISE.

Table 4.3: K_P, MVI, ISE, and Rt_R for case study 2

Controller	K_P	MVI	ISE	Rt_R
VI	0.3	0.46	2.5	0.35
VII	0.7	0.51	2.3	0.99
VIII	0.9	0.52	2.2	1.5
IX	1.5	0.55	2.1	4.0
X	2	0.56	2.1	5.6

Does MVI have a conclusive scale?

MVI and ISE showed that the performance improvement was very small, showing the span problems that occasionally happens in CLPA. The difference between a fast and very slow controller is only 10% of the scale range. On the other hand, Rt_R proved that the real performance improvement was visible. Note that both indices (ISE and MVI) need a specific benchmark for each controller, if we want to use them as a conclusive mark.

Can the performance of two controllers, measured using MVI and ISE, be compared?

Analyzing Table 4.2 and Table 4.3, other limitations can be observed. See controllers IV and VI: they have almost the same MVI, but their performance is completely different (Rt_R=3.2 and Rt_R=0.35, respectively).This simple example shows that performance evaluated by MVI or ISE cannot be compared for two or more controllers, needing a second (heuristic) benchmark used in each controller.

Increasing the time delay of the plant to 15 and the disturbance time constant to 100, two controllers were tuned ($K_P = 0.3$ and $K_P = 1.5$) for this plant and their performance was compared using MVI. Both controllers earned the same grade: MVI=0.5.

Do they have the same performance? Should the diagnostics be the same for both? Is this information enough for the CLPA?

Here, another point arises: no information about the robustness is provided. MVI gives a grade that is a mixture of performance and robustness. Consequently, the diagnostics is difficult. In this scenario, the analysis of the pair performance/robustness (Rt_R and MS), shown in Table 4.4, leads to a straightforward conclusion: controller A has very slow performance, while controller B is very fast, however its robustness is poor.

Table 4.4: MS and Rt_R for case study 3 – both controllers have same MVI

Controller	MS	Rt_R
A	1.2	0.25
B	3	4

In the fourth case, the default controller (Table 4.1) is affected by three different disturbance patterns, as shown in Figure 4.2. In the first scenario (from time 0 to 1000) the controller performs perfectly, because MVI is close to one. Just changing the disturbance characteristics (scenario 2 and 3), the controller performance changes drastically, showing big potential of improvement. Besides, the variance of the signal remained constant in the three scenarios.

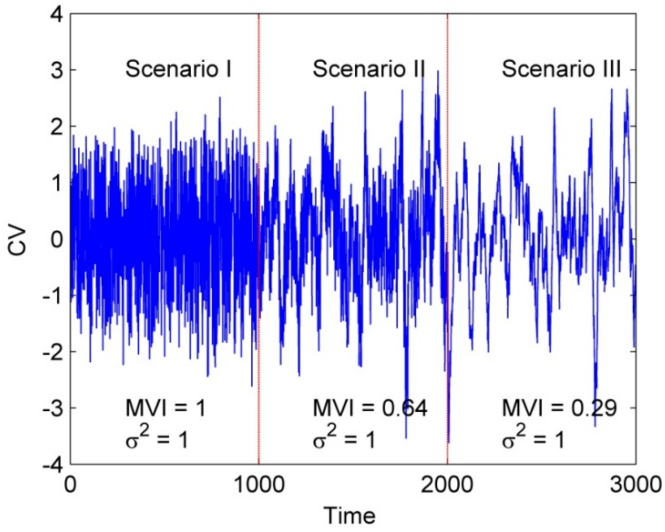


Figure 4.2: Case study 4 – disturbance pattern influence over MVI

Is this a good controller? Was MVI able to evaluate correctly the performance in this case study?

In the fifth case, the same controller is applied in a scenario where the plant gain changes during controller operation. This fact is quite common in multipurpose plants where the same controller works in several operating points (OPs). In the three OPs, the disturbance pattern also changes. Figure 4.3 shows the closed loop response for these three scenarios and the closed loop step response.

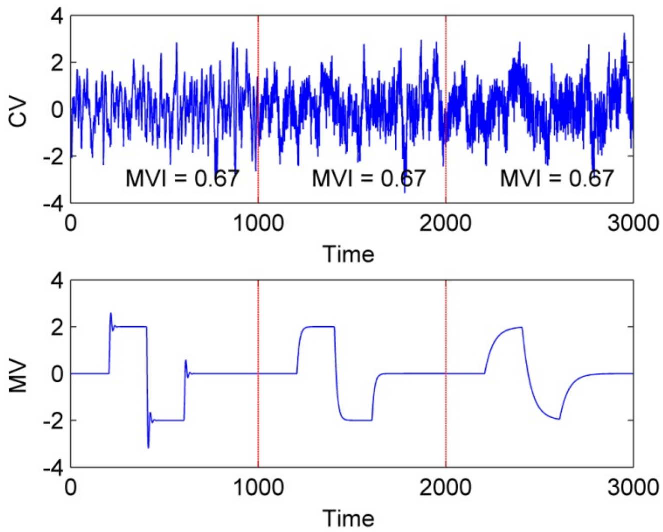


Figure 4.3: Case study 5 – disturbance pattern change masks the real controller performance

The MVI provided the same value for all scenarios, despite the fact that the closed loop performance changed abruptly, as shown by the closed loop step responses (Rt_R varies from 0.47 to 3.7).

Based on the five cases, MVI (and other widely used indices to address CLP) shows good results in some scenarios, however in many others, they do not reflect the real loop performance. The main drawbacks of MVI can be summarized as follows:

1. *Strong dependence of disturbance pattern.* As shown in case 4, the same controller can show completely contrasting performance, depending on the disturbance pattern. Considering that most of plants have disturbances with time variant patterns, one controller that today has a good performance, tomorrow it can perform fair or even badly if MVI is used as metrics.

2. *No conclusive scale*. The MVI does not have an absolute scale. For instance, the fast controller in case study 1 (controller IV) with $Rt_R = 4.4$ (MVI = 0.52) has almost the same MVI as calculated for the slowest controller in case study 2 (controller VI) (i.e., MVI = 0.51, $Rt_R = 0.27$).

3. *Low resolution range.* The span is deficient. In some cases, the difference between a poor and a very good tuning is very small. Case study 2 has deficient span: a very fast controller has MVI = 0.61 while a very slow controller has MVI = 0.51. Similar behavior is observed by the other stochastic indices.

4. *No conclusion about robustness.* Only performance is assessed, no information about robustness is provided.

At this point, one question surely arises: *Is the MVC the best benchmark to compute alone the closed loop performance?* The answer is clearly NO and an alternative will be proposed in the next section.

4.3– Deterministic metrics for performance and robustness

The main reason of stochastic performance indices failure is the absence of a common and absolute target to quantify the performance and robustness. Conclusive indices are available in the literature, however determining them in a real plant is impracticable, because invasive tests are necessary. This section discusses the advantages of deterministic indices over the ones usually used to CLPA.

4.3.1 – Performance

For stable systems, the loop performance can be addressed using the classical set of parameters that describe the system dynamics. For both open loop and closed loop step responses, the following properties can be quantified (Goodwin et al. 2001):

- Steady-state value (y_∞) – the final value of the step response;

- Rise time (*Rt*, $t_{i95\%}$-$t_{5\%}$) – the time elapsed between the moment at which the step response reaches for the first time $0.05y_\infty$ and $0.95y_\infty$. These values vary from author to author.

- Settling time (*St*, $t_{f95\%}$-$t_{5\%}$) – the time required between the moment at which the step response reaches for the first time $0.05y_\infty$ and the time that the process enters and remains inside a band whose width is $0.05y_\infty$ (Seborg et al. 2004).

- Overshoot – the ratio between maximum amount that the step response exceeds its final value (Os) and the final value (y_∞).

Figure 4.4 illustrates the mentioned characteristics.

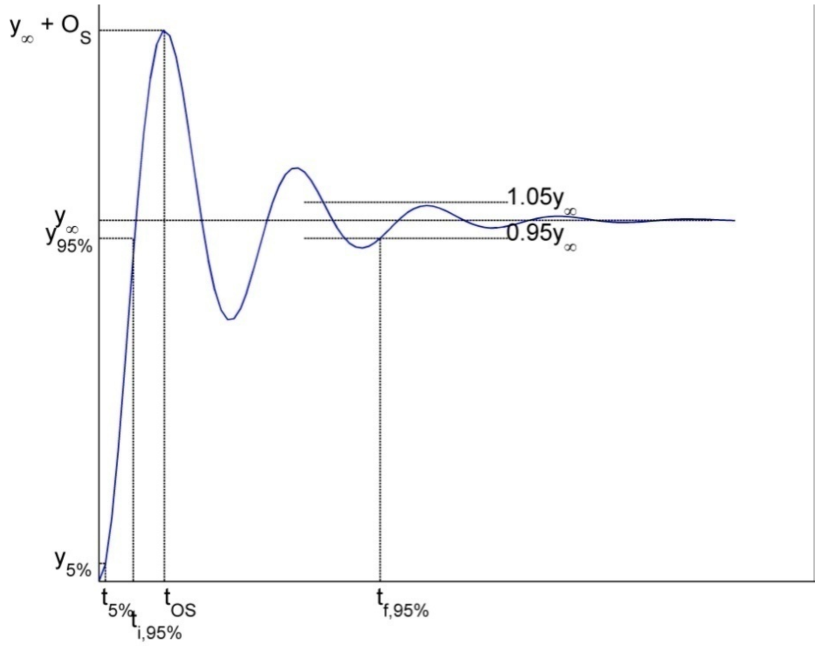


Figure 4.4: Classical performance quantifiers

Based on these parameters, the following indices can be used to evaluate closed loop performance:

- rise time ratio (Rt_R) between open and closed loop; and

- settling time ratio (St_R) between open and closed loop.

The ratio between open-loop and closed-loop rise time (Rt_R) is easier to understand and interpret for any control engineer than MVI or error based performance indices. Besides, Rt_R provides an accurate and conclusive measurement for performance assessment, i.e. not only the performance of a given controller can be analyzed under different scenarios but also different controllers. To illustrate this affirmation, Figure 4.5 shows the same controller with three distinct performances (P_1, P_2, and P_3), as a consequence of plant change.

Based on Figure 4.5, the following conclusions easily arise:

- controller P_1 has both good performance and robustness;

- controller P_2 has a sluggish performance; and
- P_3 has a very fast performance, however its robustness is poor.

These metrics have also an upper bound that is the maximum rise time ratio. This benchmark can be computed using Blaschke factorization (Trierweiler 1997), as long as the time delay and time constant are available.

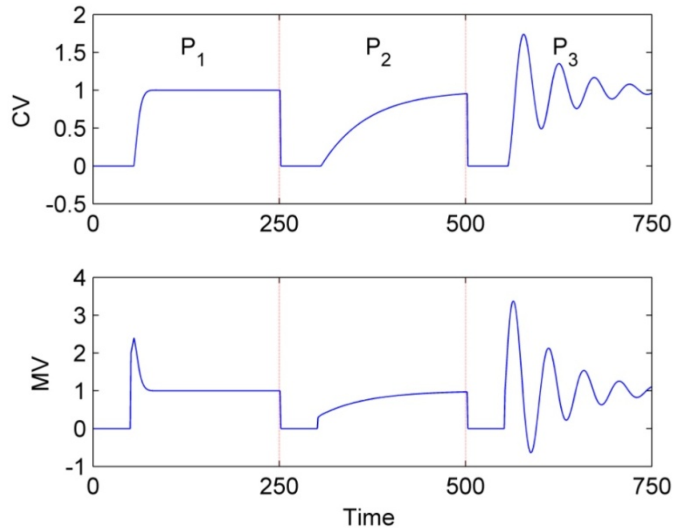


Figure 4.5: Control loop performing with (P_1) good performance and robustness; (P_2) low performance; and (P3) high performance and low robustness.

Though these indices provide a conclusive mark for performance, their computation requires intrusive tests, avoiding their large scale application.

4.3.2 - Robustness

Similar parameters can be used to address the robustness of a given loop, i.e. measure how far is the current loop from the marginal stability. Figure 4.6 shows the representation of phase and gain margins, in the Bode Diagrams. The gain margin (GM) can be defined as the maximal additional gain that would take the closed loop to reach the critical condition. The phase margin (PM) quantifies the pure phase delay that could be added to achieve the critical point.

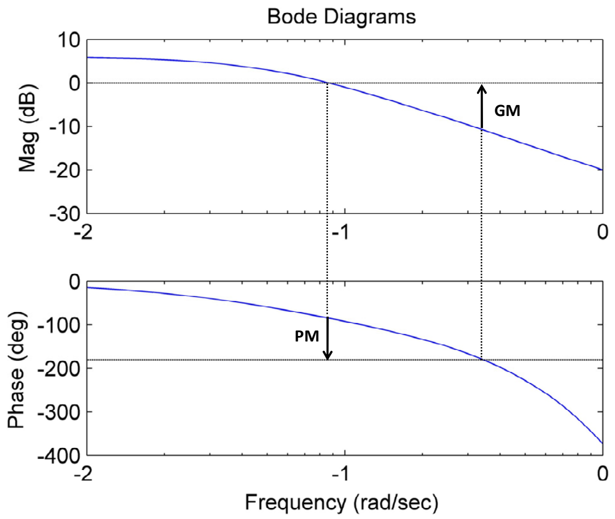


Figure 4.6: Geometrical definition of phase and gain margins based on Bode Diagrams

Another measurement for the robustness is the Maximal Sensitivity (*MS*). Based on the plot of $C(j\omega)G(j\omega)$ (Nyquist Diagram), the distance from -1 is computed (*r*) (see Figure 4.7). The *MS* is defined based on the inverse of *r*. The larger the *MS* value is, the closer the loop will be to the instability.

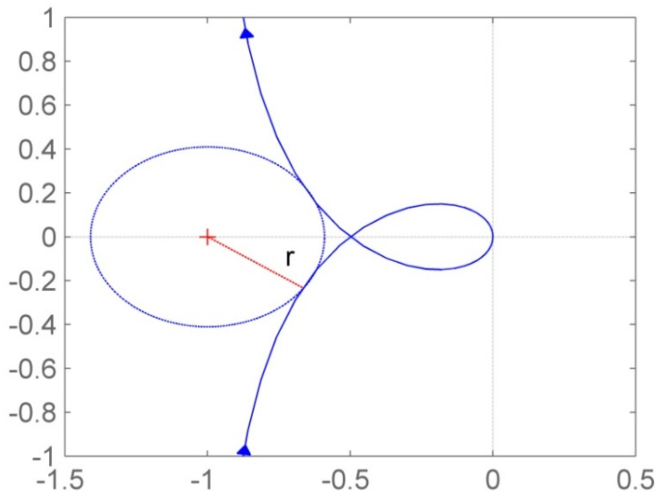


Figure 4.7: Nyquist Diagram – Maximal Sensitivity definition

Based on these indices (performance and robustness), some rules of thumb make CLPA straightforward (Seborg et al. 2004).

The velocity can be easily evaluated using Rt_R:

- values below 1 indicates poor performance;
- values between 1 and 2 indicates fair performance;

- values between 2 and 4 indicates good performance;
- values between 4 and 6 indicates very good performance;
- values higher than 6 indicates very fast performance.

A clear scenario about the controller robustness is provided by MS:

- values between 1.4 and 2 indicate a suitable robustness;
- values above 2 indicate a low robustness controller;
- values below 1.4 indicate a robust controller.

The same conclusions can be drawn using other pair of deterministic metrics (e.g. Rt_R and St_R; Rt_R and MG; among others).

4.4– Preliminary definitions

In section 4.5, the construction of PRIM will be formalized. However, first it is necessary to make a brief review about the indices used as inputs. Some of them are well know, others are defined in this work.

4.4.1 – Process information

The process information to be provided to the methodology to evaluate CLP and robustness should be minimal. Normal operating data of the controller, without setpoint activity, should be available. However, if setpoint activity is available, it will also be used in this methodology. Important process information can be obtained when the process has artificial excitation.

Considering that the process can be modeled as a first order plus time delay model, some loop parameters (e.g. time delay and/or time constant) can also be used to assess loop characteristics, however automatic process identification should be avoided. These parameters are most of the times available, and when they are not, the process data available can be used or engineer expertise can be used to obtain them.

4.4.2 – Indices that can be quantified using only normal operating data – no setpoint activity

Many indices that require only normal operating data are used to evaluate CLP. In this section, only indices that can be quantified without setpoint changes will be described.

The first is the MVI, previously defined (Section 4.2). The second set of indices is based on integral of controller error (ISE and IAE), both defined in the same section.

The third set of indices decomposes the signal (*y*) in three portions (Farenzena and Trierweiler 2007):

$$y = y_{WN} + y_{TD} + y_{FA} \tag{4.3}$$

Where:

- y_{WN} provides the white noise portion of the signal;
- y_{FA} provides the portion that can be removed by feedback controller;
- y_{TD} provides the portion that cannot be removed because of the time delay.

The indices that evaluate each contribution are:

$$\begin{aligned} nosi &= \frac{\sigma^2(y_{WN})}{TSV} \\ deli &= \frac{\sigma^2(y_{TD})}{TSV} \\ tuni &= \frac{\sigma^2(y_{FA})}{TSV} \end{aligned} \tag{4.4}$$

where σ^2 is the signal variance and TSV is the total signal variance:

$$TSV = \sigma^2(y_{WN}) + \sigma^2(y_{TD}) + \sigma^2(y_{FA}) \tag{4.5}$$

The second set of indices is based on the autocorrelation function (R_{xx}) of controller output (Box et al. 1994). The first index provides the autocorrelation slope (AcorSl) before the curve reaches the confidence interval (CI). Defining *AcorFS* as the subset of R_{xx} between lag equal to time delay (θ) and the first point before that this function crosses the confidence interval, the *AcorSl* can be defined as the slope of *AcorFS*. Figure 4.8 illustrates these definitions.

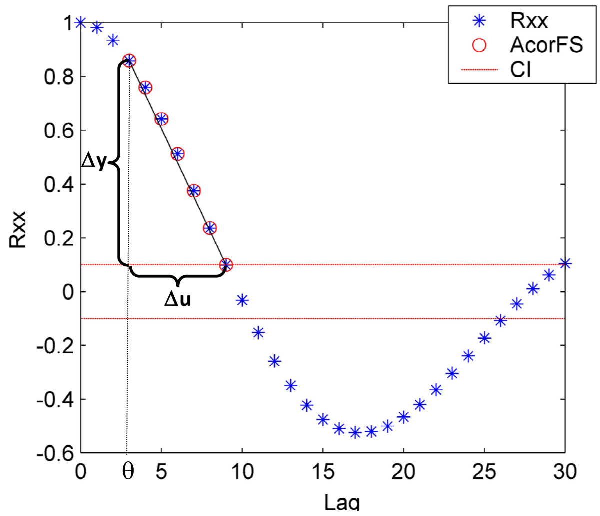


Figure 4.8: *AcorFS* and *AcorSl* definitions

AcorSl can be defined as:

$$AcorSl = \frac{\Delta y}{\Delta u} \tag{4.6}$$

The second index based on autocorrelation function is the area outside the confidence limits. Defining R_{OCL} as:

$$\begin{aligned} R_{OCL} &\triangleq |R_{xx}| - CI, |R_{xx}| > CI \\ R_{OCL} &\triangleq 0, |R_{xx}| < CI \end{aligned} \tag{4.7}$$

Thus, the area outside of confidence bonds (*AcorAr*) can be defined as:

$$AcorAr = \int R_{OCL} dLag \tag{4.8}$$

Figure 4.9 illustrates the index based on the area outside of confidence bonds (*AcorAr*).

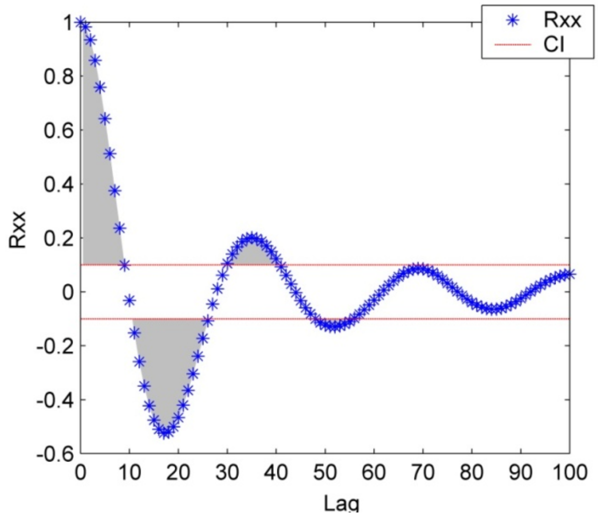


Figure 4.9: Illustration of *AcorAr* – grey area indicates the area outside confidence bounds

4.4.3 – Indices that need setpoint activity to be quantified

A significant portion of loops have frequent setpoint changes and this information can be valuable to estimate more accurately the performance/robustness pair and improve the IM.

The area of CV and MV is also computed (CV_{AR} and MV_{AR}) to be one potential IM input. These indices can be quantified using the following relation:

$$\begin{aligned} CV_{AR} &= \int_0^{tf} (CV - CV_\infty)dt \\ MV_{AR} &= \int_0^{tf} (MV - MV_\infty)dt \end{aligned} \tag{4.9}$$

Where CV_∞ and MV_∞ are respectively the controlled and manipulated variables after the process has settled in the new operating point and *tf* is the settling time of the closed-loop system.

One candidate index could be the Relative Variance Index (RVI) (Bezergianni and Georgakis 2000), however it will not be inserted in the list of possible variables. It compares the actual variance with both MVC and open loop variance.

$$RVI = \frac{\sigma_{OL}^2 - \sigma_y^2}{\sigma_{OL}^2 - \sigma_{MV}^2} \tag{4.10}$$

where σ_{OL}^2 is the open-loop variance. The main drawback of this method is that the plant and controller models should be identified to compute this index, which makes this procedure difficult to be automatized.

4.5– Inference model definition and design

This section defines the PRIM and formalizes the procedure to construct it.

4.5.1 – Definition

Definition 1: *The PRIM can be defined as a non-linear function (N) that provides deterministic metrics (I_D) for plant performance and robustness, using only indices that can be easily quantified using only normal operating data (I_S) and plants characteristics (P_C).*

$$I_D = N(I_S, P_C) \tag{4.11}$$

Table 4.5 summarizes the candidate variables for PRIM inputs and Table 4.6 shows some possible PRIM outputs.

Table 4.5: PRIM candidate inputs variables. Light grey: variables that can be evaluated without setpoint variation; and white variables: whose quantification requires at least one setpoint change

No	Name	Description
1	τ	Process first order time constant
2	θ	Process time delay
3	MV	Process minimum variance estimative
4	MVI	Minimum variance index
5	IAE	Integral of absolute error
6	ISE	Integral of square error
7	Nosi	Noise portion of the signal
8	Deli	The portion that cannot be removed by feedback controller
9	Tuni	The portion that can be removed by feedback controller
10	AcorSl	Autocorrelation slope
11	AcorAr	Autocorrelation area outside confidence bounds
12	CV_{AR}	Output variable area for a setpoint change
13	MV_{AR}	Input variable area for a setpoint change

Table 4.6: PRIM output variables

Name	Description
Rt_R	Open loop and closed loop rise time ratio
St_R	Open loop and closed loop settling time ratio
MS	Maximal sensitivity
GM	Gain margin
PM	Phase margin

4.5.2 – Non-linear model: neural network

The mathematical model used to predict deterministic PRI based on stochastic indices is a Multilayer Feedforward Neural Network (Haykin 1999). We chose such family of models because of its capability to interpolate high nonlinear functions with low number of parameters (neurons).

The net has two layers:

- first (hidden): hyperbolic tangent sigmoid transfer function and variable number of neurons;
- output layer: linear transfer functions.

The PRIM structure is shown in Figure 4.10.

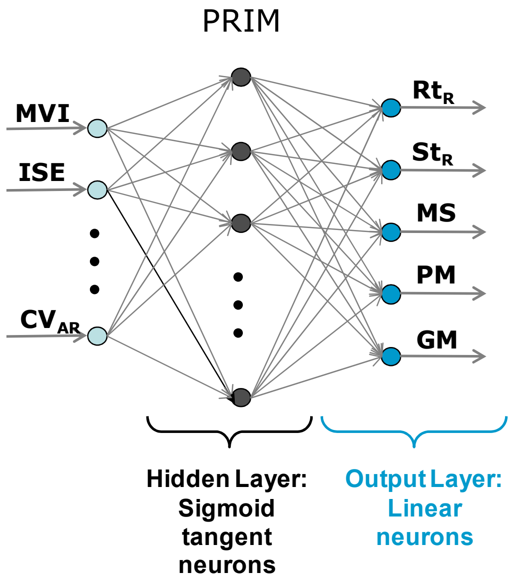


Figure 4.10:PRIM structure based on neural networks

In this work, the Neural Networks toolbox from MATLAB® version 5.0 was used to design and train the Neural Network.

One different neural network will be trained for each output. We do not train just one, with five outputs because the inputs set selected for each output are distinct.

4.5.3 – The PRIM

In this work, two distinct PRIM will be proposed: the first where setpoint variations are frequent and all 13 variables shown in Table 4.5 can be potentially used to estimate CLPR. The second, where the loop does not show frequent setpoint variation and only data with a fixed setpoint is available. In this case, only the first 11 variables of Table 4.5 can be used.

The first set of neural-networks (NNs) where setpoint activity is shown will be called NET_F, while the set where no setpoint variation is shown is called NET_N.

4.5.4 – PRIM design

This section describes the procedure to build the PRIM. The steps are equivalent to build a soft-sensor for a process variable (Rawlings 1988). Figure 4.11 summarizes the procedure to build PRIM.

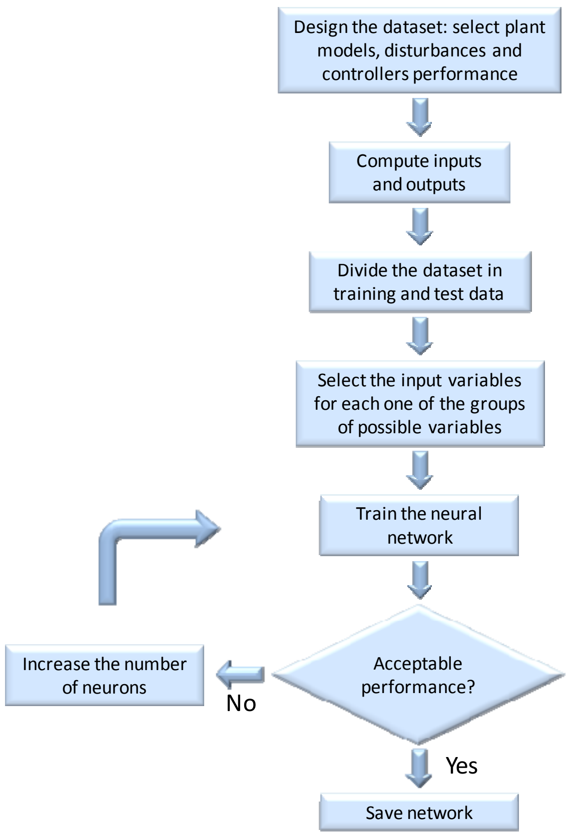


Figure 4.11: Procedure to construct the PRIM

Initially the set of plants, controllers and disturbances are chosen. The scheme of the system is shown in Figure 4.1. In this work, we will describe the procedure using only first order plus time delay plants and disturbances. Table 4.7 shows the parameters used to design the PRIM.

Table 4.7: Parameters used to design the PRIM (τ, τ_D, and θ are multiples of sample time unit set)

Parameter	Values
τ	[5, 10:10:100, 120:20:200]
τ_D	[30 50 100 200]
θ	[1:2:21, 25:5:50]
$Rt_{r,DESIGN}$	[0.1:0.1:1, 1.5:0.5:6]

Where $Rt_{r,DESIGN}$ is the desired rise time ratio between open and closed loop performance and τ_D is the time constant for the disturbance model (G_d). The notation to create each dataset follows the MATLAB notation. The vector written as $[10:10:50]$ can be understood as $[10 \quad 20 \quad 30 \quad 40 \quad 50]$.

The methodology to design the PI controller used in this case study is based on frequency domain (Faccin and Trierweiler 2004). When the desired performance is not achievable, the methodology set the controller to the best achievable performance.

The whole dataset has 26076 points. It is initially divided in two parts: training and test datasets. They have respectively 80% and 20% of the data and the points are randomly chosen (Rawlings 1988).

The NN performance is measured based on the correlation coefficient (R^2) between original and predicted values using the training dataset (Box et al. 1994). The test dataset was used subsequently to validate the generalization performance of the network.

The performance is considered as acceptable when R^2 is above 0.96, for the training dataset. If this value is smaller, then the number of neurons was increased. The test dataset was used subsequently to evaluate the prediction of the model, both measured by R^2.

Another version of IM can be built using second order plants (*G(s)*) with the following structure:

$$G(s) = \frac{K(\beta s + 1)}{\tau^2 s^2 + 2\xi\tau s + 1} \tag{4.12}$$

In this case, the set parameters [K, β, τ, and ζ] should be varied.

4.5.5 – Variables selection

As previously shown, the number of inputs is large, so it is advisable to select only the variables that better describe the output metrics. To help in variable selection, genetic algorithms (GA) (Goldberg 1989) were applied.

The algorithm has elitism, mutation and crossover as its genetic operators. The initialization method is based on roulette wheel selection. The fitness function is given by the cross correlation between the training data and the neural network predicted values. The termination criterion is based on the maximum number of generations (MNG). Table 4.8 shows the settings of GA algorithm. Their selection is based only on heuristics values.

Table 4.8: GA settings

Parameter	Values
Initial population	100
MNG	100
Mutation (%)	10
Elitism (%)	20
Crossover (%)	70

During the variable selection procedure, the neural network has a fixed number of neurons in its hidden layer (5) and the training procedure has only 1000 epochs. Results were generated considering the maximum number of variables equal to 5. One different group of variables was selected for each output, because the "best set" of input variables is distinct for each output. We also tried stepwise regression (Rawlings 1988) to select the variables, and similar results were obtained.

Table 4.9 shows the selected variables by NET_F for each output. Remember that NET_F is the PRIM where some inputs require setpoint activity to be computed.

Table 4.9: variables selected by GA for NET_F

Output	Variables
Rt_R	[τ deli AcorAr CV_{AR} MV_{AR}]
St_R	[τ deli AcorSl CV_{AR} MV_{AR}]
MS	[τ AcorAr AcorSl CV_{AR} MV_{AR}]
GM	[τ deli AcorAl CV_{AR}]
PM	[τ θ deli AcorSl CV_{AR}]

Table 4.10 shows the selected variables by NET_N for each output. Remember that NET_N is the PRIM where inputs do not need setpoint activity to be computed.

Table 4.10: variables selected by GA for NET_N

Output	Variables
Rt_R	[τ θ deli AcorSl]
St_R	[τ θ deli AcorSl]
MS	[τ deli tuni AcorSl AcorAr]
GM	[τ θ MVI deli AcorAr]
PM	[τ θ MVI AcorAr]

4.5.6 – PRIM performance

Subsequently, each neural network had its performance improved. It was trained for more 10,000 epochs, after the variable selection. If the NN performance, measured by correlation coefficient (R^2), does not reach a threshold value (0.96), the number of neurons is increased. At each step, the number of neurons was increased by a factor of 10 and the maximum number was 100. If the number of neurons is increased until 100 and the performance does not show visible improvement, then the best net with the minimum of neurons is selected, even if the desired performance was not reached. The minimum number of neurons is 5.

The cross-correlation coefficients (R^2) for each output are shown in Table 4.11, using the training and test datasets.

Table 4.11: Networks performance with the best set of input variables for training and test datasets for NET_F

Output	Neurons	R^2 training	R^2 test
Rt_R	5	0.99	0.99
St_R	10	0.99	0.99
MS	20	0.91	0.90
GM	5	0.97	0.96
PM	10	0.96	0.96

As shown in Table 4.11, the performance of PRIM is very good when the setpoint activity is present in the process variable. Also, the number of neurons is small for all cases.

Table 4.12 shows the training and test cross-correlation coefficients for NET_N for each PRIM output.

Table 4.12: Networks performance with the best set of input variables for training and test datasets for NET_N

Output	Neurons	R^2 training	R^2 test
Rt_R	10	0.98	0.98
St_R	10	0.99	0.99
MS	50	0.91	0.91
GM	10	0.98	0.98
PM	20	0.96	0.96

Similar results were obtained, even when no external excitation is inserted in the plant. Here (Table 4.12), the performance is smaller than NET_F, with a larger number of neurons.

4.6- Practical Issues about PRIM Industrial Implementation

This section discusses some practical issues about the industrial implementation of PRIM.

The PRIM allows computing conclusive indices to evaluate "control loop health". The methodology only requires normal operating data and minimum knowledge of the process.

The deterministic metrics, supplied by PRIM, allows the process engineer an effective and fast CLPR analysis, because the diagnostic based on these indices is straightforward. Moreover, the necessary time to train engineers, operators, and people that will work with CLPA tools will be shorter because few intuitive parameters should be learnt (e.g. Rt_R and MS) and the benchmark can be the same for all controllers of the same type (flow, temperature, etc) and/or characteristics (cascade, normal, buffer tanks, among others).

The PRIM performance is dependent on the correct estimation of input parameters, mainly time delay and time constant. If these values are not properly evaluated, the accuracy of the predicted indices will decrease.

Based on our limited experience in industrial applications, we see that loops where the white noise influence is high tends to spoil the PRIM accuracy, because the autocorrelation slope (AcorSl) falls in one or two lags. This scenario is very rare and occurs because the data trend does not have enough excitation and makes all indices (not only the ones provided by PRIM) meaningless. To exemplify this phenomenon, the process output of a flow controller in a Brazilian petrochemical plant is shown in Figure 4.12. It also shows the autocorrelation function (R_{XX}) for this loop.

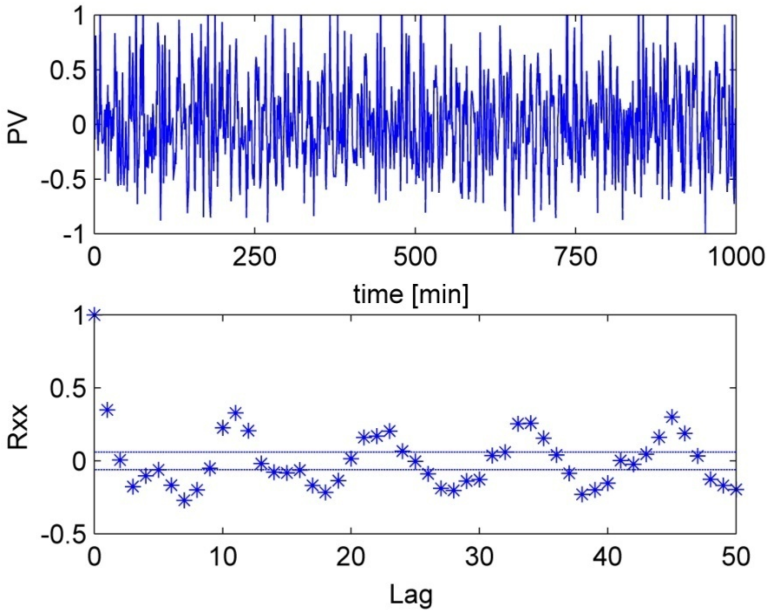


Figure 4.12: Process variable (PV) and autocorrelation plot (R_{xx}) for a flow controller in a Brazilian petrochemical plant – see that the data is normalized and has zero mean

See that R_{xx} goes inside the confidence bounds (dotted lines) in two lags. In this case, both MVI and Rt_R provide meaningless results (MVI = 1 and Rt_R = 10).

Plants where the sampling time is properly chosen and the disturbance has a fixed pattern provide more accurate IM results. In this case, the IM can be customized for one specific scenario. Loops where the time period was underestimated (Levine 1996), PRIM can provide erroneous results.

If the data is compressed, its impact should be quantified to avoid mistaken results (Thornhill et al. 2004).

4.7 – Case studies

This section details the application of PRIM methodology in the case studies, previously shown, where stochastic indices do not provided conclusive results.

Section 4.2.3 showed the application of deterministic indices, as well as stochastic indices in five case studies, highlighting the advantages of the deterministic indices and the limitations of MVI and other stochastic indices. In that section, all deterministic parameters were intrusively computed, i.e. the plant and controller models were available and setpoint changes were made. In this section, we will compare the theoretical results (TR) with the parameters predicted by PRIM (PR), using only normal operating data.

We consider here that no setpoint activity is shown, i.e. NET_N will be used for all examples. Similar (or better) results are obtained (not shown here) when NET_F is used.

In the first case study, five controllers were tuned for the same system. Table 4.13 shows the comparison between the predicted (PR) and theoretically computed (TR) Rt_R for case study 1.

Table 4.13: Predicted (PR) and theoretically computed (TR) Rt_R for case study 1 and the absolute error (A_{ERROR})

Controller	PR	TR	A_{ERROR}
I	0.54	0.29	0.25
II	0.84	0.83	0.01
III	1.3	1.8	-0.5
IV	4.8	4.4	0.4
V	7.8	8.8	-1

Table 4.13 shows that the error between the Rt_R predicted by PRIM and theoretically calculated is small, for case study 1.

Table 4.14 shows the comparison between the predicted (PR) and theoretically computed (TR) for case study 2.

Table 4.14: Predicted (PR) and theoretically computed (TR) Rt_R for case study 2 and the absolute error (A_{ERROR})

Controller	PR	TR	A_{ERROR}
VI	0.66	0.27	0.39
VII	1.3	0.75	0.55
VIII	1.8	1.2	0.6
XI	3.6	3.7	-0.1
X	5.8	5.5	0.3

Again, as shown in Table 4.14, PRIM provided the correct information about case study 2 performance.

Table 4.15 shows the comparison between the predicted (PR) and theoretically computed (TR) Rt_R and MS for case study 3.

Table 4.15: Predicted (PR) and theoretically computed (TR) Rt_R and MS for case study 3 and the absolute error (A_{ERROR})

Controller	PR	TR	A_{ERROR}
MS - A	1.1	1.2	-0.1
MS - B	2.6	3.0	-0.4
Rt_R - A	0.20	0.25	-0.05
Rt_R - B	3	4	-1

Summarizing the results of Table 4.13, Table 4.14, and Table 4.15, we can affirm that PRIM estimated with very good precision the performance and robustness for scenarios where classical stochastic indices failed. Because of PRIM potentialities, a clear picture about the performance and robustness of each loop is provided, making the analysis straightforward.

4.8- Concluding remarks

Assess control loop performance is essential to ensure plant profitability, reason that supports the industrial interest in CLP tools. The analysis is manly based on minimum variance and other stochastic indices. In this work, we highlight that they do not provide conclusive metrics for loop performance. Moreover, in many cases, the comparison between the performance of two controllers is not possible, as well as measure the performance improvement of a given controller. Besides, no information about the robustness is provided.

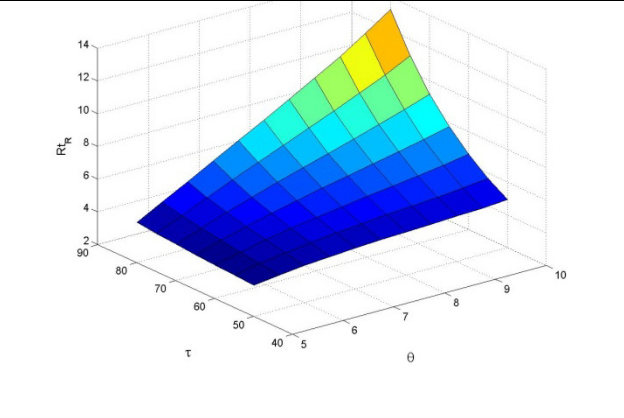
On the other hand, deterministic indices provide a clear metrics of performance and robustness, however their evaluation in industrial field is prohibitive, because intrusive tests are necessary.

This work proposes an inferential model to evaluate CLPR, providing deterministic indices that only requires stochastic metrics and information about the process. Thus, the metrics provided by PRIM make the control loop performance and robustness assessment and diagnostics straightforward.

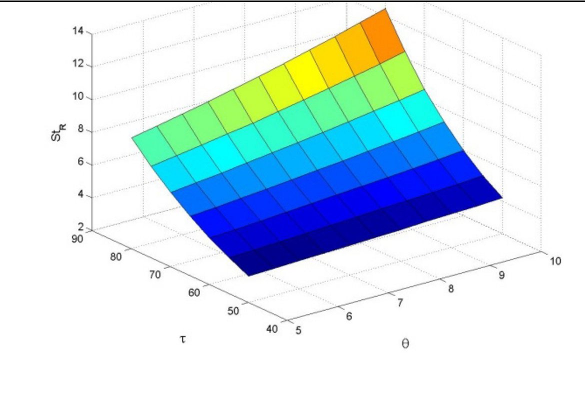
In this work, the procedure to build the PRIM was described; neural networks were used to build the IM and genetic algorithms to select the IM inputs. The proposed method was applied in a set of case studies, providing interesting results.

Appendix

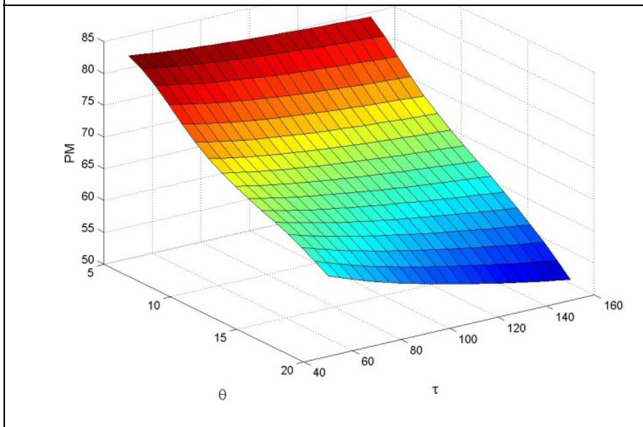
This appendix shows the sensitivity analysis for 1st order PRIM. The scope is to verify it smoothness and neural network interpolation capacity, for time delay (θ) and time constant (τ) mismatches. Here, the Rt_R, St_R, and PM will be analyzed. Figure 4.1 shows the time delay and time constant impacts over (A) Rt_R, (B) St_R, and (C) PM, using the NET_N. Similar results were obtained for the remaining networks.



(A)



(B)



(C)

Figure 4.13: Time delay and time constant impacts over (A) Rt_R, (B) St_R, and (C) PM

Figure 4.13 clear shows a smooth behavior for Rt_R, St_R, and PM models, what visually shows the quality of the interpolation generated by the networks. Besides, a small mismatch in any of these input parameters, as shown in Figure 4.13, will not imply a strong error in the output indices.

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Chapter 5

Variability Matrix: A Novel Tool to Prioritize Loop Maintenance

Abstract:📖 *It is now common knowledge that as many as 80% of the control loops in most industrial processes have considerable potential for improving control performance by reducing variability. Because of the large number of control loops in an industrial plant, controller performance monitoring is indispensable, but 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 the VM, a methodology to translate this array 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 ideas in industry. The efficacy of the proposed methodology is illustrated by successful application to two case studies.*

5.1– Introduction

The main requirement for a control system is to ensure process stability and robustness. This is the key reason for the widespread industrial interest in performance assessment methodologies and tools. A typical plant has hundreds or thousands of controllers and most of them have potential for improvement (Bialkowski 1993).

📖 *This paper is based on the paper submitted by M. Farenzena, S. L. Shah, and J. O. Trierweiler to Journal of Process Control*

Many good reviews on assessment of control loops are available in the literature (Huang and Shah 1999; Jelali 2006). A common problem in controller performance monitoring is how to prioritize loop maintenance. The answer should not only be based on the performance potential, but also 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 achieving a more profitable operating point, closer to the constraints, as shown in Figure 5.1. 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. If the variability is reduced, due to controller or process improvement (scenario II) the process operating point can be moved to a more profitable setpoint (scenario III).

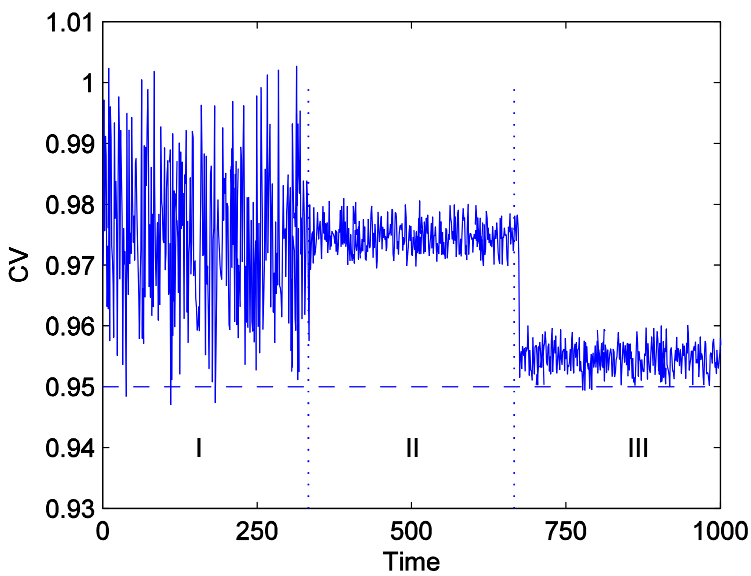

Figure 5.1: Variability reduction impact: (I) normal operating variability (II) variability reduction and (III) operating point shift.

The literature is relatively sparse in terms of quantification of economic benefits due to improvement of controller performance.

Muske (2003) proposed the idea of potential reduction in control loop variability. The economic benefit is quantified based on the shift in the mean operation towards a product specification or process constraint. The variance reduction can be based on a fixed or user-specified benchmark, e.g. minimum variance benchmark or a desired rise time or settling time benchmark. Jain (2006) proposed the Economic Performance Indicator (EPI), which is an extension of Muske's theory. This index is computed based on the difference on the present mean ($\mu_{present}$) and the optimal process mean ($\mu_{optimal}$), i.e. the mean that is achieved when the "best controller" is implemented.

$$EPI = D(\mu_{present} - \mu_{optimal}) \quad (5.1)$$

where D is the monetary gain per unit time for a unit change in operating point. In this case, the “best controller” is the minimum variance controller (Harris 1989). Thus, the EPI can be rewritten as:

$$EPI = 3D\sigma_{present}(1 - \sqrt{\eta}) \quad (5.2)$$

where $\sigma_{present}$ is the actual standard deviation and η is the minimum variance index.

Di Mascio and Barton (2001) proposed a methodology to quantify the control quality in economic terms based on the Taguchi Framework. This approach is build around the premise that the best product quality is when it achieves the nominal specification, and losses occur when the product deviates from the specified setpoint. The loss function is defined ($L(z)$) as a function of actual product quality (z). The loss function for a system where “nominal is better” is given by:

$$L = D(z - z^0)^2 \quad (5.3)$$

where z^0 is the nominal value (specification) of the product.

Craig and Henning (2000) proposed another methodology to quantify the economic benefit of Advanced Process Control (APC) projects. The authors mention that the whole part of the benefits come from the steady-state optimization. They assume that the variance of the products can be reduced by 35% to 50%. Recently, Bauer and Craig (2008) wrote a complete survey about economic assessment of advanced process control projects. Bauer et al. (2007) wrote a survey paper about how industry computes the economic performance in APC projects.

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.

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 loops 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 considered in isolation and the potential economic benefit should be computed by analyzing the whole plant and not only a specific loop. The common idea that the improvement of a given controller performance will increase the performance of the whole plant is not always true. Sometimes in an interacting system, the coupling between the channels can help or hinder overall performance. For example, decrease in the variability of a given controller can also reduce the variability in other loops in which case, one can say that the interaction helps. In other cases, the interaction may affect performance of associated loops adversely.

The main contribution of this work is the introduction of the notion of the Variability Matrix (VM). This array shows how the variability will transfer 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 5.2 highlights why the variability transfer should be considered to evaluate control loop economic benefit, using a case study. Section 5.3 introduces the concept of Variability Matrix. In section 5.4, 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 5.5. The complete methodology is illustrated by the successful application on two case studies (section 5.6). The paper ends with concluding remarks.

5.2– Variability Transfer: An Example

The methodologies previously mentioned do not consider the interaction between loops. In industrial plants this assumption can lead to wrong results, because of the high coupling among variables. This section aims to highlight this scenario, where the decrease of the variability in one channel can impact negatively (or positively) in the other loops.

Suppose a 2 x 2 system (G) controlled by two PI controllers (C) where the closed loop performance is equal to open loop, considering the rise time. The system has a disturbance in the output (d) generated passing a random signal through a first order transfer function (G_d). Table 5.1 shows the quoted parameters.

Table 5.1: Parameters of the plant in the example of the impact of the coupling

Parameter	Value
G	$\begin{bmatrix} \frac{1}{30s+1} & \frac{0.9}{15s+1} \\ \frac{-0.9}{10s+1} & \frac{1}{40s+1} \end{bmatrix}$
C	$\begin{bmatrix} \frac{30s+1}{30s} & 0 \\ 0 & \frac{40s+1}{40s} \end{bmatrix}$
G_d	$\frac{1}{80s+1}$
$\sigma^2(d)$	1

Note that the same disturbance signal is introduced in both channels. Then the actual process outputs (y_1 and y_2) variances are computed (var_{act}).

Later, the performance of channel 1 is increased by 4 times and the performance of channel 2 remained the same. Again, the new set of variances is computed (var_1). In the third scenario, only the performance of controller 2 is increased by 4 times and the output variance computed, (var_2).

Table 5.2 shows the variances in the three scenarios and the perceptual variance change (Δ%), given by:

$$\Delta\% = \frac{var_i - var_{act}}{var_{act}}, i = 1{,}2 \tag{5.4}$$

Table 5.2: Impact in the variance caused by variable coupling

	var_{act}	var_1	$\Delta\%$	var_2	$\Delta\%$
y_1	0.24	0.14	-42	0.16	-30
y_2	0.86	1.2	35	0.26	-69

As shown in Table 5.2, increasing the performance in controller 1 has the expected behavior: output 1 (y_1) decreases its variance by 42%, however almost the contrary impact is seen in output 2 (y_2), i.e. it increases the variance in 35%. Controller 2 has a peculiar behavior: increasing its performance means decreasing the variance not only in y_2 (69%), but also in y_1 (30%).

5.3- Variability Matrix: Concepts and Definition

5.3.1 – Preliminary Definitions

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

1. Main Loops: Loops that directly control the products specification. Their performance improvement affects the product variability, which can be directly translated into profitability.

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

5.3.2 – 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 5.2.

$$
\begin{array}{cc}
 & \begin{array}{ccccccc} \multicolumn{4}{c}{\text{Main Loops}} & \multicolumn{3}{c}{\text{Auxiliary Loops}} \\ Mn_1 & Mn_2 & \cdots & Mn_m & Aux_1 & \cdots & Aux_{l-m} \end{array} \\
\text{Main} \begin{array}{c} Mn_1 \\ Mn_2 \\ \vdots \\ Mn_m \end{array} & \begin{bmatrix} VM_{1,1} & VM_{1,2} & \cdots & VM_{1,m} & VM_{1,m+1} & \cdots & VM_{1,l} \\ VM_{2,1} & VM_{2,2} & \cdots & VM_{2,m} & VM_{2,m+1} & \cdots & VM_{2,l} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ VM_{m,1} & VM_{m,2} & \cdots & VM_{m,m} & VM_{m,m+1} & \cdots & VM_{m,l} \end{bmatrix}
\end{array}
$$

Figure 5.2: Schematic representation of Variability Matrix

In Figure 5.2 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. Row 1 shows the impact on the variability of Mn_1 when the performance of all other loops is changed.

To illustrate these two definitions, consider the hypothetical system illustrated in Figure 5.3.

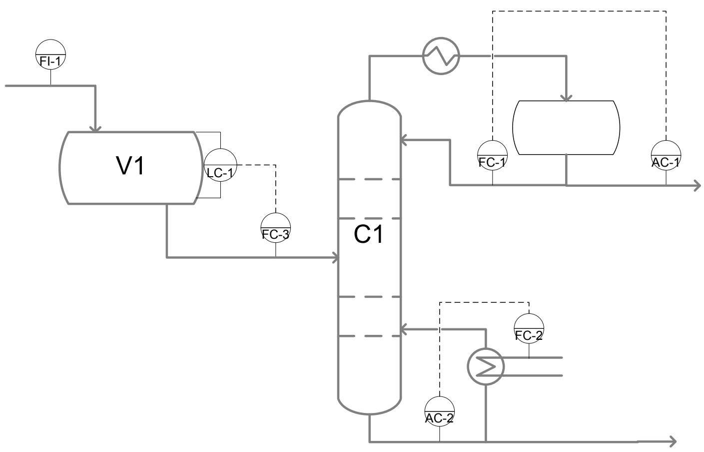

Figure 5.3: Hypothetical system to illustrate the concepts of main and auxiliary loops

The system is composed by one tank to buffer feed disturbances (V1) and one distillation column (C1) responsible for splitting the products. This column is fed by two components and the feed flow (FI-1) is the main disturbance. The system has 3 control loops, as shown in Table 5.3:

Table 5.3: Controlled and manipulated variables of the system

Loop	Controlled variables	Manipulated variables
L1	Light product composition in the top (AC-1)	Total reflux flow (FC-1)
L2	Heavy product composition in the bottom (AC-2)	Steam flow in the heat exchanger (FC-2)
L3	Level of tank 1 (LC-1)	Output flow (column feed flow (FC-3)

In this case, it is easy to divide the variables:

- Main loops – L1 and L2, because they control directly the products compositions;
- Auxiliary loops – L3, because it does not control a product quality, however it has significant impact in the final variability.

5.3.3 – VM Computation

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 ($\mathrm{var}_{\mathrm{act},i}$, $i = 1\ldots m$);
4. For each loop j ($j = 1\ldots l$)
    a. Calculate the best performance achievable (see section 5.4.2) 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 Eq. 5.5.

$$VM(i,j) = \frac{var_{act,i} - var_{best,i,j}}{var_{act,i}} \tag{5.5}$$

This structure for VM elements was chosen for two main reasons: 1) it provides a direct measure of the variability improvement potential for each loop; and 2) it is dimensionless, a fact that allows the comparison of the impact of two or more loops in the plant. For example, consider the VM of:

$$\begin{bmatrix} 0.3 & 0 & -1.2 \\ -0.7 & 0.9 & -1.5 \end{bmatrix} \tag{5.6}$$

Initially, we can verify that this plant has 2 main loops and one auxiliary loop. From this VM, by examining column 1, we can conclude that: if the performance of main controller 1 is improved, its variance will decrease 30%; however, if 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 column 2, the main loop 2 has potential reduction in variability of 90%. This controller has no influence on the main loop 1 variance; furthermore improving the performance of the auxiliary loop (3rd column) will lead to variability increase in both 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 buffering disturbances. Based on this assumption, we define the Complementary Variability Matrix (*CVM*). The values are computed with actual loop variance ($var_{act,i}$) and the variance of the loop with the worst performance acceptable ($var_{wor,i,j}$). The structure is the same as shown before, and the elements are computed as follows:

$$CVM(i,j) = \frac{var_{act,i} - var_{wor,i,j}}{var_{act,i}} \tag{5.7}$$

The same procedure as considered earlier can be used to evaluate the Complementary Variability Matrix (*CVM*). Only step 4.a 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 5.4.

5.3.4 – VM Dependence of the System Parameters

From a preliminary inspection, VM seems to be analogous to static RGA (Skogestad and Postlethwaite 2005), where only the process static gains have impact in the analysis. However, VM is not only a function of process gains, but also depends on process behavior (dynamics and time delays), disturbance patterns and correlation among the disturbances, controller structure (e.g. PI, PID, MPC, among others), closed loop performance, and best performance achievable. The VM values are specific for each process: even two systems where the models and controllers are the same can have a completely different VM, because of the disturbance pattern.

5.4– Practical Issues in Computing VM

5.4.1 – Computing the VM

This section presents the methodology to evaluate VM in industrial settings 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 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 in all loops. For this case, the following steps are contemplated:

I. identify the controller order and parameters (C) using *structured target factor analysis* (STFA) (Fotopoulos et al. 1994);

II. estimate the time delay (Tuch et al. 1994);

III. identify the process model (G) using *Subspace Identification* (Overschee and Moor 1996);

IV. identify the disturbance model (G_d) using *Subspace Identification*;

V. with G, C, and G_d available, the VM can be estimated applying the methodology shown in section 5.3.3.

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

5.4.2 – 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 is 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 tank controllers (Smith 2002).

5.5 – Quantifying the Economic Benefits Based on VM

This section describes how to use the VM to evaluate the Control Loop Economic Benefit (CLEB), as the key information to prioritize loop maintenance.

Initially, the square root of the variability matrix ($\sqrt{\text{VM}}$) is defined, where each element can be computed as follows:

$$\sqrt{VM}_{i,j} \triangleq \frac{\sigma_{act,i} - \sigma_{best,i,j}}{\sigma_{act,i}} \tag{5.8}$$

i.e. they are computed using the standard deviation, instead of variance.

We assume here that the economic benefic can arise only from setpoint change and better usage of the utilities (Jain 2006; Muske 2003). Assuming that the process should operate 3 standard deviations away from the constraint (as shown in Figure 5.1), the actual reference value (setpoint) respects this assumption and the process operates above the desired operating point, then the potential operating point change for the main variable *i* when controller *j* has its performance improved ($POPC_{i,j}$) by variability reduction is given by:

$$POPC_{i,j} = 3\left(\sigma_{act,i} - \sigma_{best,i,j}\right) \tag{5.9}$$

Where $\sigma_{\text{act,i}}$ is the actual standard deviation of main variable *i*, and $\sigma_{\text{best,i,j}}$ is the standard deviation of main variable *i*, when controller *j* has its variability improved.

Using the $\sqrt{\text{VM}}$ concept, the *POPC* can be rewritten as:

$$POPC_{i,j} = 3\sigma_{act,i}\sqrt{VM}_{i,j} \tag{5.10}$$

Then the *CLEB* earned by setpoint change ($CLEB_j^y$) is given by:

$$CLEB_j^y = \sum_{i=1}^{m} 3D_{y,i}\sigma_{act,i}\sqrt{VM}_{i,j}\ , j = 1 \ldots l \tag{5.11}$$

Where $D_{y,i}$ is the economic benefit earned by a unitary change in main variable *i*. and *l* is the total number of loops.

The second part of the benefit is provided by the utilities, i.e. by the new set of manipulated variables achieved by the operating point change. In this scenario, a linear programming problem should be solved:

$$\min_{\Delta u_{\mathrm{j}}} -D_{u,i}\,\Delta u_{\mathrm{j}}$$

sj. (5.12)

$$\mathrm{u}_{\mathrm{max,j}} > \Delta u_{\mathrm{j}} > \mathrm{u}_{\mathrm{min,j}}$$
$$\mathrm{G}_0\Delta u_{\mathrm{j}} - POPC_j = 0$$

Where Δu_j is the change in manipulated variables allowed by performance improvement in controller *j*, i.e. after the operating point change by $POPC_j$ in the main loops, $D_{u,i}$ is the economic benefit earned by a unitary change in manipulated variable of controller *j*, $u_{max,j}$ and $u_{min,j}$ are the maximum and minimum values for Δu_j , respectively, and G_0 is the static gain matrix of the plant. The values of $D_{y,i}$ and $D_{u,i}$ can be easily estimated based on products and utilities cost. From the linear programming, the optimal set of Δu is obtained (Δu_{OPT}).

The first constraint ensures that the values of Δu_j will respect the maximum and minimum values for each manipulated variable. The second obligates the system to achieve the new setpoints ($POPC_j$).

The *total control loop economic benefit* for the improvement in loop *j* ($CLEB_j$) is given by:

$$CLEB_j = \sum_{i=1}^{m} 3D_{y,i}\sigma_{act,i}\sqrt{VM}_{i,j} + D_u\Delta u_{OPT,j}, j = 1 \ldots l \tag{5.13}$$

Where $\Delta u_{OPT,j}$ is the optimal Δu for the improvement in controller *j*, obtained when the linear programming problem is solved.

Analogously, the *Complementary Control Loop Economic Benefit* (*CCLEB*) can be computed. In this case, instead of VM, CVM should be used. Thus, the concept of $\sqrt{CVM}$ should also be defined:

$$\sqrt{CVM}_{i,j} \triangleq \frac{\sigma_{act,i} - \sigma_{wor,i,j}}{\sigma_{act,i}} \tag{5.14}$$

The *total complementary control loop economic* using CVM is given by:

$$CCLEB_j = \sum_{i=1}^{m} 3D_{y,i}\sigma_{act,i}\sqrt{CVM}_{i,j} + D_u\ \Delta u^c_{OPT,j} \tag{5.15}$$

where $\Delta u^c_{OPT,j}$ is the optimal Δu when controller j has its performance decreased.

Similar expressions can be derived for processes where the operation is below of the restriction or when it should remain inside constrains.

To exemplify the previous definitions, the distillation column shown in Figure 5.3 will be used. The parameters of this case study are shown in Table 5.4:

Table 5.4: Parameters to compute *CLEB*

Parameter	Value
$\sqrt{\boldsymbol{VM}}$	$\begin{bmatrix} 0.6 & -0.3 & -0.3 \\ -0.2 & 0.4 & -0.1 \end{bmatrix}$
G_0	$\begin{bmatrix} 1 & -0.3 & -0.1 \\ -0.4 & 1 & -0.05 \end{bmatrix}$
D_y (\$/day)	$[10 \quad 4]$
D_u (\$/day)	$[2 \quad 4 \quad 0.1]$
$\boldsymbol{\sigma_{act}}$	$[1 \quad 1]$
u_{max}	$[2 \quad 2 \quad 2]$
u_{min}	$-[2 \quad 2 \quad 2]$

In this case, the *CLEB* is given by:

$$CLEB = [17 \quad -4 \quad -12] \tag{5.16}$$

i.e. improving the performance of controller 1 means increasing plant profitability in \$17/day, while improving performance in controllers 2 and 3 means respectively spending \$4/day and \$12/day.

5.6– Case studies

5.6.1 – Wood and Berry Distillation Column Model

The pilot-scale distillation column proposed by Wood and Berry (1973) is the first case study. The plant model is given by:

$$\begin{bmatrix} x_D(s) \\ x_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8}{16.7s+1}e^{-s} & \frac{-18.9}{21s+1}e^{-3s} \\ \frac{6.6}{10.9s+1}e^{-7s} & \frac{-19.4}{14.4s+1}e^{-3s} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{5.17}$$

where x_D and x_B 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 minutes time constant. The VM analysis of this case study is presented next 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, setpoint activity is assumed. This serves as a good excitation for closed loop identification. For case 3, details of closed-loop based *Subspace Identification* method are shown in Appendix B.

The PI controllers were tuned to have a performance where the desired 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 remaining parameters necessary to compute CLEB are arbitrarily set, as shown in Table 5.5:

Table 5.5: Parameters of the case study 1 to compute *CLEB*

Parameter	Value
D_y (\$/day)	$[10 \quad 5]$
D_u (\$/day)	$[1 \quad 1.7]$
u_{max}	$[-10 \quad 10]$
u_{min}	$[-10 \quad 10]$

Our objectives here are to evaluate the VM, considering the three possible scenarios, and to evaluate the CLEB.

Initially, the VM will be calculated. In the first scenario, the controller and plant model were available. The VM was computed using the methodology shown in section 5.3.3.

$$VM = \begin{bmatrix} 0.57 & -0.17 \\ -0.18 & 0.41 \end{bmatrix} \tag{5.18}$$

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 5.4.1). In this scenario, the VM was estimated to be:

$$VM = \begin{bmatrix} 0.60 & -0.19 \\ -0.19 & 0.46 \end{bmatrix} \tag{5.19}$$

Notice that the estimated VM closely matches the true VM shown in Eq. 5.18. In the third scenario, both controller and plant model were identified using closed loop data. The estimated VM for this scenario is:

$$VM = \begin{bmatrix} 0.60 & -0.19 \\ -0.18 & 0.46 \end{bmatrix} \tag{5.20}$$

Even for this case, where controller and plant model were first identified using *Subspace Identification*, a good estimate of VM was obtained.

Our second objective is to prioritize loop maintenance. Based on VM and loops variances, $\sqrt{VM}$ is computed.

$$\sqrt{VM} = \begin{bmatrix} 0.35 & -0.08 \\ -0.09 & 0.23 \end{bmatrix} \tag{5.21}$$

Then, $\sqrt{CVM}$ is also computed:

$$\sqrt{CVM} = \begin{bmatrix} -0.43 & 0.12 \\ 0.09 & -0.42 \end{bmatrix} \tag{5.22}$$

Subsequently, the *CLEB* and *CCLEB* are computed.

$$\begin{aligned} CLEB &= [8.8 \quad 1.3] \\ CCLEB &= [-11 \quad -3.1] \end{aligned} \tag{5.23}$$

Where both are given in $/day.

The maintenance list for this hypothetical case indicates that the most important controller to maintain or improve performance is loop 1. Moreover, *CLEB* and *CCLEB* show that both loops should have fast performance and decreasing performance means decreasing plant profitability.

5.6.2 – Shell Benchmark Process

The Shell Control Problem benchmark was proposed by Prett and Morari (1987). The system is characterized by the high interaction among channels and large time delays. It involves one heavy oil fractionator, as shown in Figure 5.4.

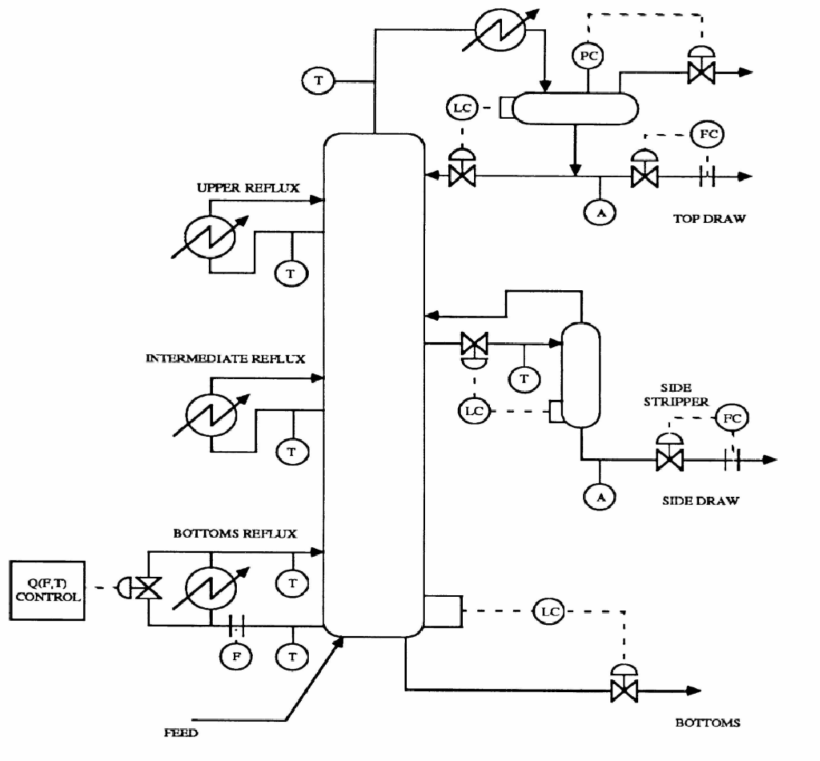

Figure 5.4: Shell fractionator schematic representation

It has three product draws, three side circulating loops and a gaseous feed stream. The system consists of seven measured outputs, three manipulated inputs and two unmeasured disturbances. In this case study, we will reduce the problem to a 3 input and 3 output case. The three controlled variables are: top end point (*y1*); side endpoint (*y2*); bottom reflux temperature (*y3*). The manipulated variables are: top draw (*u1*); side draw (*u2*); bottom reflux duty (*u3*). The system has also two disturbances: upper reflux (*d1*); intermediate reflux (*d2*). The process output can be written as:

$$y = Gu + G_d d \tag{5.24}$$

Where G is the plant model

$$G = \begin{bmatrix} \frac{4.05}{50s+1}e^{-27s} & \frac{1.77}{60s+1}e^{-28s} & \frac{5.88}{50s+1}e^{-27s} \\ \frac{5.39}{50s+1}e^{-18s} & \frac{5.72}{60s+1}e^{-14s} & \frac{6.9}{50s+1}e^{-15s} \\ \frac{4.38}{33s+1}e^{-20s} & \frac{4.42}{44s+1}e^{-22s} & \frac{7.2}{19s+1} \end{bmatrix} \tag{5.25}$$

and G_d is the disturbance model:

$$G_d = \begin{bmatrix} \frac{1.2}{45s+1}e^{-27s} & \frac{1.44}{40s+1}e^{-27s} \\ \frac{1.52}{25s+1}e^{-15s} & \frac{1.83}{20s+1}e^{-15s} \\ \frac{1.14}{27s+1}e^{-s} & \frac{1.26}{32s+1} \end{bmatrix} \tag{5.26}$$

Where the time constant and time delays are reported in minutes. The MPC from Matlab® (MPC toolbox V. 2.2.2) was applied in this study. The analysis for this case is reported under two scenarios: (I) where controller and plant models are available and (II) when both are unavailable.

The actual performance in this case was computed based on closed loop rise time when it is set equal to the open loop case. The desired performance for each channel is three times faster than open loop. The VM for this scenario is:

$$VM = \begin{bmatrix} -0.39 & 0.10 & 0.26 \\ -0.12 & -0.16 & 0.28 \\ -0.24 & -0.60 & 0.32 \end{bmatrix} \tag{5.27}$$

The VM shows that improving the performance of controller 1 and 2 will result in an increase in the variance of all main loops. Retuning loop 1 means increasing its variance by 39% and increasing the variances of loops 2 and 3 by 12% and 24% respectively. On the other hand, improvement of loop 3 performance means a decrease in its variance by 32% and corresponding reductions in variances in loop 1 and loop 2 by 26% and 28%, respectively.

The answer to improving plant profitability lies not only in VM but also in CVM, i.e. some controllers should not have their performance improved, but rather detuned. The CVM for this case is:

$$CVM = \begin{bmatrix} 0.15 & 0.13 & -0.12 \\ 0 & 0.28 & -0.13 \\ -0.30 & -0.29 & -0.44 \end{bmatrix} \tag{5.28}$$

In the second scenario, both controller and plant are assumed to be unavailable, only setpoint activity is assumed. In this case, the VM is estimated using the procedure shown in section 5.4.1. The estimated VM is:

$$VM = \begin{bmatrix} -0.42 & 0.06 & 0.26 \\ -0.15 & -0.27 & 0.28 \\ -0.32 & -0.74 & 0.32 \end{bmatrix} \tag{5.29}$$

Both plant model and controller are identified using subspace identification from Matlab® (system identification toolbox version 6.1.1, function n4sid). Both models have 9 states.

Eq. 5.29 shows that the estimated VM compared with the original (Eq. 5.27) is fairly good. We attribute the success of this fairly accurate VM estimation to the direct closed loop subspace identification method under reasonable level of setpoint activity.

5.7– Conclusions

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

- industrial plants have many loops with considerable potential for performance improvement and therefore a 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 based on closed loop identification;

Appendix A: Some Peculiar Behaviors

Intuitively, the diagonal elements of the VM should have a positive sign and the off-diagonal elements negative sign, i.e.: improving the performance of a given controller will reduce its variability; and transfer variability to the other loops, increasing their variability. However, this may not always be the case:

Proposition 1: *Diagonal elements of VM can have negative sign, i.e. the performance improvement of a given controller can increase its variability.*

Proof: Consider a SISO system with linear PI type controller that is affected by an output disturbance (d). Suppose that the disturbance is a pure white-noise random signal. Considering that d is random, it is not possible to predict its future values based on the past values. In this case increasing loop gains will likely increase y variability. In this case, the diagonal VM element will have a negative sign.

Proposition 2: *Off-diagonal elements can have positive sign, i.e. the performance increase of a given controller can also decrease the variability in other interacting loops. Typically this happens when interactions help in accommodating disturbances.*

Proof: Consider the triangular system shown in Figure 5.5.

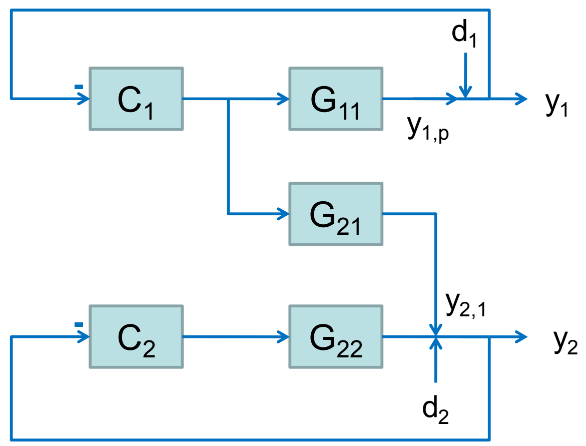

Figure 5.5: Schematic representation of the triangular system

Consider the case when C_1 reduces the output variability when it is compared with the open loop case (i.e. $\sigma^2(d_1 + y_{1,p}) < \sigma^2(d_1)$), and upon improving C_1 performance, y_1 will also decrease its variability.

$$\sigma^2(d_1) > \sigma^2(d_1 + y_{1,p1}) > \sigma^2(d_1 + y_{1,p2}) \tag{5.30}$$

Where p_1 and p_2 are the controllers performance and $p_2 > p_1$ (i.e. closed loop performance in the second scenario (p_2) is faster than p_1). Considering the case when:

$$\begin{gathered} G_{11} = G_{21} \\ d_1 = d_2 \end{gathered} \tag{5.31}$$

Then $y_{1,p} = y_{2,1}$. From the loop 2 and $y_{2,1}$, it is clear to observe that improving the performance of loop 1, will also have the effect of reducing the variability of y_2. This will occur as $y_{2,1}$ will help offset the effect of d_2 (in the same way as $y_{1,p}$ offsets d_1). Thus leading to:

$$\sigma^2(d_2) > \sigma^2(d_2 + y_{2,1,p1}) > \sigma^2(d_2 + y_{2,1,p2}) \tag{5.32}$$

Appendix B: Plant and Controller Identification

This section gives details about controller and plant model identification.

In the *Wood and Berry* case study, the subspace algorithm available in Matlab (*n4sid*) was used. In this case, 4 states are used for the controller model and the same number for plant model.

Figure 5.6 shows open loop step response for Wood and Berry case study (results available in section 5.6.1):

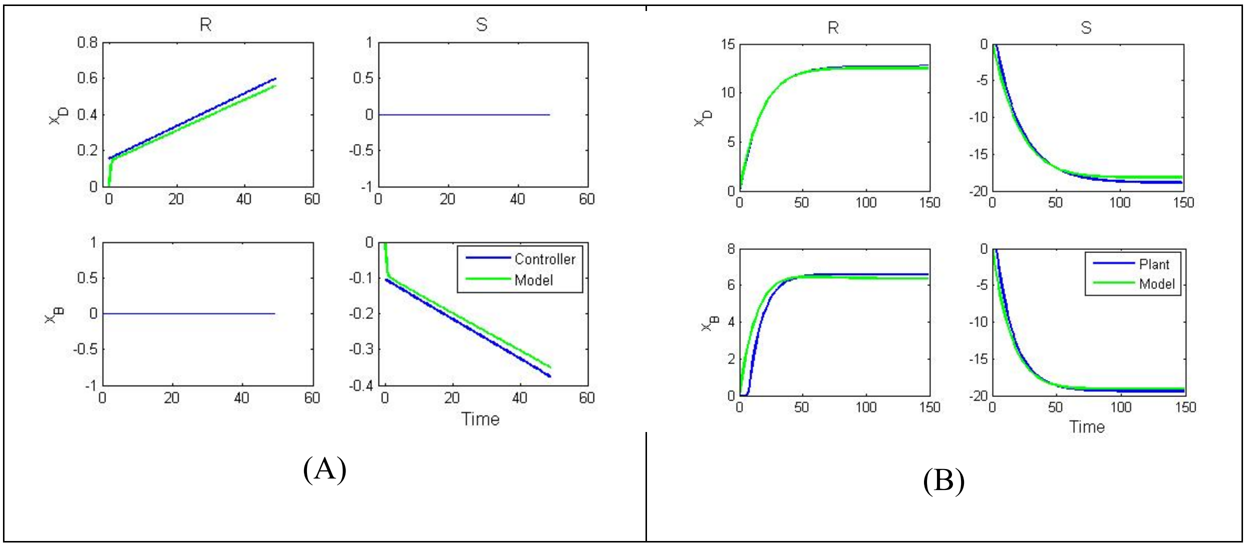

Figure 5.6: Open loop step response for Wood and Berry case study: (A) controller (B) plant model

Figure 5.6 clearly shows the good identification for both plant and controller models for Wood and Berry case study.

Similar results were obtained for Shell benchmark problem (see Figure 5.7), where plant identification is shown (Figure 5.7A), as well as the comparison between plant outputs and model predicted values (Figure 5.7B):

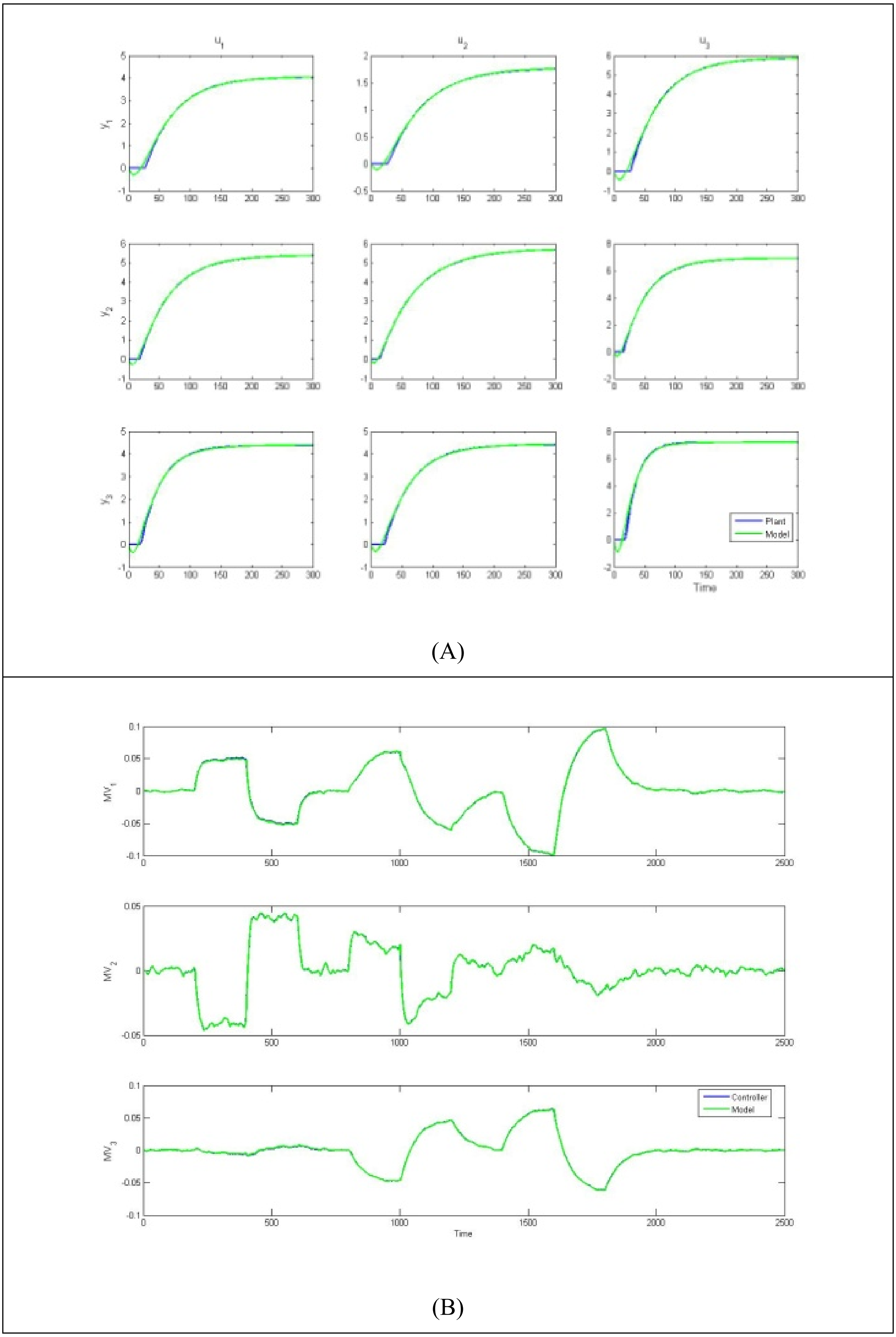

Figure 5.7: Responses for Shell Benchmark problem: (A) plant model open loop step response and (B) closed loop response of the controller

Again, Subspace Identification was used, with 9 states for plant model. Figure 5.7 illustrates the good quality of the identified model.

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Chapter 6

A Novel Technique to Estimate the Stickband in a Sticky Valve

Abstract:📖 *This work proposes a new method to quantify valve stiction that requires only normal (PV and OP) operating data. The technique is based on pattern recognition, where a neural network, called Stiction Inference Model (SIM), predicts the stickband, based on the process data and controller output patterns. The SIM is described, as well as the procedure to its construction: the dataset construction, the variable selection and the network training. The SIM obtained has a compact size (10 neurons) and a very good performance (R^2=0.96). The proposed method was applied in a set of sticky valves providing fruitful results.*

6.1– Introduction

To diagnose the "valve health" is important to eliminate plant oscillations, allowing the process to achieve a more profitable operating point (Thornhill et al. 2003b). The villain in chemical plants is high static friction (or stiction). Reports show that 20-30% of all control loops have bad performance because of stiction (Bialkowski 1993). That is why preventive maintenance is essential to avoid off-spec products and waste of energy or raw materials. This scenario demands an automatic technique to detect and quantify valve stiction.

Modern valves (also called "Intelligent valves") provide on-line information about the valve behavior, including the diagnostics of stiction. However, their price is high and their number in chemical plants is still small (Ekness 2004).

Valve static friction or stiction has received recently significant attention in the literature. Many methodologies are available to diagnose automatically this defect. Choudhury et

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📖 *This chapter is based on the paper submitted by M. Farenzena and J. O. Trierweiler to Control Engineering Practice* al.(2004) use high-order statistics to assess the valve health. Horch (1999) proposes a simple method based on PV and OP correlation. Singhal and Salsbury (2005) propose a measurement based on the area before and after the peak of PV data. Rossi and Scali (2005) extended Horch's method where the stiction is detected based on the interpolation of triangular, sinusoidal and wave-shape curves. Yamashita (2006) proposed a method based on valve movements patterns.

Also, there are methodologies to compute the stiction band. Gerry and Ruel (2001) propose an intrusive technique to diagnose and compute the stiction. This method is very expensive because it requires open loop tests. Shoukat Choudhury et al. (2004) propose two methods to evaluate the valve stiction: based on c-clustering and ellipsis interpolation.

Considering that usually the sticky valve cannot be removed, only detecting stiction is not enough, but also compensating its effect is important. Some authors proposed methods to efficiently compensate stiction. Hägglund (2002) proposed a method where periodical steps are inserted in controller output to overcome the stiction. Srinivasan and Rengaswamy (2008) proposed two techniques to compensate stiction. The first, two movements were evaluated to overcome the stiction. The second one, the stiction compensator is analogous to MPC controller, where its effect is calculated during a period and the first action is taken.

The impact of oscillations, caused by stiction, tight tuning or external disturbance, has been studied for several authors (Jiang et al. 2007; Thornhill et al. 2003a; Thornhill et al. 2003b; Xia and Howell 2005). Recently, Thornhill and Horch (2007) wrote a complete review in this area.

The main drawback of the methodologies to quantify stiction is that intrusive tests are required or the position of the stem must be available. Using only normal operating data and considering that only OP and PV are available, there is no methodology to compute the stiction. This is the main contribution of this work: propose a method to compute the stiction band based only in normal operating data, i.e. only process variable (PV) and controller output (OP) is required. No information about the stem is necessary.

The chapter is segmented as follows: initially the phenomenon of valve stiction is defined (section 6.2). In section 6.3, the Stiction Inference Model (SIM) will be defined and its construction detailed. The proposed technique is applied in a set of sticky valves in section 6.4. The chapter ends with the concluding remarks.

6.2– Stiction definition

6.2.1 – What is stiction and what is its effect in the plant?

The phenomenon of stiction can be summarized as follows (Ruel 2000): "*Stiction is the resistance to the start of motion, usually measured as the difference between the driving values required to overcome static friction upscale and down scale. The word stiction is a combination of the words stick and friction, created to emphasize the difference between static and dynamic friction. Stiction exists when the static (starting) friction exceeds the* *dynamic (moving) friction inside the valve. Stiction describes the valve's stem (or shaft) sticking when small changes are attempted. Friction of a moving object is less than when it is stationary. Stiction can keep the stem from moving for small control input changes, and then the stem moves when there is enough force to free it. The result of stiction is that the force required to get the stem to move is more than is required to go to the desired stem position. In presence of stiction, the movement is jumpy.*"

The impact of stiction in the plant can be summarized as proposed by Horch (1999). The valve is stuck in a position because of (high) static friction (stiction). The setpoint of the valve increases, due to the integrating part of the controller, until the stiction is overcome. Then the valve jumps to a new position, where it gets stuck again. Most of times, this new position is on the other side of the desired setpoint, such that the motion starts again in the opposite direction. This phenomenon inserts periodical oscillations in the control loop, increasing its variability.

6.2.2 – Stiction model

Nowadays, there are many attempts to describe the stiction phenomenon. Here, the method proposed by Choudhury et al. (2004) will be described.

The basic control scheme is shown in Figure 6.1, where SP is the setpoint, OP is the control signal, MV is the manipulated variable and PV is the controlled variable. Usually, only SP, OP and PV are recorded in DCS and MV is not, and it is not available in most of the cases.

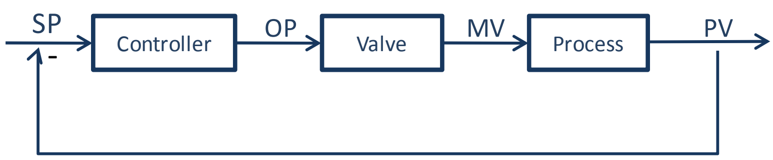

Figure 6.1: Control system scheme

A valve "suffering from stiction" has in the phase plot (Figure 6.2) four components: deadband (*DB*), stickband (*SB*), slip jump (*SJ*) and moving phase (*MP*).

When the valve changes the direction (A), the valve becomes sticky. The controller should overcome the deadband (AB) and stickband (BC), then the valve jumps to a new position (D). Then the valve starts moving, until its direction changes again or the valve comes to rest, between D and E.

The deadband and stickband represent the behavior of the valve when it is not moving, although the input of the valve keeps changing. Slip jump represents the abrupt release of potential energy stored in the actuator chambers due to high static friction in the form of kinetic energy as the valve starts to move. The magnitude of the slip jump is crucial to determine the limit cycle amplitude and frequency.

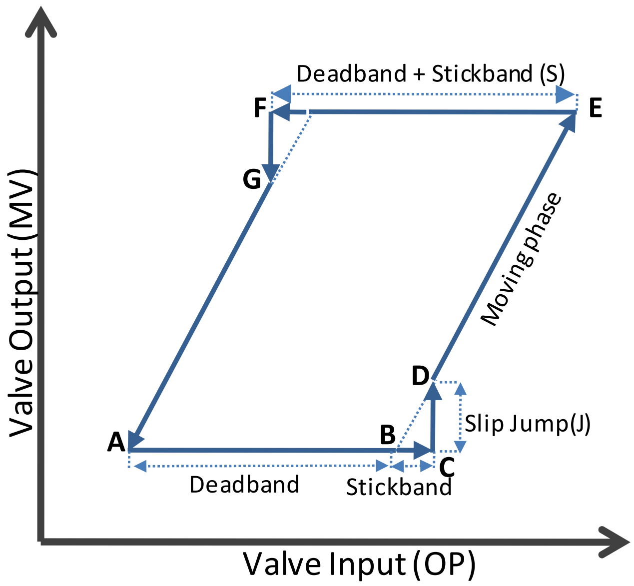

Figure 6.2: Typical input-output phase plot of a sticky valve

The stiction causes a limit cycle in the PV, as shown in Figure 6.3. Depending on *J* and loop parameters, stiction imposes different PV patterns (Rossi and Scali 2005). Figure 6.3A shows the wave-shape pattern, while Figure 6.3B shows the triangular pattern, caused by valve stiction.

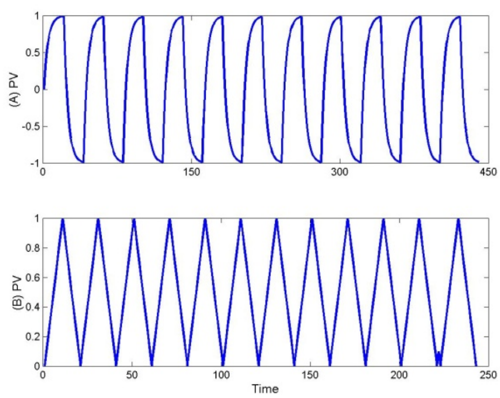

Figure 6.3: PV patterns caused by valve stiction – (A) wave-shape and (B) triangular.

6.3– Stiction Inference Model (SIM)

6.3.1 – Definition

The SIM can be defined as an inference model to provide the stickband (*SB*), whose inputs are parameters obtained only from normal operating data. Figure 6.4 illustrates the SIM structure. In this work, we considered that the deadband is negligible comparing with the sickband and it is set to zero in all simulations. In the case where DB is large, the model will predict the sum of DB and SB.

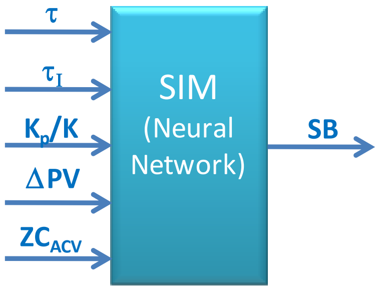

Figure 6.4: Stiction Inference Model Structure

The SIM output is the stickband (*SB*). The SIM inputs are:

- $\frac{K_P}{K}$: ratio between controller and process gain;
- τ: process time constant;
- τ_I: controller integrating constant;
- Δ_{PV}: Difference between the maximum and minimum value in PV;
- ZC_{ACV}: Number of zero-crossings in the autocovariance function (Thornhill et al. 2003b).

These inputs were selected from a larger group of variables. The candidate variables and the procedure to select them will be described in section 6.3.3.

In the proposed methodology, the stickband (*SB*) is evaluated, not the slipjump (*J*) as usually is computed. The main advantage of computing *SB* is that this value is more intuitive to the engineer, because it is expressed in the same units as the OP. To translate *SB* into *J*, the valve curve can be used.

Figure 6.5 shows the procedure followed to build the SIM.

Initially, the dataset was designed, i.e. the candidate inputs and the output were generated for a SISO loop, with variable parameters. Next, the dataset was divided in two: train and test datasets.

Subsequently, the inputs were selected and the neural networks were trained. When the performance obtained for a net is good, the procedure stops. Each step will be described in details in the following subsections.

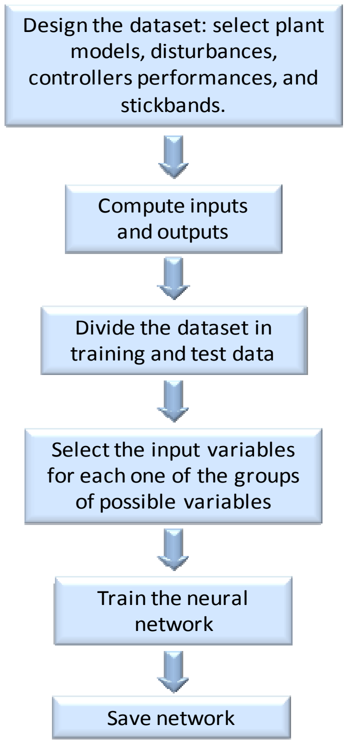

Figure 6.5: Procedure to build the SIM

6.3.2 – Dataset design

The dataset was designed based on a SISO loop, whose scheme is shown in Figure 6.6.

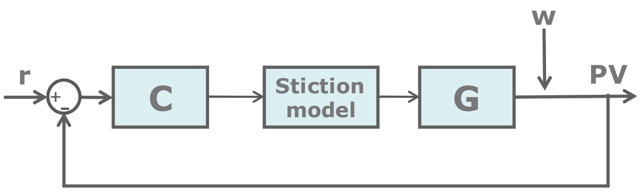

Figure 6.6: SISO loop scheme used to design SIM

Where *C* is the PI controller, *G* is the first order plus time delay plant. The stiction model is the model proposed by Choudhury et al. (2004), described in Section 6.2. The input *w* is white noise and *r* is the reference.

Table 6.1 shows the variable parameters to generate the dataset. Table 6.2 shows the interval for each parameter. Table 6.3 shows the fixed parameters and their values.

Table 6.1: Variable parameters to generate the dataset

Param.	Description
K_p	Controller gain
τ_I	Controller integral constant
τ	Process time constant
SB	stickband

Table 6.2: Parameters intervals

Param.	Interval
K_p	[0.1:0.2:1.1, 2:1:5]
τ_I	[0.3τ:0.3τ:3τ]
τ	[5:5:20, 30:10:100]
SB	[0.5:0.5:5]

Table 6.3: Fixed parameters in the dataset construction

Param.	Description	Value
K	Process gain	1
θ	Process time delay	1
$\sigma^2(w)$	White noise variance	0.1
DB	Deadband	0

The notation of previous tables is based on Matlab vectors construction – (iv:step:fv) – where *iv* is the initial value, fv the final value, and step is the step size between points.

The number of different scenarios in the dataset is 16800.

Subsequently, the complete dataset was divided in two datasets:

- Training dataset – 80% of the points
- Test dataset – 20% of the points

The points are divided randomly (Rawlings 1988). The first one is used to train the neural network, while the second is used to verify its performance and interpolation capacity.

6.3.3 – Variables selection

This section describes the candidate variables to build the inference model and the procedure to select the best subset of them to describe the stiction. The candidate variables come from different sources:

1. $\frac{K_P}{K}$: ratio between controller and process gain;
2. τ : process time constant;
3. τ_I: controller integrating constant;
4. τ_I/τ: ratio between τ_I and τ;
5. Δ_{PV}: Difference between the maximum and minimum value in PV;
6. Δ_{OP}: Difference between the maximum and minimum value in OP; Figure 6.7 illustrates Δ_{PV} and Δ_{OP}.

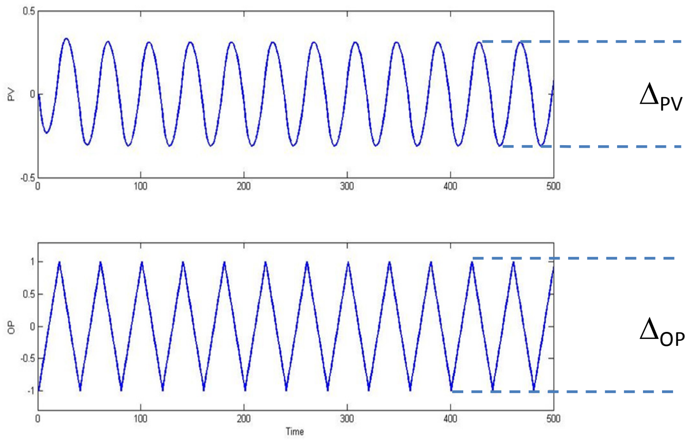

Figure 6.7: Δ_{PV} and Δ_{OP} in PV and OP plots

7. E_W: integral of square error of error between PV and the best wave-shape curve interpolation (PV_W) (see (Rossi and Scali 2005));
8. E_T: integral of square error of error between PV and the best triangular curve interpolation (PV_T); Figure 6.8 illustrates PV_T and PV_W;

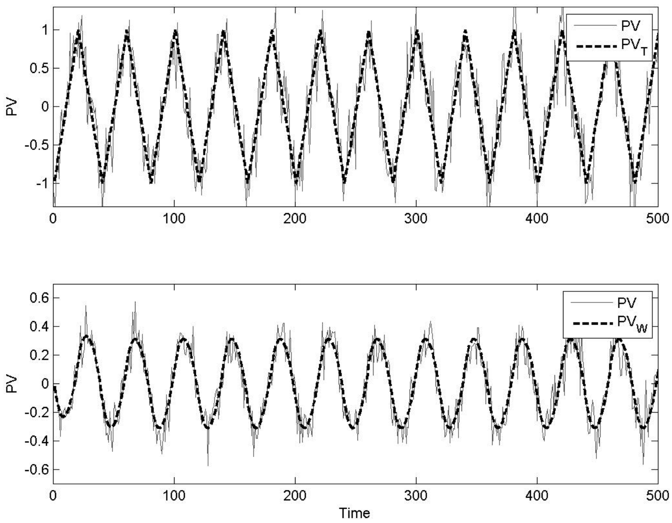

Figure 6.8: (A) E_T and (B) E_W illustration in PV plots

E_W and E_T are given by:

$$E_W = \int_{t_i}^{t_f} |PV - PV_W| dt$$
$$E_T = \int_{t_i}^{t_f} |PV - PV_T| dt \tag{6.1}$$

9. ZC: Number of zero-crossings in the zero-mean data;

10. ZC_{ACV}: Number of zero-crossings in the autocovariance function (Thornhill et al. 2003b).

The autocovariance function (Thornhill et al. 2003b) of an oscillatory time trend is also oscillatory with the same period. The influence of noise is reduced, when compared with the time trend itself. Figure 6.9 illustrates ZC and ZC_{ACV}.

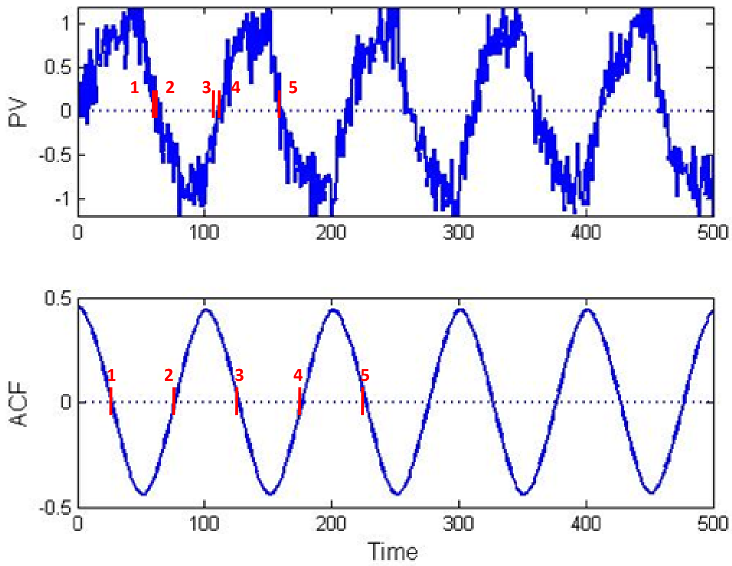

Figure 6.9: (A) ZC in PV plot and (B) ZC_{ACV} in the autocovariance plot (ACF)

Note that the autocovariance function is less sensitive to the noise than the ZC in the PV.

The variables were selected using stepwise regression (Rawlings 1988). The inputs selected were:

- $\frac{K_P}{K}$;
- τ;
- τ_I;
- Δ_{PV};
- ZC_{ACV}.

6.3.4 – Neural-network training

To interpolate the training dataset, we use a feedforward backpropagation neural network (Haykin 1999), from Matlab® 5.3 (R11, Neural Network toolbox ver. 3.0.1).

In the hidden layer, hyperbolic tangent sigmoid neurons were used, while in the output layer, linear neurons were used. In the training step, the layer performance is measured using mean square error. The training function used was Levenberg-Marquardt backpropagation (*trainlm*) and the learning function was Gradient descent with momentum weight and bias (*learngdm*).

The algorithm available in Matlab® gives random initial guesses for weights and biases. However, this technique is not repetitive, i.e. two training procedures with the same inputs and outputs datasets do not provide the same final network. Sometimes, the network performance is abruptly different. The cause is obvious: the objective function has several local minima and the best obtained depends on the initial guess. To overcome this limitation, the following procedure was implemented:

- Initially 20 networks with random initial weights and biases were trained until 100 epochs;

- The network which had the best performance was selected and then trained until 10000 epochs.

We try networks with different number of neurons in the hidden layer to select the one that better predict the stickband, with the minimum number of neurons. Table 6.4 shows the networks performance, with different number of neurons, with the training and test datasets.

Table 6.4: Networks performance – output variable: stickband

Neurons	R^2 Training dataset	R^2 Test dataset
5	0.94	0.95
10	0.96	0.96
20	0.97	0.96
50	0.98	0.96

Based on Table 6.4, the best net configuration has 10 neurons in the hidden layer.

The final SIM structure is:

- Neural network model with 2 layers;

- 1st layer (hidden): 10 hyperbolic tangent sigmoid neurons;

- 2nd layer (external): 1 linear neuron.

6.4– Case studies

In this section, the SIM will be applied to 8 datasets that are not used to train or test the model. Figure 6.10 shows the PV for each dataset. In the right side of the figure, the stickband (*SB*) is shown.

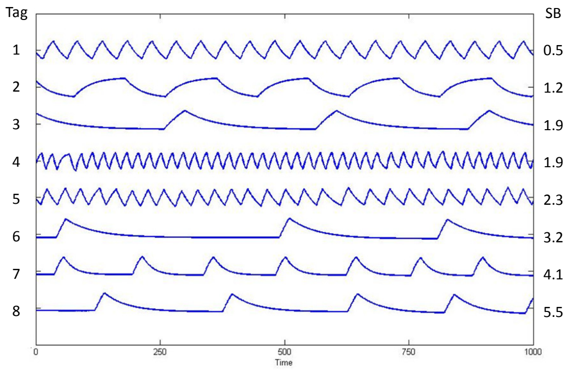

Figure 6.10: Simulated datasets with valve stiction

The comparison between predicted (SB_p) and original (SB) values is shown in Table 6.5.

Table 6.5: Comparison between predicted and original stickband

Tag	*SB*	SB_p
1	0.5	0.5
2	1.2	1.2
3	1.9	1.8
4	1.9	2
5	2.3	2.1
6	3.2	2.6
7	4.1	3.9
8	5.5	4.6

Table 6.5 corroborates the good performance of the SIM, because small errors are detected in all channels.

6.5– Concluding remarks

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

- valve problems impose profits losses, because it inserts oscillation in the plant;
- all methods to compute stiction needs the valve position (MV), however this usually is not available;
- in this work, a Stiction Inference Model (SIM) was proposed;
- it is based on neural networks and its inputs are only normal operating data from OP and PV;

- the neural network performance obtained was very good (R^2=0.96) with small number of neurons (10);

Appendix A – SIM Sensitivity Analysis

The scope of this appendix is to draw a sensitivity analysis for the Stiction Inference Model (SIM) to analyze its smoothness behavior, when the input parameters have a mismatch. The network used in this work is the one selected in the previous analysis: 10 neurons in the hidden layer and the inputs are $\frac{K_P}{K}$, τ, τ_I, Δ_{PV}, and ZC_{ACV}.

Initially, an intermediate point was selected to generate the sensitivity analysis. The values for each variable was [2, 50, 35, 1.3, 373], respectively. The same procedure for other points was repeated, however almost the same behavior was seen in all of them. Then, one vector of values was computed, varying the original value from -50% to +50%.

In the first analysis the controller and process gain ratio and process time constant are analyzed, as shown in Figure 6.11.

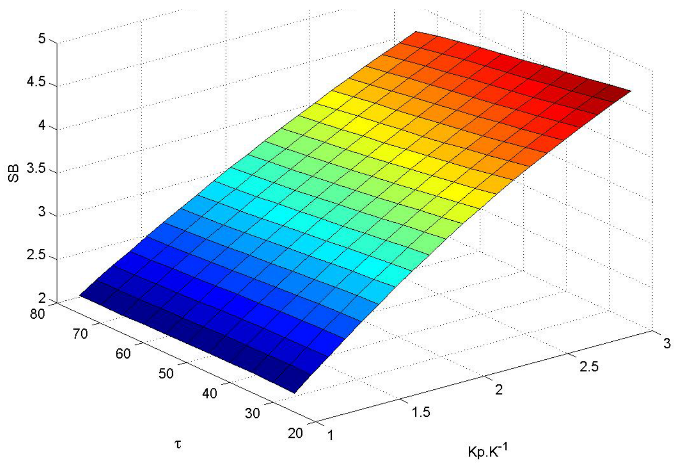

Figure 6.11: Sensitivity analysis for $\frac{K_P}{K}$ and τ

Figure 6.11 shows that the neural network interpolates the stiction data smoothly, without “jumps”. Also, the small mismatch between the original and the provided parameters will not have a strong impact in the model output.

In the second analysis the impact of the controller integral time constant (τ_I) and the process variable amplitude (Δ_{PV}) was analyzed. The procedure is the same as previously described. Figure 6.12 shows the SB behavior with these two variables.

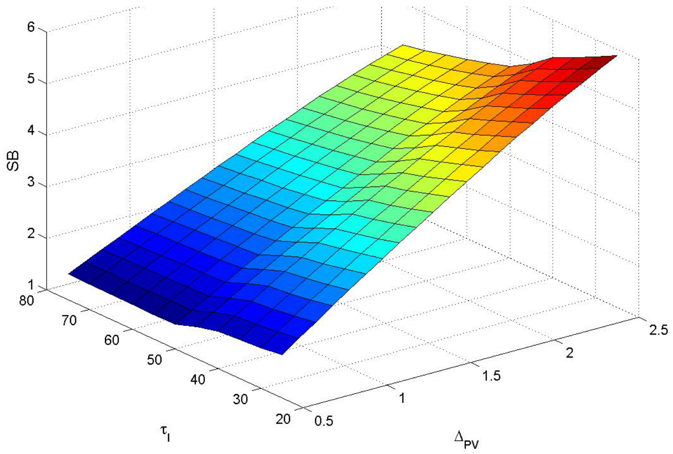

Figure 6.12: Sensitivity analysis for τ_I and Δ_{PV}.

Again, the interpolation has a quasi-linear behavior, as shown in Figure 6.12. A small mismatch in these parameters will not have a strong impact in SB prediction.

In the third analysis the impact of Δ_{PV} and ZC_{ACV} was analyzed, as shown in Figure 6.13.

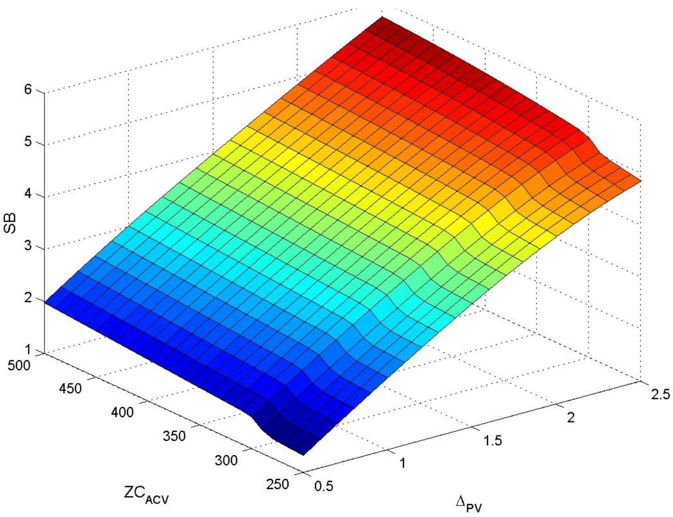

Figure 6.13: Sensitivity analysis for τ_I and Δ_{PV}.

The plot shown in Figure 6.13 repeats the behavior seen in the two previous: the neural network showed a very smooth interpolation.

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Chapter 7

Model-Plant Mismatch Evaluation Using Independent Component Analysis

Abstract: 🕮 *This work proposes a methodology to evaluate the Model-Plant Mismatch (MPM), based on Independent Component Analysis (ICA). The main application for this work is to evaluate the quality of the model used by Model Predictive Controllers (MPC). The methodology can deal with two scenarios: the first where setpoint variations are available; and the second where only normal operating data is available. In the later, the actual performance should be compared with a base-case. Due to its flexibility, the proposed method can easily be applied in industrial controllers to evaluate MPM. Besides, a discussion about what industry understands about MPC performance assessment and what are the restrictions and frontiers for this field are both presented. The proposed work is applied in the Wood and Berry and Shell control problem benchmark showing fruitful results.*

7.1– Introduction

Beyond PI and PID type controllers, MPCs are the most popular controllers available in the industrial field. Despite the fact that MPC technology has less than 30 years, linear and non-linear MPCs were present in more than 4500 applications until 2003 (Qin 1998). Many reviews about MPC technology, algorithms, and applications are available in literature (Qin 1998). The economic impact of MPC is reported in several works (Wei et al. 2007) and it is also well known in the industry.

🕮 *This chapter is based on the paper presented by M. Farenzena and J. O. Trierweiler at the Advanced Control in Chemical Processes Conference (ADCONIP 2008), Jasper, Canada.*

Once applied, the performance of industrial controllers (not only MPCs) decreases due to several factors, e.g.:

- Change of process dynamics
- Change of operating point
- Changes in disturbance pattern
- Process changes.

Some works report that more than 60% of industrial controllers have some kind of performance problem (Bialkowski 1993). That is the reason why "maintenance" is the key word to get the maximum benefit from predictive controllers.

The task of diagnosing the poor performance of MPC is a challenge. The source of the poor performance can be the tuning parameters, model quality, and controller design, among others (Patwardhan and Shah 2002). The work of Patwardhan and Shah (2002) shows the influence of these parameters over the MPC performance.

Many works have been proposed aiming to assess the performance of multivariable or predictive controllers. Schäfera and Cinar (2004) propose a methodology where the control performance is quantified based on the cost function. To diagnose the MPC poor performance, the actual cost function is compared with the LQG benchmark. Kadali and Huang (2002) also used the LQG controller as benchmark. Ghraizi et al. (2007) proposed a methodology to address the MPC performance based on the predictability of controller behavior. Huang et al. (1997) used minimum variance controller as a benchmark. Gao et al. (2003) reports the application of this methodology to evaluate the performance of two industrial controllers. Kamrunnahar et al. (2002) proposed a method to evaluate multivariable control performance based on ARMarkov approach. DeVries and Wu (1978) proposed a methodology based on one-step-ahead prediction. In the work of Kozub (1997), the benchmark is specified by the engineer, based on intuitive measurements, like rise time or settling time.

The works previously mentioned show when MPCs have a poor performance, however they do not diagnose the cause, which is also a challenge for the academia. The poor performance of a MPC can came from several sources:

- tuning;
- model plant mismatch;
- disturbances;
- regulatory control;

- non-linearity;

among others.

The main contribution of this work is an automatic methodology to evaluate the model-plant mismatch (MPM) using Independent Component Analysis (Comon 1994). The methodology proposed in this work allows to:

- point the channel where the mismatch is high;
- work with industrial models, with small mismatch in all channels. In this case, only a small number of channels have larger mismatches.

Also, the methodology can be potentially applied in industrial plants because only the process model to be evaluated and the process data are required.

The chapter is segmented as follows: in section 7.2 we define the meaning of MPC performance assessment and the difficulties. In section 7.3, Independent Component Analysis (ICA) is briefly described, which is the basis of the methodology introduced in section 7.4 to evaluate the MPM. In section 7.5, the methodology is applied in two case studies and the concluding remarks are presented in section 7.6.

7.2 – Model predictive control performance assessment

The concept of MPC assessment addresses not only closed loop performance, but also should answer other questions:

- Is the model adequate for the advisable performance?
- The model is poor and some channels have big mismatches. Which are the channels?
- Is the economical layer working properly?
- Is the linear MPC enough or the process non-linearity is high and a non-linear MPC is necessary?

The complexity of these questions is addressed in the fact that the answers are not independent. For example, the optimization layer can have poor performance if the economical impact of each variable is not properly set or the model is not correct. Again, the model can be the answer for all questions, if it has a big mismatch.

This is the central objective of this work. A methodology to distinguish the channels that have significant MPM is proposed.

On the other hand, the industry imposes several constrains that can turn the problem infeasible:

- Only routine operating data and the plant model are available;
- The controller model is in most cases unavailable;
- No invasive tests are allowed.

Based on these assumptions, the problem becomes more difficult.

The schematic representation of the system is shown in Figure 7.1 :

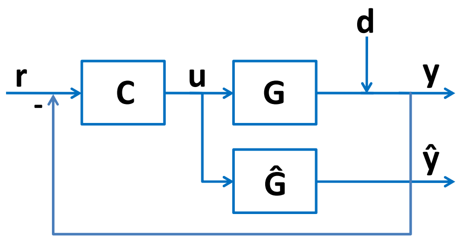

Figure 7.1: IMC structure with plant model (G) and model used inside controller ($\hat{G}$)

where y is the process outputs, u the manipulated variables, r the reference signal, d is the output disturbance, C the controller (MPC), G the plant and $\hat{G}$ is the plant model, and $\hat{y}$ is the predictable output. The process output can be written as:

$$y = \frac{CG}{1+CG} r + \frac{1}{1+CG} d \tag{7.1}$$

If there is no setpoint variation, the term $\frac{CG}{1+CG} r$ will be zero. It is considered that controller model and the disturbance are also unknown. Based on these assumptions, it is easy to see that only process outputs are insufficient to evaluate the MPM.

Using the manipulated variables (u), the same system can be written as:

$$y = Gu + d \tag{7.2}$$

and the predicted output ($\hat{y}$) can be written as:

$$\hat{y} = \hat{G}u \tag{7.3}$$

If the disturbance d is unknown and the system does not have imposed excitation, it is not possible to evaluate the MPM.

Based on the previous explanation, it is clear to see that:

- excitation (setpoint variations or steps on *u*) should be available; or
- the actual model performance should be compared with a base case;

to evaluate the MPM in an industrial MPC.

Another difficulty that should be overcome is highly correlated inputs, whose source is the multivariable controller. To transpose this barrier, the inputs are decomposed in independent inputs, using Independent Component Analysis (ICA) (Comon 1994), whose brief description is showed in the next section.

7.3– Independent Component Analysis

The Independent Component Analysis (ICA) of a set of random vectors consists of searching for a linear transformation that minimizes the statistical dependence between its components (Comon 1994). The ICA is used in several different areas such as: biomedical (Melissant, 2005); pattern recognition (Sharma and Paliwal 2006); chemistry (Shashilov et al. 2006); and image processing (Ferreira and Figueiredo 2006), among others.

The basic idea of ICA is described as follows. Suppose that *n* process variables are measured $x_1, \ldots, x_n$, that are the linear combination of *n* independent components $s_1, \ldots, s_n$.

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \ldots + a_{jn}s_n \tag{7.4}$$

The independent component analysis (ICA) allows to find each independent component (s_j), using only the process (measured) variables $x_1, \ldots, x_n$ (Hyvarinen and Oja 2000).

Without loss of generality, we can assume that both process variables and independent disturbances have zero mean and variance equal to one. The starting point of ICA is that each component is statistically independent and each component must have non-Gaussian distributions.

The problem to be solved can be written as:

$$x = As \tag{7.5}$$

or

$$s = Wx\,. \tag{7.6}$$

Where *A* and *W* are the weighting matrices, *x* are the measured process variables, and *s* the independent components. The matrix A is called significance matrix.

Considering

$$y = w^T x = w^T As = z^T s \tag{7.7}$$

since a sum of two independent random variables is more Gaussian than the original variables (central limit theorem), $z^T s$ is more Gaussian than any of the s_i. The product becomes least Gaussian when it is equals to s_i, i.e., when only one element of z is nonzero. Therefore, we could take as $\boldsymbol{w}$ a vector that maximizes the non-Gaussianity of $\boldsymbol{w}^T\boldsymbol{x}$. This vector would necessarily correspond to a z which has only one non-zero component. This means that $w^T x$ equals one of the independent components (Hyvarinen et al. 2001).

To measure the non-Gaussianity the classical fourth order cumulant or Kurtosis is used (Mendenhall and Sincich 1984). The algorithm used in this chapter to estimate the independent components is the FastICA, proposed by (Hyvarinen and Oja 2000).

7.4– MPM evaluation

This section introduces the methodology to evaluate MPM, which is based on Independent Component Analysis (ICA) (Comon 1994).

The basic assumptions to apply the proposed methodology are:

- the controlled variables (y) and manipulated variables (u) are available without any degree of compression;
- the controller (MPC) model is not available;
- the plant model used by MPC is available.

In the following, the procedure to evaluate MPM in MPC controllers will be described in two different scenarios, previously mentioned.

7.4.1 – Scenario 1 – The plant has enough excitation

In this scenario, setpoint changes are necessary (or variations in the manipulated variable) to evaluate MPM in MPCs. The methodology to evaluate MPM is described subsequently:

1. Collect process data y and u, and process model ($\hat{G}$), with n inputs and m outputs;
2. Decompose the n inputs into independent components ($ui_{,k}$, $k=1 \ldots n$);
3. Match each input with its respective independent component, based on the significance matrix;

4. Consider that each independent input (ui_k. $k=1...n$) is fed separately. Then the independent outputs ($yi_{j,k}$) are calculated. The number of independent outputs is $n \, . \, m$.

5. Describe each plant output (y_j, $j=1...m$) as a function of the independent outputs ($yi_{j,k}$), solving the linear least square problem:

$$\min_{h_j} \left| y_j - h_{j,1} yi_{j,1} - h_{j,2} yi_{j,2} - \cdots - h_{j,n} yi_{j,n} \right| \tag{7.8}$$

Then the linear parameters $h_{j,k}$ are obtained.

6. Write each predicted output ($\hat{y}_j$, $j=1...m$) using the independent outputs, as described in the previous step:

$$\min_{\hat{h}_j} \left| \hat{y}_j - \hat{h}_{j,1} \hat{y}i_{j,1} - \hat{h}_{j,2} \hat{y}i_{j,2} - \cdots - \hat{h}_{j,n} \hat{y}i_{j,n} \right| \tag{7.9}$$

Then the linear parameters $h_{j,k}$ are obtained.

7. Compose the H and $\hat{H}$ matrixes:

$$H = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,n} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ h_{m,1} & h_{m,2} & \cdots & h_{m,n} \end{bmatrix} \tag{7.10}$$

$$\hat{H} = \begin{bmatrix} \hat{h}_{1,1} & \hat{h}_{1,2} & \cdots & \hat{h}_{1,n} \\ \hat{h}_{2,1} & \hat{h}_{2,2} & \cdots & \hat{h}_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{h}_{m,1} & \hat{h}_{m,2} & \cdots & \hat{h}_{m,n} \end{bmatrix} \tag{7.11}$$

8. Compute the MPM matrix, by the element-by-element ratio between H and $\hat{H}$.

The MPM can be evaluated based on the distance from unit of each element (channel). Again, the source can be a variation in the channel dynamics, a gain change, or a variation in time delay.

One rule of thumb useful for the analysis is also proposed, based on our limited experience. If channels have values between 0.8 and 1.5, the MPM is acceptable. Otherwise, the MPM is significant. Values higher than 5 or smaller than 0.4 denote a big MPM.

7.4.2 - Scenario 2 – The plant does not provide enough excitation

This scenario is useful for practical applications, where no invasive tests are allowed and MPC controllers work most of time with a fixed reference (*r*). However, as shown in section 7.2, the problem becomes infeasible if the disturbance is unknown.

In this case, where the reference is fixed, two restrictions should be imposed to overcome this lack of process information:

- the disturbance is estimated or
- one scenario where the MPM is small is used as base-case. This can be the MPC commissioning scenario or another one where the MPM is small.

The methodology to evaluate MPM when the process is not enough excited is described below:

1. Estimate the process disturbance for the base-case. Considering that

$$G \approx \hat{G} \tag{7.12}$$

and apply in:

$$\begin{aligned} y &= Gu + d \\ \hat{y} &= \hat{G}u \end{aligned} \tag{7.13}$$

Using the normal operating data of a base-case where the MPM is small, the disturbance d can be estimated as:

$$d = y - \hat{y} \tag{7.14}$$

2. Evaluate the H and $\hat{H}$ matrix, as shown in Procedure 1;

Again, the MPM can be evaluated by the element-by-element ratio between H and $\hat{H}$.

The main drawback of the proposed methodology is that if the disturbance pattern changes, the methodology can lead to wrong results. However, assume a fixed benchmark (base-case) as a necessary artifice to overcome the low information provided by the process, where no enough excitation is provided.

7.5– Case studies

In this section the methodology to evaluate the MPM will be applied in two case studies.

7.5.1 – Case study 1 – Wood and Berry system

The pilot-scale distillation column proposed by Wood and Berry (1973) is the first case study. The plant model is given by:

$$\begin{bmatrix} x_D(s) \\ x_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8}{16.7s+1}e^{-1s} & \frac{-18.9}{21s+1}e^{-3s} \\ \frac{6.6}{10.9s+1}e^{-7s} & \frac{-19.4}{14.4s+1}e^{-3s} \end{bmatrix} \begin{bmatrix} R(s) \\ S(s) \end{bmatrix} \tag{7.15}$$

where x_D and x_B are the overhead and bottom products composition, and R and S are the reflux and steam flow rate, respectively. The time constants and time delays are expressed in minutes.

The MPC controller from Matlab® (MPC toolbox V. 2.2.2) was applied in this case study. The disturbance was generated passing a random signal through a first order transfer function with unitary gain and 60 minutes time constant. The MPC parameters for Wood and Berry are shown in Table 7.1.

Table 7.1: MPC parameters used for Wood and Berry

Parameter	Value
Sampling time	0.5 min
Prediction Horizon	50 min
Control Horizon	10 min
Input Weights	[1 1]
Output Weights	[1 1]

The analysis will take place in 3 scenarios:

- no MPM with setpoint variations;
- channel (y_1-u_1) with 10%, 30%, and 50% gain mismatch and plant with setpoint variations;
- channel (y_1-u_2) with 50% gain mismatch and plant with no setpoint variations.

The MPM matrix obtained for the first scenario is:

$$MPM = \begin{bmatrix} 1.0 & 1.0 \\ 0.93 & 0.99 \end{bmatrix} \tag{7.16}$$

and it shows that the MPM is almost inexistent.

The matrixes for the second scenario are:

$$\begin{aligned} MPM_{10\%} &= \begin{bmatrix} 1.4 & 1.0 \\ 0.94 & 0.99 \end{bmatrix} \\ MPM_{30\%} &= \begin{bmatrix} 4.4 & 1.1 \\ 0.95 & 0.99 \end{bmatrix} \\ MPM_{50\%} &= \begin{bmatrix} 1.3 & 1.0 \\ 0.93 & 0.99 \end{bmatrix} \end{aligned} \tag{7.17}$$

Eq. 7.17 shows that the methodology pointed to the right channel where the MPM is high. However, it is not possible to quantify the mismatch, but this is not the aim of this work.

In the third scenario, the MPM obtained is given below:

$$MPM = \begin{bmatrix} 1.1 & 0.12 \\ 0.93 & 0.99 \end{bmatrix} \tag{7.18}$$

Eq. 7.18 shows that the methodology can show the correct channel where the MPM is high, even when no setpoint changes are available.

7.5.2 – Case study 2 – Shell Control Problem

The Shell Control Problem benchmark was proposed by Pratt and Morari (1997). It involves one heavy oil fractionator, whose schematic representation is shown in Figure 7.2. The system is characterized by the high interaction among channels and large time delays.

The fractionator has three product draws, three side circulating loops and a gaseous feed stream. The system consists of seven measured outputs, three manipulated inputs and two unmeasured disturbances. In this case study, we will reduce the problem to a 3 input and 3 output case. The three controlled variables are:

- Top End Point (y_1);
- Side Endpoint (y_2);
- Bottom Reflux Temperature (y_3).

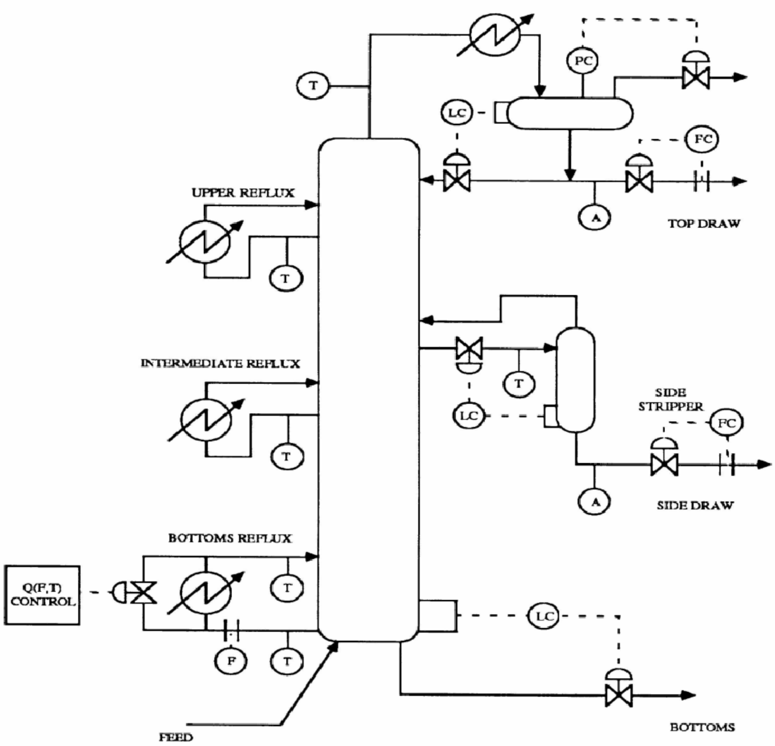

Figure 7.2: Shell Control Problem schematic representation

The manipulated variables are:

- Top Draw (u1);
- Side Draw (u2);
- Bottom Reflux Duty (u3).

The system has also two disturbances:

- Upper reflux (d_1);
- Intermediate reflux (d_2).

The process output can be written as:

$$y = Gu + G_d d \tag{7.19}$$

Where G is the plan model:

$$G = \begin{bmatrix} \frac{4.05}{50s+1}e^{-27} & \frac{1.77}{60s+1}e^{-28} & \frac{5.88}{50s+1}e^{-27} \\ \frac{5.39}{50s+1}e^{-18} & \frac{5.72}{60s+1}e^{-14} & \frac{6.9}{50s+1}e^{-15} \\ \frac{4.38}{33s+1}e^{-20} & \frac{4.42}{44s+1}e^{-22} & \frac{7.2}{19s+1}e^{-19} \end{bmatrix} \tag{7.20}$$

and G_d the disturbance model:

$$Gd = \begin{bmatrix} \frac{1.2}{45s+1}e^{-27} & \frac{1.44}{40s+1}e^{-27} \\ \frac{1.52}{25s+1}e^{-15} & \frac{1.83}{20s+1}e^{-15} \\ \frac{1.14}{27s+1} & \frac{1.26}{32s+1} \end{bmatrix} \tag{7.21}$$

The time constant and time delays are reported in minutes. The MPC from Matlab® was used in this study, whose parameters are shown in Table 7.2**:** .

Table 7.2: MPC parameters used for Shell Case Study

Parameter	Value
Sampling time	0.2 min
Prediction Horizon	20 min
Control Horizon	4 min
Input Weights	[0.03 0.05 0.05]
Output Weights	[1 1 1]

The analysis will be accomplished in two scenarios:

- no model-plant mismatch;
- small gain mismatch in all channels and two channels were the gain mismatch is large.

Initially, the signals were generated, considering two setpoint variations in each controlled variable, for each scenario. Then, the proposed methodology was applied. In the first scenario the MPM matrix is:

$$MPM = \begin{bmatrix} 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 \end{bmatrix} \tag{7.22}$$

Based on Eq. 7.22, it is easy to see that the methodology shows that both models are equal.

In the second scenario, the gain is also divided by a factor of 2 in channels (y_1 x u_2) and (y_1 x u_3). The MPM matrix obtained is:

$$MPM = \begin{bmatrix} 1.0 & 1.4 & 0.1 \\ 1.0 & 1.0 & 1.0 \\ 1.0 & 1.0 & 1.0 \end{bmatrix} \tag{7.23}$$

Eq. 7.23 shows that the methodology correctly pointed the channels where the MPM is large.

7.6– Conclusions

In this chapter a methodology to detect Model-Plant Mismatch based on Independent Component Analysis (ICA) is introduced. This scenario is very useful to diagnose the model quality in MPC applications.

The first contribution of this work is the proposal of a methodology for two scenarios: one where enough process excitation is available and other where only normal operating data is available. In the first, the MPM is quantified and the disturbance pattern evaluated. This information is used when only normal operating data is available (scenario 2).

The methodology initially decomposes the manipulated variables in its independent components. Then, they are fed in the available model and, based on individual contributions, the MPM is evaluated.

The methodology was applied in two case studies: Wood and Berry distillation column and Shell benchmark problem. In both cases the methodology showed reliable results, correctly pointing the channels where the mismatch was located.

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Chapter 8

Concluding remarks and further work

This chapter shows the main contributions of this work. It also provides some suggestions for further works about the thesis issue.

8.1– Concluding remarks

Chapter 3

This chapter shows how to decompose the impact of white noise, time delay and control loop performance in the final loop variability. This decomposition helps the engineer in the CLPA, when MVI is used. The following three novel indices have been proposed:

- *nosi* – white noise influence;
- *deli* – time delay influence;
- *tuni* – influence of the controller performance. The influence of the controller order is captured by $tuni_{PID}$, which can quantify how much from the total variance can be removed by a PID controller.

Moreover, a new method to evaluate the process minimum variance when a PID controller is applied was proposed. The application in a set of case studies has shown interesting results and potential industrial application.

Main contributions:

- *Methodology to decompose the impact of white noise, time delay, and control loop performance in the final loop variability, using only normal operating data and time delay.*
- *Methodology to compute the achievable MV for PID controllers.*

Chapter 4

Traditional (or stochastic) performance indices do not provide conclusive metrics. The analysis, when it is based on minimum variance index or other stochastic indices, is most of times nebulous and the diagnostics difficult. This scenario shows that better indicators to make the analysis easier and straightforward are required. Deterministic indices (ratio between open loop and closed loop rise time, settling time, maximal sensitivity, among others) provide a clear picture of the controller performance and robustness, but intrusive tests are required and their computation in the whole process is not possible.

A methodology to estimate deterministic metrics to evaluate CLPR based on stochastic indices is the central point of this chapter. The Performance and Robustness Inference Model (PRIM), proposed in this work, shows that this translation is possible. The procedure to build the PRIM was described, as well as its application in case studies, showing very good results.

Main contributions:

- *Highlight some drawbacks of MVI and other stochastic indices, showing that better metrics are required;*

- *Break out of paradigm: use deterministic indices to evaluate controller performance and robustness, because they provide conclusive metrics of loop health.*

- *Allow the on-line estimation of deterministic indices. To achieve this target, we propose an inference model to estimate these indices, based on stochastic metrics and plant parameters.*

Chapter 5

A methodology to compute the economic impact of each control loop, as a tool to prioritize loop maintenance, is the central aim of this chapter. The concept of Variability Matrix, which is an array that shows the impact of performance improvement of a given loop on the whole plant, is introduced. Based on the VM, a methodology to translate this array into a potential loop economic benefit metric is also suggested. The work shows two scenarios where VM can be quantified: the ideal scenario where plant model and controller are available and the second where they are not, thus allowing the application of these ideas in the industry. The efficacy of the proposed methodology is illustrated by its successful application to two case studies.

Main contributions:

- *Introduce the concept of VM and*

- *Showed how to use the VM concept to prioritize loop maintenance.*

Chapter 6

A methodology to quantify the stickband in sticky valves is the central proposal of this chapter. Analogous to PRIM, an inference model to estimate the stickband, called Stiction Inference Model (SIM) is proposed. The procedure to build the SIM (candidate variables, inputs selection, neural network training and test), as well as its structure (inputs, number of neurons) are described. This method is applied in a class of control valves, providing fruitful results.

Main contribution:

- *The proposal of a model to estimate the stickband in control valves that use only controller output (OP) and process output (PV).*

Chapter 7

This chapter proposes a methodology to evaluate the Model-Plant Mismatch (MPM), based on Independent Component Analysis (ICA). This issue is very important to diagnose one of the responsible factors for bad performance of Model Predictive Controllers (MPC). The methodology can work in two scenarios: the first where setpoint variations are available; and second where only normal operating data is available. Due to this flexibility, the proposed method can easily be applied in industrial controllers to evaluate MPM. The proposed method was applied in two case studies and reasonable results were obtained.

Main contribution:

- *The proposal of a simple method to point the channels where the model-plant mismatch is high. This method is based on Independent Component Analysis.*

8.2– Directions for further work

Automatic computation of time delay and time constant

The PRIM is dependent on the correct estimation of time delay and time constant. Other methodologies and indices (Harris, nosi, deli, tuni, among others) are equally dependent on these parameters. It is well known that in most cases, this value is not estimated, only a default value is used, or the engineer informs the value based on his experience. After the commissioning of the CLPA tool, these values are updated if the loop has a bad performance. Thus, an automatic methodology to estimate time delays and time constants is required to help CLPA.

In the literature, several methodologies are available to estimate time delay for process controllers (Agarwal and Canudas 1987; Ahmed et al. 2006; Drakunov et al. 2006; Elnaggar et al. 1991; Liang et al. 2003; Tuch et al. 1994) or two generic signals (Emile and Comon 1998; Kosel et al. 2002; Sharma and Joshi 2007; So 2001).

To investigate the best methodologies and the scenarios where each one performs better, as well as when they fail, proposing ideas to overcome the limitations, is a further work that will help not only to improve the efficiency and reliability of CLPA tools, but also to reduce its commissioning time.

Translate performance improvement in variability reduction

The PRIM provides the actual loop performance and robustness. Based on this information, what is the impact in the variability if the controller performance is improved? Actually, this information is not provided by the PRIM. Build an inference model that translates performance improvement (e.g. the rise time ratio increases from 1 to 6) in variability reduction is an important step to help the engineer in the CLPA.

MPC controller performance assessment

Despite the fact that MPC technology has less than 30 years, linear and non-linear MPCs were present in more than 4500 applications until 2003 (Qin 1998). However, the task of diagnosing the poor performance of MPC is a challenge. The source of the poor performance can be (Patwardhan and Shah 2002):

- Tuning
- Model Plant mismatch
- Disturbances
- Regulatory control
- Non-linearity

Many works have been proposed aiming to assess the performance of multivariable or predictive controllers (see, e.g., Huang et al. (1997)). These works (try to) diagnose the poor performance of multivariable or MPC controllers, however they do not diagnose the cause.

Specific methodologies to evaluate the cause of MPC bad performance are required and should be subject for further developments.

Nonperiodical disturbances

In the literature, there is a massive work to detect and diagnose the root cause of periodical disturbances (Thornhill and Horch 2007). In chemical plants, detecting nonperiodical disturbances is as important as detecting oscillations. The development in this area is scarce. Apply signal processing techniques like Independent Component Analysis (ICA) (Hyvarinen and Oja 2000; Xia et al. 2005) or partial correlations (Fried and Didelez 2005) can be used to isolate disturbances.

Industrial application

Apply the proposed methodologies in industry and verify (or not) their efficacy is another required step to consolidate this thesis results. The following methodologies/indices need a more intensive industrial application:

- PRIM;
- Four indices that decompose variability impacts (nosi, deli, tuni, and $tuni_{PID}$);
- Variability Matrix.

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