CONTROL LOOP PERFORMANCE MONITORING IN AN INDUSTRIAL SETTING

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for the degree of Master of Engineering

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and, any editorial work, paid or unpaid, carried out by a third party is acknowledged.

Ghassan H. Al Soraihi

October, 2006

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SUMMARY

The wide range of applications for single input single output controllers have encouraged interest in monitoring their performance. Over the past two decades researchers in the area have found many performance enhancement opportunities by applying these techniques. These are most evident in large operational plants with hundreds of controllers being monitored at the same time.

Early performance measures were based on minimum variance control as a benchmark for controller performance Many other procedures have since emerged that have improved the level of accuracy in these performance measures. In addition, these improvements made it easier to implement control loop performance monitoring in large industrial settings. Performance indices that address specific control objectives such as steady state operations, set-point change, and disturbance rejection were developed. Other indices focused on addressing specific problems such as detection of controller oscillation and control valve problems. Furthermore, general performance settings for large scale implementation were identified.

This thesis looks at the performance measures in use for single input single output controllers. The work here looks at incorporating these different measures for a specific manufacturing plant. Ways for identifying the goals and objectives of controllers in a system are presented. Furthermore, measures that most accurately indicate if these goals and objectives are being met are offered.

The concept is demonstrated on a distillation system in a gas plant. It is shown how using these objective driven techniques can provide the user with sound results. These results do not require much user analysis to identify sources of problems and areas of improvement.

As a result of this thesis the following paper has been presented

[I] Al Soraihi, G and Vinay, T., "Statistical methods for process and control performance monitoring – A review of the Literature." Presented at the 7th Biennial Engineering Mathematics and Applications Conference in Melbourne, Australia 25th-28th Sept 2005

CHAPTER 1
INTRODUCTION TO CONTROL LOOP PERFORMANCE MONITORING

1.1 General

Control Loop Performance Monitoring (CLPM) has attracted a great deal of interest in recent years. Researchers have shown that control system performance can be improved by implementing CLPM techniques. These improvements mean that a processing plant would be able to produce more on-specification products using a safe, reliable, and economical control system.

The idea behind CLPM is to be able to detect degradations in control performance, and identify and rectify the root-causes of control system problems with the least amount of delay. These are control problems that would make the system operate in an unsafe, unstable, or uneconomical manner, thus, producing off-specification products, consuming more energy, and losing profit making opportunities.

A processing plant is made-up of one or more processing units; each one contains a number of controllers. Each controller in a plant has a specific objective which contributes to the overall control system strategy of the plant which is required to produce the final products. These products need to meet a predefined set of customer specifications in order for the plant to make a profit from its production process. Controllers are collections of hardware and software components that are needed to achieve a specific task or objective in a control system. In the gas processing industry these controllers are used to control flow, level, temperature, pressure etc. A control loop would contain a sensor, final control element such as a valve, and control algorithm such as Proportional, Integral, and Derivative control (PID). An example of a flow control loop is shown in Figure 1.

Various reasons can cause such controllers to perform badly. A sensor could be miscalibrated and providing inaccurate readings. A valve might have non linear stiction that would cause oscillations in the system. The tuning parameters of the control algorithm may be incorrect or even cause the controller to be unstable. As these controllers operate in a continuous process one bad controller could affect the performance of many other control loops in the plant.

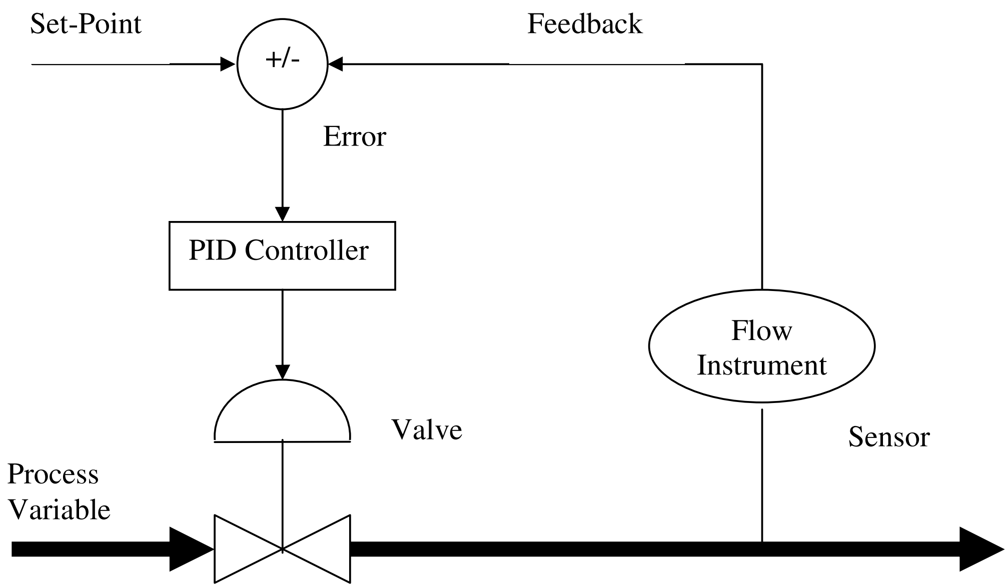

Figure 1: Feedback Control Loop Structure for a typical flow control system

1.2 Value and Benefits

The value of monitoring the performance of control loops can be shown from different aspects. Currently many process plants implement Advanced Process Control (APC) applications that are based on plant models. It is a well known fact that most of the benefits achieved from these applications are due to the improvements made to the regulatory controllers in the plant. Figure 2 shows the typical application hierarchy of these systems. Thus, whenever changes to this regulatory control layer occur they affect the performance of the APC application as the plant dynamics deviates more and more from the models. In fact with the passage of time the APC applications would continue to produce less and less profits due to changes likely to occur over time on the regulatory layer until at some point they are turned off by the plant personnel. So a once very profitable application is turned off due to a lack of performance from the regulatory level controllers. Thus the performance of all the levels above the basic instruments level depends on the performance of this level.

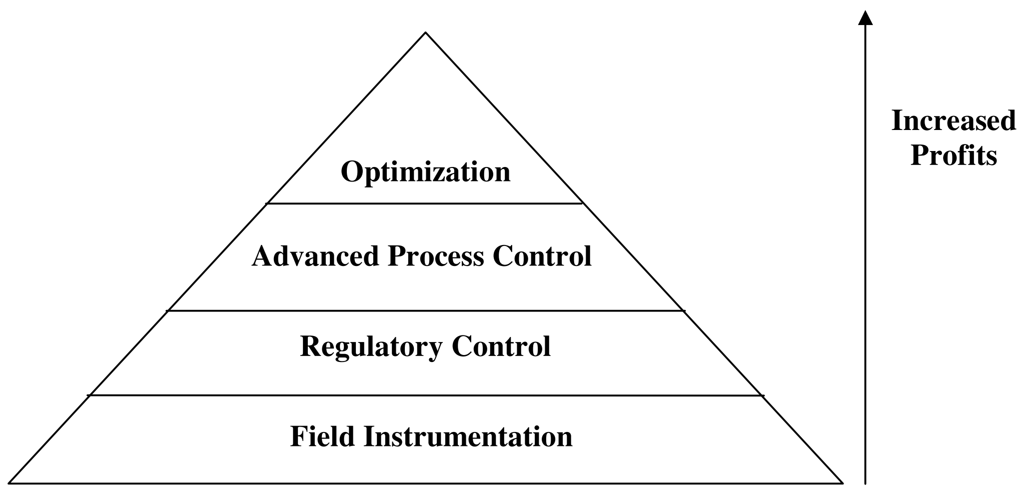

Figure 2: Application Hierarchy

Furthermore, oscillations are one of the most common disturbances in process plants. An oscillating process means that the plant must lower its target values to guarantee that it does not violate any product specifications. This lower target means that the plant had to lower its products quality thus losing potential profits.

1.3 Sources of Implementation Problems

A number of commercial software applications that provide CLPM tools have appeared in the market in recent years. These applications calculate different performance measures and indices to provide the engineer with the means to assess the performance of the controllers in his/her plant. Nevertheless, CLPM is still an area of performance enhancements due to a number of factors: the most important factor is lack of training for plant engineers on how to use and interpret the results of these new applications. One of the major arguments behind automation of CLPM is that plant engineers are overwhelmed with the number of activities they have to deal with on a daily basis. Adding to this an application that produces a number of indices for each controller in the plant and expecting the engineer to react to the results produced by these applications without a clear understanding of what each index means and represents is a recipe for failure.

An objective of CLPM is to detect the root cause of problems in the control system. Let that be a controller that is the source of an oscillation shared by other controllers, a problem with the tuning of the controller, or a hardware problem with one of the controller components such the sensor or the valve. And to complete the picture CLPM should be able to offer suggestion for the resolutions of these problems.

The solution to these problems requires an engineer to employ his knowledge of the process and utilize a CLPM system to improve the performance of the plant. This process knowledge includes plants overall control objectives, individual controller objectives, controller interactions, and critical controllers. The engineer should be able to use the results provided by the CLPM to come up with an objective analysis of the plant control system performance and direct maintenance efforts to the controllers that have the greatest affect on plant control objectives.

1.3 Specifications for CLPM

A successful CLPM implementation would need to meet the following criteria:

1. Online implementation utilizing plant data and requiring no additional instrumentation, and easily accessible to plant personnel.
2. Provide clear metrics to analyse the performance of the controllers.
3. Provide means for the engineer to pinpoint the sources of problems.
4. Be able to assess the performance of individual controllers based on their specific control objectives.

1.4 Introduction of Thesis Content

An explanation of Control Loop Performance and the value it adds to the control system functionality is individually discussed in Chapter 1. In this thesis Control Loop Performance is viewed as the performance of the Single Input Single Output controllers in a system.

In this research an intensive review of the literature is presented. The review includes all the major developments in the area of Control Loop Performance Monitoring in the last decade. An outline of steps needed to calculate the performance indices are given and applied to a Deethanizer system. Operational data from a Gas plant Deethanizer system are used to calculate the performance indices, the results are analysed and poor performing control loops are identified.

1.4.1 Chapter 2: Review of Current CLPM Techniques

Chapter 2 provides an intensive literature review of CLPM techniques. Detailed discussion is given of past and current algorithms used in CLPM. The advantages and disadvantages of each are highlighted. The review also covers oscillation detection and diagnosis as well as CLPM implementation issues. Finally, an overview is given of the extensions made to CLPM to cover Multi Input Multi Output systems (MIMO).

1.4.2 Chapter 3: Derivation of Performance Indices

Chapter 3 provides an explanation on how to derive and calculate the different performance indices. It also discusses some of the preparations that are needed to implement a CLPM system in an industrial setting.

1.4.3 Chapter 4: Deethanizer System

This chapter describes the Deethanizer system at Saudi Aramco (www.saudiaramco.com) Juaymah Gas Plant, Saudi Arabia where the author of this thesis is employed and has had six years of working experience. It starts with a description of the process flow and operation. Then an overview of some of the control strategies used on the system is given. An explanation of the types of controllers used in the system follows. The control objective of each controller and how it affects the overall control scheme is explained. An insight into some of the known problems and interactions in the system are given.

1.4.4 Chapter 5: Deethanizer System Analysis using CLPM

Chapter 5 contains a case study where the previously discussed performance indices are evaluated and used to assess the performance of the Deethanizer control system. Data obtained from the actual gas plant are used for this study.

Next a comparison study between the performance analyses of three similar Deethanizer plants in the same facility is presented.

The Results are shown to indicate the controllers with the worst overall performance and having the most harmful effect on the plant's performance.

1.4.5 Chapter 6: Conclusion and Future Research

The control loop performance analysis based on the proposed methods, calculation of the various performance measures, and evaluation of the results are summarized. Recommendations and suggestions that are related to the performance studies are made. Approaches for further improvement of control loop performance evaluation are discussed.

CHAPTER 2

REVIEW OF CURRENT CLPM TECHNIQUES

This chapter reviews the various CLPM techniques introduced in the literature. A discussion of the different algorithms for calculating the performance measures and their advantages and disadvantages are presented. This is followed by a review of the procedures used to detect oscillations. Finally, an overview of how some of these techniques have been modified to cover multi input multi output systems is presented.

2.1 Single Input Single Output Performance

In 1989 Astrom [1] introduced the concept of Minimum Variance Control (MVC) for a regulatory process with a known time delay. This is a controller that would, in theory, minimise the effect of noise disturbance on the system output. This ideal controller provides a useful benchmark for the performance evaluation of practical controllers. Thus whatever controller we use will only in practice be able to give an output variance greater than that of the MVC controller.

Harris [2] used this concept of ultimate control and developed a performance index against which the performance of control loops can be measured. Comparing the variance of the controller to its MVC became the basis of the MVC performance index later known as the Harris Index. What was appealing about this index is that only knowledge of the process time delay and closed loop output data are needed to calculate this index. The Harris index is based on fitting a time-series model to the process output data and calculating the output variance. The index (I_p) is measured by comparing the actual output variance σ_y^2 to the output variance obtained by using a minimum variance controller σ_{MV}^2.

$$I_p = \frac{\sigma_y^2}{\sigma_{MV}^2}$$

The Harris index will always have a value equal to or greater than one. In order to compute the Harris index a set of normal operating output data $y(t)$ and knowledge of the process dead-time d (expressed as the number of sample periods) is required. The output data is used to determine a time-series model of the process

$$y(t) = \frac{C(q^{-1})}{A(q^{-1})} e(t)$$

A series expansion (pulse response) of this model would give:

$$\begin{aligned} y(t) &= (h_0 + h_1 q^{-1} + h_2 q^{-2} + \ldots) e(t) \\ &= \sum_{i=0}^{\infty} (h_i q^{-i}) e(t) \end{aligned}$$

The first d elements of the series expansion coincide with the coefficients of the series expansion of the noise process $e(t)$.

In theory, a minimum-variance controller completely removes all influences from the noise signal sample (occurring at a given instant) after the time-delay d.

$$y(t) = (h_0 + h_1 q^{-1} + \ldots + h_{d-1} q^{-(d-1)}) e(t)$$

Thus the minimum variance would be:

$$\sigma_{MV}^2 = (h_0^2 + h_1^2 + h_2^2 + \ldots + h_{d-1}^2) \sigma_e^2$$

It is suggested [3] to use the estimated time-series model to evaluate the current variance σ_y^2 since that would eliminate the need to find the noise variance σ_e^2 since it will be cancelled. This form will also guarantee that $I_p \geq 1$.

$$I_p = \frac{\sum_{i=0}^{\infty} h_i^2}{\sum_{i=0}^{d-1} h_i^2}$$

Despite its appealing features the Harris index has some serious shortcomings. The following example from Astrom and Wittenmark [4] is used here to illustrate these problems.

The example system is described by the following equations with a time delay of 2 sample periods.

$$A(z) = z^3 - 1.7z^2 + 0.7z$$
$$B(z) = z^3 + 0.5z^2$$
$$C(z) = z^3 - 0.9z^2$$

It can be shown that the MVC in this case is:

$$u(t) = \frac{-(0.66z^2 - 0.56z)}{z^2 + 1.3z + 0.4} y(t)$$

Figure 3 shows the implementation of the above MVC in SIMULINK® [5]:

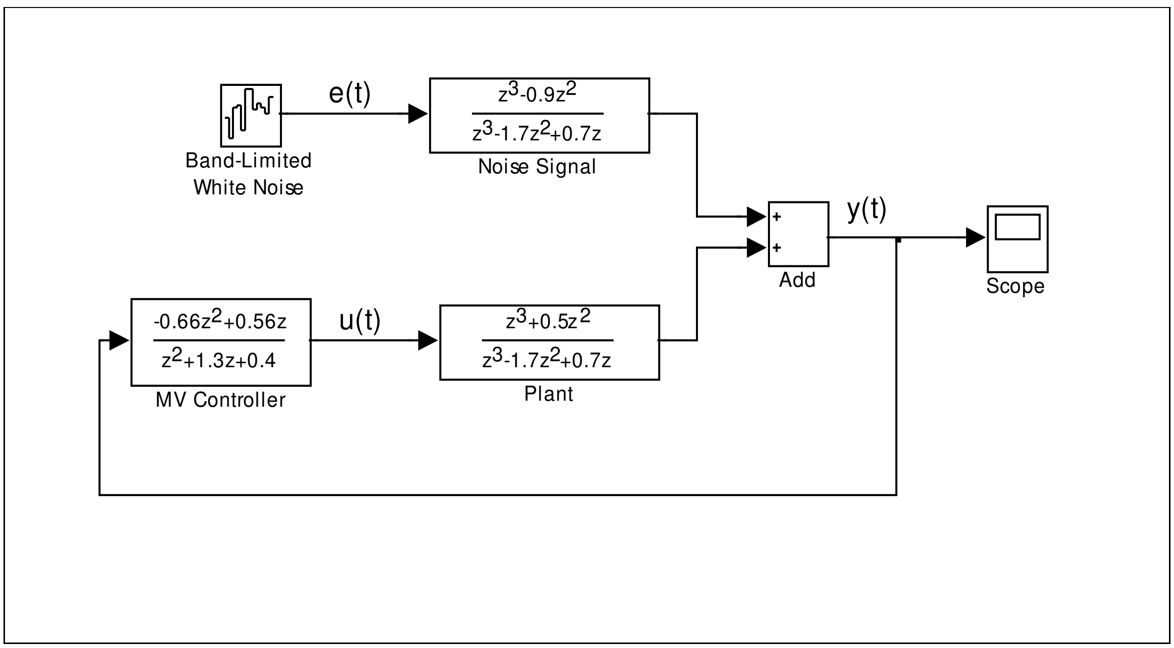

Figure 3: MV Controller Matlab Simulink Model

We compare the system with the MVC to the same system controlled by a proportional controller with a gain of 0.06 we get the output in Figure 4.

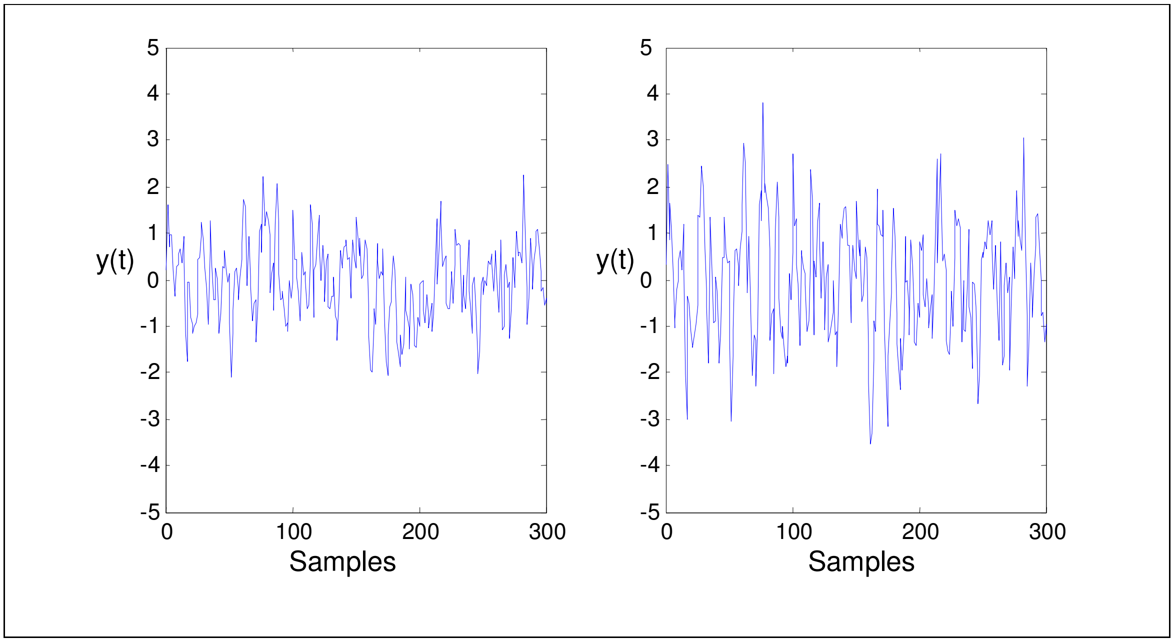

Figure 4: Left: output generated from a MV Controller. Right: output generated from a P-Controller

For comparison we work backward to find the input data needed for each controller Figure 5.

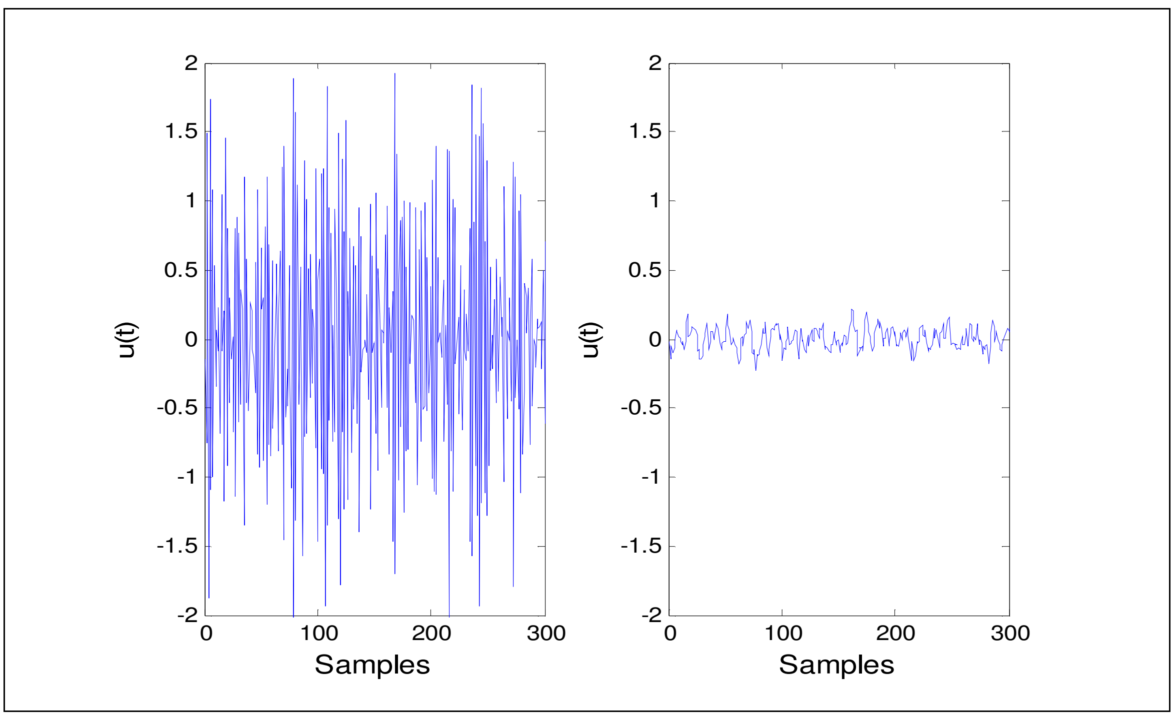

Figure 5: Left: input signal from MV-Controller. Right: input signal from P-Controller

Table 1: Variance of input and output signals

	MV Control variance	P Control variance	Ratio
Output	0.6851	1.6285	2.37
Control Signal	0.7353	0.0059	124.63

As can be seen form Table 1 the variance of the output signal from the MV controller is much less than that from the P-controller. On the other hand, the variance of the control signal required to achieve the MVC compared to that from a P-control is more than a hundred times bigger. It means that the actuator must have a much larger working range in order to achieve that small difference in the output variance. In many practical cases it is not worth wearing down the actuator in order to achieve that goal.

Thus the Harris Index has been known to be overly optimistic in regards of achieving MVC control. It assesses only dead-time as a performance limiting factor and is based on stochastic control only. Further more, dead-time is often unknown or time-varying. Harris index does not have an upper bound making it difficult to use for controller performance comparison or alarm limit setting.

As an improvement to the Harris index Desborough and Harris [6] introduced the normalized performance index. This index was calculated by comparing the ratio of the variance of the MVC controller with the mean square error (*mse*) of the output data. It was bounded by 0 for MVC control and 1 for worst control as compared to MVC.

$$\eta(b) = 1 - \frac{\sigma_{MV}^2}{mse(y_t)}$$

Further developments and work in this area revealed limitations of the minimum variance control performance measure. One of which was that different control structures such as the widely used Proportional, Integral and Derivative (PI/PID) control would have a very low value when measured against the MVC controller. Another one is the fact that MVC assumes that the reference input value remains constant, which is not the case with many controllers in the field. MVC assumes that the only limitation on the performance of the controller is the time delay where in fact many other factors may also play a role in limiting performance such as external disturbances. [7]

Based on such findings different methods were sought for controller performance monitoring. One such method was Rhinehart's [8] watchdog. This controller performance watchdog was developed to monitor the deviation of the process variable from set-point in a control loop. If the deviation is too high for a preset of consecutive periods an alarm is raised indicating that there is a problem with the controller.

If the process is at the set-point then the process variance can be calculated as

$$S_1^2 = \frac{1}{N-1}\sum_{i=1}^{N}(d_{1,i})^2$$

If N is large the process variance would be calculated by:

$$S_2^2 = \frac{1}{2}\frac{1}{N-1}\sum_{i=1}^{N}(d_{2,i})^2$$

where:

d_1 = difference between set-point and process variable.

d_2 = difference between two consecutive process variables.

N = number of data points collected.

The value of the watchdog index would be

$$r = \frac{S_1^2}{S_2^2}$$

The larger the value of r the worst would be the controller performance.

Hagglund [9] introduced the control loop performance monitor (CLPM). The basis of the CLPM is that the controller is performing well if it is not oscillating. Oscillations are recognized as load disturbances in the signal. A load disturbance is detected by checking the Integral of Absolute Error (IAE) of the signal.

$$IAE = \int_{t_{i-1}}^{t_i} |\, e(t) \,|\, dt$$

First, the acceptable % of peak to peak oscillation amplitude (a) is selected. Then, the IAE_{lim} is found from $IAE_{\lim} = \frac{2a}{\omega}$ where ω is the ultimate frequency or if that is unknown it could be calculated by $\omega = \frac{2\pi}{T_i}$ where T_i is the integral time. The value of the *IAE* is monitored every time the control error's sign is changed. Once the value of *IAE* is greater than IAE_{lim} then a load disturbance has occurred.

A supervision time (T_{sup}) is used to monitor the number of times the *IAE* exceeds its limit where T_{sup} = 50 T_i. If the number of detected oscillations within the supervision time exceeds a limit value given as 10 by Hagglund an oscillation is deemed to be present.

Review papers in the area of control loop performance monitoring started to appear in the late nineties as more and more work was done in the area such as Qin [10], Cinar and Undey [11] who reviewed autocorrelation patterns to determine the first order exponential output error decay trend:

$$e_t = \frac{1}{1-\lambda q^{-1}} a_t \quad \text{with} \quad \lambda = \exp\left(-\frac{T}{\tau}\right)$$

where T is the sampling interval and τ is the first order response time constant. The autocorrelation pattern is given by

$$\rho_e(k) = \lambda^k$$

The closed-loop potential index (CLP) is then defined by:

$$CLP = \frac{\sigma_{MV}^2}{\sigma_e^2}$$

The variance of the output error gives the closed loop performance bound:

$$\sigma_e^2 = \frac{1}{1-\lambda^2} \sigma_a^2,$$

where $\sigma_{mv}^2 = \sigma_a^2$ if $k = 0$

Another review paper by Harris et al [12] developed the extended horizon performance index:

$$\eta(k+m)=\eta(k)-\frac{\sum_{j=k}^{m-1}\psi_j^2}{\sum_{j=0}^{\infty}\psi_j^2}$$
$$k>0$$
$$\eta(0)\overset{\Delta}{=}1$$

Where k is the process time delay, m is the step ahead prediction, ψ is the impulse weights and $\eta(k+m)$ is the extended horizon index value.

This index compares the deviation of controller performance from the achievable minimum variance controller. This makes it more appealing since it can detect deterioration in PI/PID controllers.

It became more and more evident that practical implementations of the MVC benchmark alone does not hold since many controllers in the field do operate under system changes such as set-point. Thus the need to have criteria to measure controller performance based on these needs arises. Swanda and Seborg [13] developed performance indices based on set-point change data. These are dimensionless values and are based on the settling time value and the *IAE* values.

$$T_s=\frac{t_s}{\theta_a}$$

where T_s is the dimensionless settling time index, t_s is the settling time and θ_a is the apparent time delay.

$$IAE_d=\frac{IAE}{|r_o|\theta_a}$$

where IAE_d is the dimensionless IAE index and r_o is the size of the set-point step changes.

Furthermore, Hagglund [14] showed that the Idle index can be used to show instances when the controller is behaving badly. He showed that values near 1 mean the controller is behaving sluggishly, and values near -1 need to be associated with an oscillation analysis to infer that the controller is behaving well. The Idle index is given by this formula:

$$I_i = \frac{t_{pos} - t_{neg}}{t_{pos} + t_{neg}}$$

where the following is updated every sampling instant:

$$t_{pos} = \begin{cases} t_{pos} + h & \text{if } \Delta u \Delta y > 0, \\ t_{pos} & \text{if } \Delta u \Delta y \le 0, \end{cases}$$

$$t_{neg} = \begin{cases} t_{neg} + h & \text{if } \Delta u \Delta y < 0, \\ t_{neg} & \text{if } \Delta u \Delta y \ge 0, \end{cases}$$

where h is the sampling period, u is the control signal, and y is the process output.

Horch and Isaksson [15] devised the modified index which is a modification on the Harris index. The idea behind this index is that instead of placing all the poles in the origin (in order to achieve deadbeat response) as the case in the Harris index one pole is placed outside the origin to give a more realistic measure of the ultimate performance target of the controller. In order to drive this modified index one would calculate the modified variance as:

$$\begin{aligned}
\sigma_{\text{mod}}^2 &= \left(\sum_{i=0}^{k-1} h_i^2 + h_{k-1}^2 \mu^2 \sum_{i=0}^{\infty} \mu^{2i} \right) \sigma_v^2 \\
&= \left(\sum_{i=0}^{k-1} h_i^2 + h_{k-1}^2 \frac{\mu^2}{1-\mu^2} \right) \sigma_v^2 \\
&= \sigma_{mv}^2 + h_{k-1}^2 \frac{\mu^2 \sigma_v^2}{1-\mu^2} \\
&= \sigma_{mv}^2 + \sigma_\mu^2
\end{aligned}$$

where

k = is the degrees of freedom

u = is the location of the pole

v = is the disturbance

Thus the controller modified performance index would be calculated as:

$$I_{\text{mod}} = \frac{\sigma_y^2}{\sigma_{\text{mod}}^2}$$

However this method required knowing where to place the pole which makes it hard to implement on a large scale processing plant. It is unusual to make the response of the closed loop system faster than about three times the open loop response [15].

Thornhill et al [16] presented more proof that the performance measures give different results when they are under different disturbances. Indicating that performance needs to be compared to the goals and objectives of the controller.

Grimble and Uduehi [17] argued that combining economical and performance benchmarks would give the most effective measure of the performance of the control system.

In their efforts to address the problem of performance monitoring Xia and Howell [18, 19] focused on categorizing the controllers current performance under predefined states. Each state describes a different behaviour that would give an idea of the performance of the controller. Signal to noise ratio indices are used to determine threshold values for each performance state.

Hugo [20] discusses the different performance monitoring techniques from a control engineer's perspective, in determining the affect of the control loop performance on the final product quality and deciding on the need to implement advanced controls.

Huang et al [21] took a different view of the performance problem, where they analysed controller performance using a path analysis technique. This method only uses the data from the plant to identify sources of variability and disturbances in the plant.

Grimble [22] introduced the Genaralized Minimum Variance index (GMV). This index is based on using the dynamic cost function to get a stable control system.

Uduehi et al [23] introduce a Generalized Predictive Control (GPC) benchmark. This benchmark allows for assessing the performance of predictive controllers as well as comparing the performance of non-predictive controllers to the performance of a predictive controller.

Qin [24] in his paper addressed the statistical methods used in monitoring the process behaviour. Qin goes into detail description of the squared prediction error, Hotellings's statistic and Hawkins' statistic, Mahalanobis distance and how to combine these indices for better fault detection results.

Horton et al [25] looked into finding performance assessment measures for a specific control loop type namely the level controller. This came by due to the fact that performance requirements differ significantly among various control loops. For example, the requirements for a level controller are different than those for a temperature controller.

In other reviews of the control loop performance indices such as Harris et al [12] and Harris and Seppala [26] they worked on subdividing controllers according to their different operational objectives. This categorization seemed more appropriate since different controllers behave differently under different operating conditions. Thus performance measures for set-point, steady state and disturbance rejection were identified. A review paper by Jamsa-Jounela et al [27, 28] gives an overview of a performance application that provides operators with control loop performance metrics to show how well the controllers are performing. They give formulas for calculating the indices and they added a valve performance index. This index tells how long the valve is near the upper or lower 10% of its range. Jamsa-Jounela et al classified control performance indices into different categories. They identified three control situations and found indices for each.

First, the controllers are under steady state conditions:

Permanent error (PE) is the difference between the set-point and the process variable. Since the objective of this control would be to keep the process variable at set-point this index is a reasonable representation of the achievement of this objective. Thus this index can be calculated by:

$$PE_i = \gamma.PE_i + (1-\gamma).p_i$$

where

$\gamma =$ the forgetting factor

$PE_i =$ the previous value of the index

$$p_i = \begin{cases} -1, e_i < -e_{\lim} \\ 0, -e_{lin} < e_i < e_{\lim} \\ 1, e_i > e_{\lim} \end{cases}$$

and the forgetting factor would be calculated as

$$\gamma = 1 - \frac{1}{5\tau}$$

where: τ is an estimate of the time constant of the process.

They also showed that the Harris index which is based on MVC is also appropriate for this type of control.

Second, the case of set-point change:

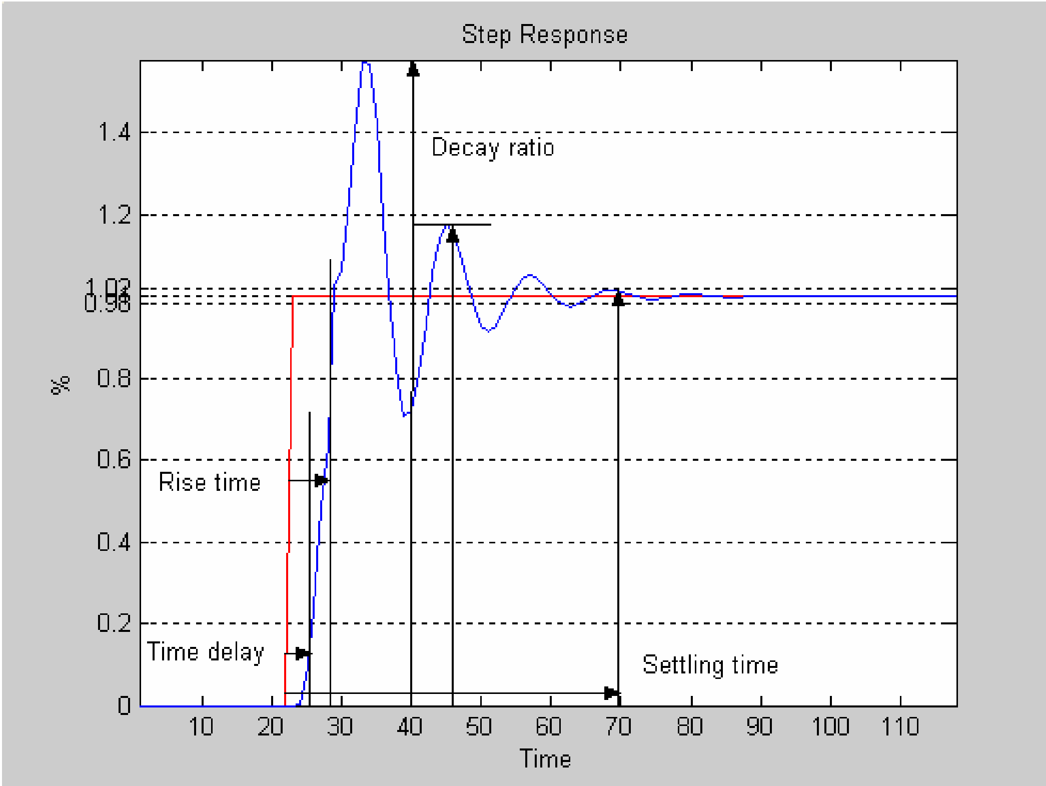

Figure 6: Step Response

In this case as Figure 6 shows the control objective is for the process variable to follow set-point changes as closely as possible. In order to measure the controller performance under this control objective the following indices are suggested:

- Overshoot size (AMP):

This index calculates the size of the overshoot compared to the set-point step size.

$$AMP = \frac{y_{pv,\max} - y_{pv,\min}}{\Delta y_{sp}}$$

where $y_{pv,\max/\min}$ are the maximum and minimum values of the process variable after the rise time and Δy_{sp} is the magnitude of the set-point change. The larger the value of AMP the worse would be the performance of the controller under set-point change.

- Integral of the time-weighted absolute error (ITAE):

Continuous oscillation or sluggish controller tuning could cause long term differences between the set-point and process variable. This can be monitored by calculating ITAE:

$$ITAE = \int_0^{\tau} t \mid y_{pv}(t) - y_{sp}(t) \mid dt$$

- Normalized indices:

Calculated by Astrom(1992) and Swanda and Seborg [13] describe the performance of the controller based on rise time and settling time.

- Index of rise time:

$$SPD = \frac{t_{rise}}{\tau}$$

- Index of settling time:

$$TIME = \frac{t_{settling}}{\tau}$$

Third, control under disturbance rejection:

Under this control situation Jamsa-Jounela et al suggest the use of the Idle Index suggested by Hagglund. [14]

Thornhill et al [16] also shared in this view and looked at finding specific performance measures for controllers under set-point changes.

Li et al [29] developed the relative performance monitor (RPM). In this method the controller performance is compared against a model. A shift in the performance of the controller is detected as performance fault.

Ko and Edgar [30] looked specifically at the PID single loop case.

Remy [31] reviewed the causes of poor performance and went over performance measures. He then described the process of deriving MVC benchmarks.

Rice et al [32] from Control Station Inc., described some of the performance indices used in their application. They also went over some of the calculations since as software developers they understood that users need a better understanding of the performance measures in order for their applications to be successful. They also introduced the Standard Variation index.

$$\text{Standard Variation} = \frac{\left(\dfrac{\sum |PV - SP|}{n-1}\right)}{Average(PV)}.100\%$$

where: PV : Measured Process Variable

SP : Set Point

n : Number of Data Points

Using this method a smaller Standard Variation will represent less deviation from set-point. Some factors that can impact on the Standard Variation included the number of set-point changes as well as the number of disturbances that impact the process.

Horch and Heiber [33] introduced different measures to assess the performance of control loops in a large scale implementation. Some of the criteria they used are summarized in Table 2 below.

Table 2: Performance Indices

Index	Description
CE mean (%)	Mean of control error
CE std (%)	Standard deviation of control error
OP std (%)	Standard deviation of controller output
CE skewness	Skewness of control error
CE kurtosis	Kurtosis of control error
Std ratio	Ratio of standard deviation of control error and controller output
Maximum bic	Maximum bicoherence
Correlation coefficient	Correlation coefficient between control error and controller output

Ling et al [34] looked at the problem of control loop performance monitoring from a different perspective. They worked on addressing performance monitoring and equipment fault detection as a single problem of abnormal event detection. They used cluster trending analysis to detect abnormalities in the controller signal. When two cluster trends deviate from the normal cluster trend and the entropy of the cluster is greater than a predetermined threshold level an abnormal event is detected. This could be a drop in the loop performance or equipment malfunction.

Ingimundarson et al [35] devised a method for monitoring controller performance by using the tuning parameters of the controller. In this method they use the extended horizon performance index but instead of selecting the prediction horizon and alarm limits based on the type of controller they selected them based on the controller tuning.

Li et al [36] used a method based on goodness of control to monitor the performance of the controller. An index is calculated during a period of good performance and that is used as a benchmark for the controller performance. They use the *r-statistic* which was suggested by Rhinehart [8] to assess the controller performance. Their method addressed the problem of *r-statistic* not being able to show bad control when an oscillation is present in the signal.

2.2 Oscillation Detection

No evaluation of control loop performance is complete without an evaluation of oscillation. Oscillations are one of the major sources of controller performance problems. Oscillations in control loops can arise from different sources such as bad tuning, valve friction, disturbance oscillations, or due to other control loops oscillations. Different oscillation detection methods have been reported in the literature, such as the work of Hagglund and Thornhill [37] where a significant number of zero crossings would indicate an oscillation.

The principle behind this method is to monitor successive zero crossings of the controller error using the Integral of Absolute Error (IAE):

$$IAE = \int_{t_{i-1}}^{t_i} |\, e(t) \,|\, dt$$

Where t_{i-1} and t_i are consecutive instances of zero crossings. The IAE will be compared to a predetermined limit value, $IAE_{\lim}$ when it exceeds this limit a load disturbance will most likely have occurred. To detect an oscillation it must have $IAE \geq IAE_{\lim}$ where $IAE_{\lim} = \dfrac{2a}{\omega}$, a is the % of the peak to peak oscillation allowed and $\omega = \dfrac{2\pi}{T_i}$; where T_i is the controller integral time.

Another method to detect oscillations in control loops was suggested by Miao and Seborg [38] where they used the autocorrelation coefficients of the controller output data to determine the value of the decay ratio, $\Re$. If $\Re$ is greater than a predetermined threshold value it is determined that the signal is oscillatory.

Other oscillation detection methods focused on distinguishing whether the cause of the oscillation is from static friction (stiction) in the control valve or from an external disturbance. Horch [39] used the cross-correlation between the input to the controller and the process output to distinguish the two different sources of oscillations. Another method developed by Choudhury et al [40] used higher order statistics to distinguish between sources of oscillations in control loop and determine if they are from internal or external sources.

Other researchers have focused on detecting multiple oscillations in control loops since oscillations might be from different sources having more than one oscillation present is likely to happen. In this work a method that detects the presence of multiple oscillations based on zero crossing of the auto-covariance function (ACF) was used. The use of ACF is recommended because it reduces the effect of the noise signal, and the period and magnitude of the oscillations are found [9, 37, 41-43]

Further work in detecting and isolating sources of plant wide oscillations were also reported in the literature such as [44-48] which are all based on principal component analysis (PCA) methods.

2.3 Implementation of Controller Performance Monitoring

A successful implementation of control loop performance monitoring in an industrial setting is more than the calculation of different performance indices. Methods that identify the type of performance degradation detected are needed. Identification of control loop interactions is important to understand how their respective performance is affected by each other. Procedures to locate sources of poor controller performance are essential for a proper attack on the problem. Knowledge of the process (process, controllers, and equipment) being monitored plays a key role in the performance monitoring system. Nevertheless, the goal of a performance monitoring system is to improve performance, so identifying means of rectifying problems and enhancing performance are very important in any controller performance monitoring system.

Methods to assess control loop performance on large scale systems began to surface such as the work done by Stanfelj et al. [49]. They developed a method to monitor a large number of controllers in a plant. Their method was a Hierarchical Diagnostic system made up of three stages. At the first stage, the system would check for standard deviation, constraint violation frequencies, off-specification products and safety valve openings performance threshold limits. Once a controller violates the threshold limits set in the first stage the second stage of the analysis is invoked. MVC performance is used to measure the controller performance at this level. If results show that the controller can be improved using the current equipment and configuration, the third stages is invoked. Finally, at this stage corrective action is identified in the form of improvements to model accuracy or tuning parameter adjustments.

Continuing to work on developing systems that monitor the performance of a large number of controllers in a plant Harris et al [50] developed a system that is based on an expert system to automate this process. Lynch & Dumont [51] also develop a system methodology to run control loop performance system they monitor three important aspects the MVC performance, estimated time delay, and input-output static relation to indicate when the controller behaviour drifts away from linear operation.

Thornhill et al [52, 53] and Thornhill and Hagglund [37] implemented the Control Loop Performance Assessment (CLPA) introduced by Desborough and Harris [6] in a refinery setting where they worked on identifying key measures that would make the implementation of such performance monitoring systems feasible in a refinery with hundreds or even thousands of control loops. These include identifying initial values for prediction horizon, number of terms in the model, sampling interval and data ensemble length. With these parameters identified for the limited number of controller types in a plant (Flow, Pressure, Level, Temperature) it is much easier to implement a plant wide performance monitoring system without specifying the parameters for each and every controller in the plant. Control loop performance monitoring systems using these basic settings given in Table 3 can accurately assess the performance of the controllers in a plant. All controllers of the same type would be assigned the same basic settings once analysis has been done, specific controllers that do not meet the performance requirements would have their basic settings reassessed.

Table 3: Recommended Values for Refinery Controllers

Loop Type	Sampling Interval	Prediction horizon, b
Pressure	20 s	100 s
Liquid flow	6 s	30 s
Temperature	60 – 120 s	360-600 s
Steam or gas flow	60 s	300 s
Level	20 s	100 s
Ensemble length	500-1500 samples	
Length of AR model, m	30 terms	

More papers that discuss the practical issues in implementing these performance measures to specific applications emerged such as Bulut et al [54] where they showed this for an Oil production platform. Fu & Dumont [55] combined the work done in performance monitoring using MVC based indices with oscillation detection to come up with a scheme for an overall performance monitoring system in a plant setting. Hoo et al [56] in their paper too had gone over past developments in control loop performance monitoring. They selected different benchmarks to come up with an application that undergoes the performance monitoring process. Paulonis and Cox [57] also discussed the problems associated with implementing performance monitoring on large scale plants. They showed which indices need to be looked at and what do they represent.

2.4 Controller Performance Monitoring Applications

In recent years a number of commercial applications to monitor control loop performance have become available in the market. These applications look at individual controllers in the plant and sort these controllers according to performance based on one of the given performance indices.

Some of the latest applications in the market are given in Table 4.

Table 4: Performance Monitoring Applications

Software	Company
Loop Scout www.loopscout.com	Honeywell www.honeywell.com
Process Doctor	Matrikon www.matrikon.com
Plant Triage www.expertune.com/planttriage.html	Expertune
Aspen Watch	Aspentech www.aspentech.com
Loop Optimizer	ABB www.abb.com

A number of papers that highlight the successful use of these applications in specific settings can be found in the literature [58-62]

Newer versions of these tools run Multi-Input-Multi-Output (MIMO) analysis as well as controller interaction analysis and Model Predictive Control (MPC) performance monitoring.

2.5 Controller Performance Monitoring Specifications

In order to implement a control loop performance monitoring application in a plant wide setting certain requirements must be considered. Hugo [20], Hoo [56] and Burch [62] identify some of the requirements in a performance monitoring system:

a. Independent of disturbance or set-point spectrum.
b. Does not require plant testing.
c. Automatic.
d. Minimum process knowledge is required.
e. Use absolute performance measures.

f. Able to detect performance deteriorations due to tuning, model mismatch and equipment failures.
g. Contain root-cause analysis.
h. Assess profit from controller performance.
i. Rank controllers based on performance.
j. User friendly interface.
k. Reports that clearly identify problems and indicate performance.

2.6 Multi Input Multi Output Controller Performance Monitoring

In many cases a control problem is so complicated that a multi-input-multi-output (MIMO) control system is needed. These systems are made up of a collection of single controllers acting together to achieve the control objective. Extensions to the Minimum Variance Control performance benchmark were made in order to apply it to MIMO controllers [63, 64]. Furthermore, work to enhance the assessment of the MIMO MVC benchmark was made and the Generalized Predictive control benchmark developed by Uduehi et al. was developed for MIMO controllers. [65]

More work on identifying methods to implement MIMO performance monitoring is reported by Byung-Su & Edgar, and by Huang et al. [66, 67]

2.7 Conclusion

There is considerable variation among the various available loops in process plants. It is therefore unrealistic to express their performance on the basis of a single performance index alone. In analysing the performance of control loops the particular features and limitations of the control loop will have to be taken into account.

CHAPTER 3
MATHEMATICAL REPRESENTATIONS OF THE CONTROLLERS

In this chapter we go over the steps needed to calculate the performance indices from available plant data. The chapter begins with a description of the data needed for the analysis. Then the steps and formulae that show how to calculate the different performance indices from the plant data are given. Furthermore, an explanation of what type of performance measure is appropriate for a particular situation is discussed.

3.1 Performance Analysis Structure

The analysis of the performance of controllers in an operating unit needs to follow some basic guidelines. These guidelines are developed based on the amount of affect the performance measure has on the overall operation of the unit's controllers. First, an assessment of oscillations in the plant is done. This assessment detects the presence of oscillations that are shared between plant control loops. Furthermore, the oscillation assessment also measures oscillations present in each control loop. Second, each control loop is tested for performance indices that measure how the controller is performing according to its control objectives. This includes control for set-point tracking, disturbance rejection and steady state operation. The flow diagram in Figure 7 shows how the performance assessment process would take place.

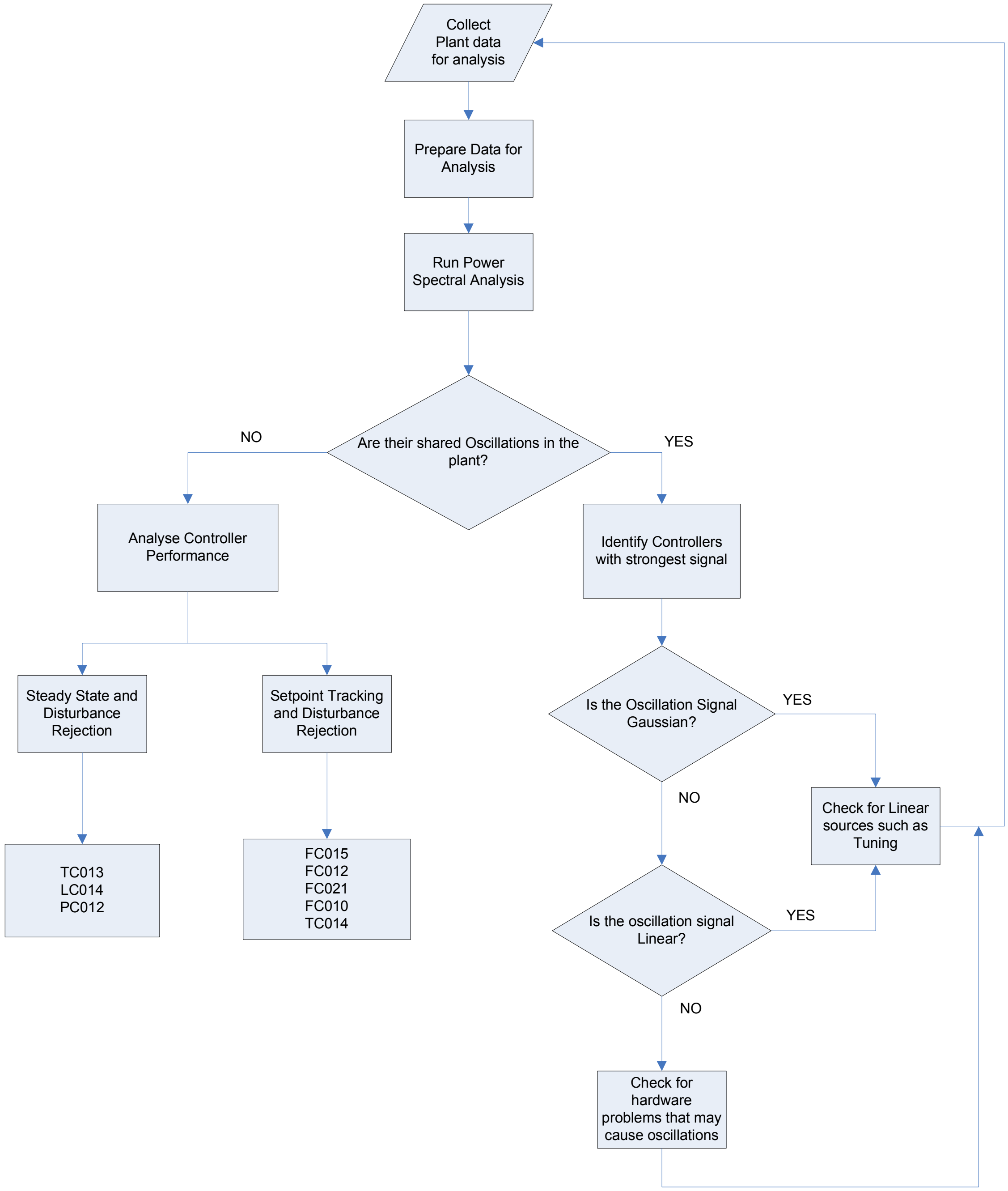

Figure 7 : Performance Analysis Flow

3.2 Data Preparation

In a plant data is collected continuously from the Distributed Control System (DCS) and stored into plant historians. A typical plant would have a network setup similar to that in Appendix I [68].

In order to save disk space these data historians tend to run different formulae on the collected data such as data compression. These changes can affect the quality of the data collected and thus affect the performance indices calculated from them. It is a common practice to remove data compression from data that will be used in a performance monitoring application.

3.3 Minimum Variance Index

3.3.1 Harris Index

Table 5: Minimum Variance Index

1	Estimate Time series model	$y(t)=\frac{C(q^{-1})}{A(q^{-1})}e(t)$
2	Time delay	D
3	Calculate Series-expansion	$y(t)=(h_0+h_1q^{-1}+\ldots+h_{d-1}q^{-(d-1)})\,e(t)$
4	Calculate minimum achievable variance	$\sigma_{MV}^2=(h_0^2+h_1^2+h_2^2+\ldots+h_{d-1}^2)\,\sigma_e^2$
5	Calculate actual output variance	σ_y^2
6	Compute performance index	$I_p=\frac{\sigma_y^2}{\sigma_{MV}^2}$

The Minimum variance index that was first suggested by Harris [2] is calculated from a set of output data from the controller and knowledge of the controller time delay. Horch [3] summarized the steps needed to calculate the index as given in Table 5.

The time-series model can be fitted to any of the following structures:

1. Auto-regressive moving average (ARMA) model:

   The process variable *y(t)* is described by $A(q^{-1})y(t)=C(q^{-1})e(t)$. The problem with this is that in order to estimate the parameters, one has to solve a nonlinear optimisation problem.

2. Moving average (MA) model:

   The process variable *y(t)* is described by $y(t) = C(q^{-1})e(t)$. The problem with this is that in order to model closed-loop systems with slow decay, a large number of parameters would be required. To estimate the parameters, one has to still solve a nonlinear estimation problem.

3. Auto-regressive (AR) model:

   The process variable *y(t)* is described by $A(q^{-1})y(t) = e(t)$

   The estimation of the parameters is simple and the problem can be formulated as a linear regression with a closed-form solution.

Since it is simpler to estimate the parameters of an AR model and using a high-order AR model is usually sufficient to approximate an ARMA process, the AR model will be used to describe the process.

The parameter estimation in the $A(q^{-1})$ polynomial can be done in a number of ways:

1. Least-square method.
2. Forward-backward method.
3. Yule-Walker method.
4. Lattice filters.

The estimate time-series model does not change significantly when using different estimation methods for the AR-parameters.

Whatever model structure is chosen for the estimation one has to choose a certain model order. Reasonable values which have been tested in practice [3] are shown in Table 6.

Table 6: Suggested Model order

Model structure	Model order
AR	15-25
ARMA	8-12
Laguerre	10

Detail explanation of the Laguerre model structure can be found in Wang and Cluett [75].

3.3.2 Control Loop Performance Assessment (CLPA)

The CLPA was introduced by Harris and Desborough [6]. It can be calculated by following the steps in Table 7.

Table 7: CLPA Index Calculation

1	Calculate the controller error	$e = sp - pv$ $Y(n)$
2	Find the forward prediction using autoregression time series model	$\hat{y}(n)$
3	Use a predefined step ahead prediction horizon	B
4	Use the most suitable number of terms in the model, *m*	$\hat{y}(i+b) = a(0) + a(1)Y(i) + a(2)Y(i-1)$ $+ \ldots + a(m)Y(i-m+1)$
5	Fit the model to an *n* ensemble of the controller error using least squares fit	
6	Calculate the residuals	$r(n) = Y(n) - \hat{y}(n)$
7	Calculate the index	$\eta = 1 - \dfrac{\sigma_r^2}{mse(Y_i^2)}$

The CLPA index gives a value between 0 and 1. A value of the index close to 1 means that the error in the controller is predictable thus the performance is poor. Contrarily, an index value near 0 means the error is not predictable and the performance is good.

3.4 Error Based Indices

3.4.1 Idle Index

The principle behind the Idle index is that when a controller is subjected to a load disturbance the control signal (SP) and the process output (PV) initially go in opposite directions and $\Delta u \Delta y < 0$. After the initial response takes place, if after a long time period the correlation between the two signals is positive the response is considered sluggish.

The signal is assumed to have a positive static process gain with no set-point changes present in the data. The index is calculated by updating positive and negative times every sampling instant.

$$t_{pos} = \begin{cases} t_{pos} + h & if\ \Delta u \Delta y > 0, \\ t_{pos} & if\ \Delta u \Delta y \leq 0, \end{cases}$$

$$t_{neg} = \begin{cases} t_{neg} + h & if\ \Delta u \Delta y < 0, \\ t_{neg} & if\ \Delta u \Delta y \geq 0, \end{cases}$$

The value of the index is bounded between [-1,1] when the index is close to positive one the control is deemed sluggish, and when it is closer to negative one the control is good.

$$I_i = \frac{t_{pos} - t_{neg}}{t_{pos} + t_{neg}}$$

To calculate this index online a recursive version of the formula is introduced by Hagglund [14] where

$$\begin{aligned} & if\ \Delta u \Delta y > 0\, then\, s = 1 \\ & \quad else\, if\ \Delta u \Delta y < 0\, then\, s = -1 \\ & \quad else\, s = 0 \\ & if\ s \neq 0\, then\ I_i = \gamma I_i + (1-\gamma) s \end{aligned}$$

This formula uses a factor γ to estimate the time horizon. γ, which is calculated using the supervision time which is found from $T_{\sup} = t_{pos} + t_{neg}$. Then $\gamma = 1 - \frac{h}{T_{\sup}}$; where h is sampling time.

3.5 Set-Point Change Indices

3.5.1 Amplitude Index

To calculate this index a step change response of the system is taken and from that the maximum and minimum values of the PV are used with the step change to calculate the index.

$$AMP = \frac{y_{pv,\max} - y_{pv,\min}}{\Delta y_{sp}}$$

This index compares the size of the overshoot resulting from the set-point change to that of the actual set-point change. The bigger the value of *AMP* the worse is the performance of the controller. [27]

3.5.2 Integral Time of Absolute Error

In order to calculate this index we take the sum of multiplying the time by the error (sp-pv). This value would be divided by the sampling time to calculate the integral.

$$ITAE = sum_{0\to t}\left(\frac{t\,(y_{sp}(t) - y_{pv}(t))}{t_{sampling}}\right)$$

This index will calculate the long term deviation in the signal that is usually caused by oscillations or sluggish control. [27]

3.6 Value of Simple Statistics

In this section we will briefly discuss some of the simple statistical values used in many control loop performance monitoring application.

3.6.1 Control Mode

This shows the user how long the controller is acting in its intended operational mode. Usually a controller can have one of three operational modes (Cascade, Auto, and Manual) knowing how long the controller was in each mode gives the user a first indication that the controller is having problems.

3.6.2 Standard Deviation and Variance

Values of the standard deviation and the variance of the controller's set-point (SP), Process variable (PV) and controller output (OP) can show how much change the controller is subjected to. By comparing these values some conclusion regarding the presence of a problem can be made.

3.7 Oscillation Analysis

Oscillations are one of the most common sources of problems in operational plants. Many different methods have been proposed in the area of detecting and measuring oscillations. In this section we will look specifically at detecting plant wide oscillations and detecting single loop oscillations.

3.7.1 Plant Wide Oscillations

In a large plant with many controllers acting on one unit, it is of great importance to detect the presence of an oscillation that is shared by a number of control loops in the plant. This usually means that the oscillation is coming from a common source thus finding this source and eliminating it would resolve the problem from the whole plant.

To do this we will use the spectral principal component analysis method. In order to implement this method first the data must be pre-processed for the calculation as in Table 7.

Table 8: Spectral data pre-processing steps

1	Mean centre the time trend and remove linear trends
2	Calculate the spectra
3	Filter the spectra if required
4	Scale the spectra to the same total power
5	Scale the auto-covariance function so that the covariance at zero lag is unity.

After that the spectra can be calculated for the analysis.

The power spectral correlation index (PSCI) is the correlation between the power spectra of two different measurements. This index measures how similar the spectral signals are. The index is calculated by finding the Discrete Foriear Transform (DFT) after removal of the mean values from the time series data. The PSCI of the two spectra $\left|X_i(\omega)^2\right|$ and $\left|X_j(\omega)^2\right|$ is calculated using the following formula.

$$Correlation\left(\left|X_i(\omega)\right|^2, \left|X_j(\omega)\right|^2\right) = \frac{\sum_{wk} \left|X_i(\omega_k)\right|^2 \left|X_j(\omega_k)\right|^2}{\sqrt{\sum_{wk} \left|X_i(\omega_k)\right|^4 \sum_{wk} \left|X_j(\omega_k)\right|^4}}$$

As a result of this calculation the value of PSCI is always between 0 and 1.

3.7.2 Oscillation Detection

Oscillations are detected using the spectra found in the previous step. The presence of a peak in the spectra indicates that there is an oscillation at that frequency.

3.7.3 Oscillation Diagnosis

Higher order statistics are used to test the data and determine whether the oscillation in the signal is caused by Gaussian linear sources or not. This classification helps in directing the root cause of the controller problem to the most probable source of the oscillation. To achieve this we use the Non Gaussian Index (NGI) and Non Linearity Index (NLI). [40]

3.7.4 Conclusion

The methods used in the calculation of the different performance indices were discussed and introduced in this chapter. These methods are used in Chapter 5 to assess the performance of the system.

CHAPTER 4
DEETHANIZER SYSTEM

The Deethanizer system is a two stage distillation process. It is a common process in the Oil and Gas industry. In this chapter we will explain the basic process, the control system and some known problems and interactions. Distillation is one of the most common processes in the manufacturing industry and is covered in great detail in the literature [69-71].

4.1 The Deethanizer Process

The Deethanizer system receives input feed in the form of a mixture of light and heavy hydrocarbon products. These products usually are classified based on the number of carbon atoms they are made of so the lightest product would be Ethane ($C2H4$), the next one would be Propane ($C3H6$), next Butane ($C4H8$) and so on. The basic principle in a distillation column is that lighter products evaporate at temperatures lower than heavier ones. Thus it is possible to separate the light product from the mixture if the right temperature is applied to the system. In this case this will leave us with a product of Ethane with some impurities in the form of Propane that evaporated with the Ethane. The quality of the Ethane product is determined by how much impurities it contains.

The process flow for this system is that the feed is preheated to a predefined temperature. A flow controller controls how much of the feed gets into the system. The feed then enters a distillation column made up of a series of trays. These trays allow liquid to flow down and gas to flow up the column. To control the distillation process a heat exchanger is used to heat up the lower part of the column in order to send more Ethane up the column and a cooler is used in the upper part of the column to send more Propane down the column. The amount of hot and cold additives to the system is determined based on the product quality required. Thus if we need less Propane in the Ethane product we add more cold product (reflux) to the system. Like wise if we need more Ethane in the upper product we add more hot product (reboiler) to the system. These changes also affect the quality of the product coming out of the lower part of the Deethanizer system, the Propane plus product (C3+), but in the opposite way.

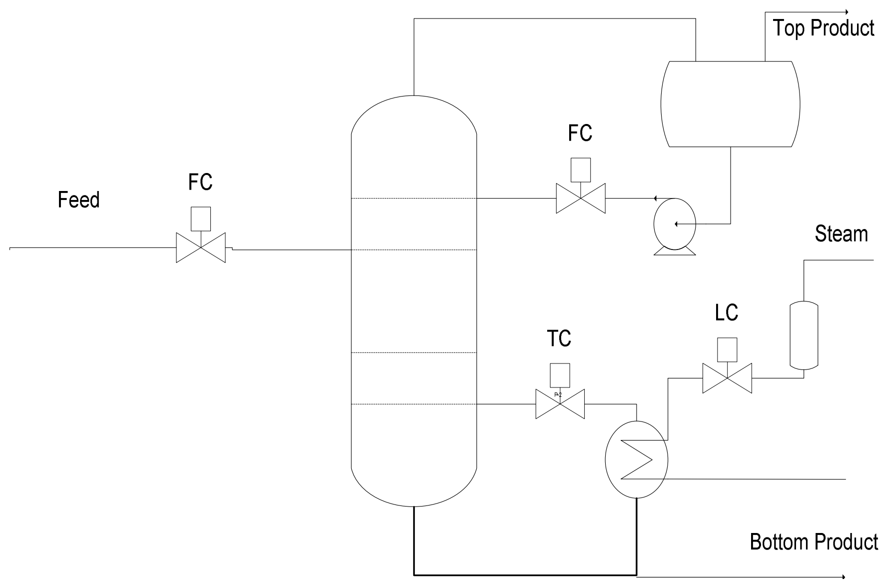

Figure 8: Deethanizer System

The system is made up of a collection of instruments that we will now explain briefly.

4.2 The Column

The main component of Deethanzier system is the distillation column. The column is basically a vessel that has many trays, the number of trays in the column depends on the type of operation, feed it is designed to take in, and the resulting product. The feed enters the system from the side of the column. The lighter product leaves the system from the top and the heavier product or products leave from the bottom.

4.3 The Controllers

The Deethanizer system is made up of a collection of different Single Input Single Output (SISO) controllers. These controllers have different tasks and different objectives in the system. The most common controllers will be explained next.

4.3.1 Flow Control

Flow controllers are used to control the flow of feed in/out of a system. A flow controller is usually made up of a sensor, a valve, and a controller Figure 9. The sensor reads the current flow rate; the controller uses the valve to change the flow rate according to its targets. Flow loops are relatively faster (with response times of the order of 20 seconds) with very small dead times usually limited by valve response (time constant). By nature flow measurements are very noisy thus a PI controller is usually used although an I control can also be used. Due to their fast nature and being relatively easier to tune, flow loops are usually used with other control loops (Temperature, pressure, level) to control the process.

Figure 9: Flow Control

4.3.2 Temperature Control

The temperature controllers are used to manipulate the temperature of the system and keep it at a specific target Figure 10. This is done either by directly connecting the temperature controller to the valve or using a flow controller between the valve and the temperature controller.

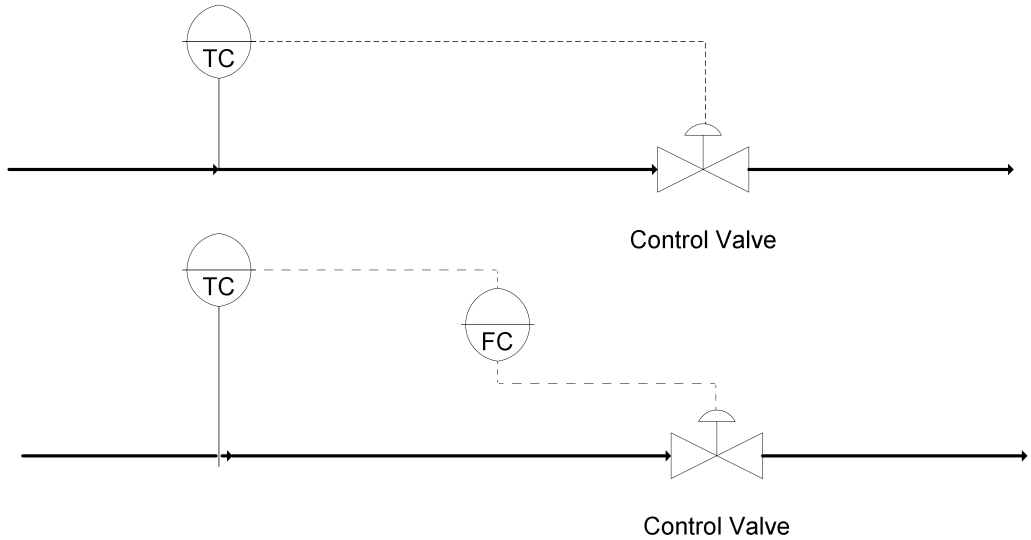

Figure 10: Temperature Control

4.3.3 Pressure Control

Pressure controllers are used to manage the pressure of the system. They are usually used for safety and flow control reasons. In a pressure control loop flow is controlled to manipulate the pressure thus a pressure loop has the same features as the flow loop as in Figure 11. In a column the pressure is usually controlled with an atmospheric vent at the coldest point of the condenser; or alternatively, by manipulation of draw-off of gases from the collector drum. In the field pressure control loops are either connected directly to the valve or cascaded with a flow controller that controls the valve.

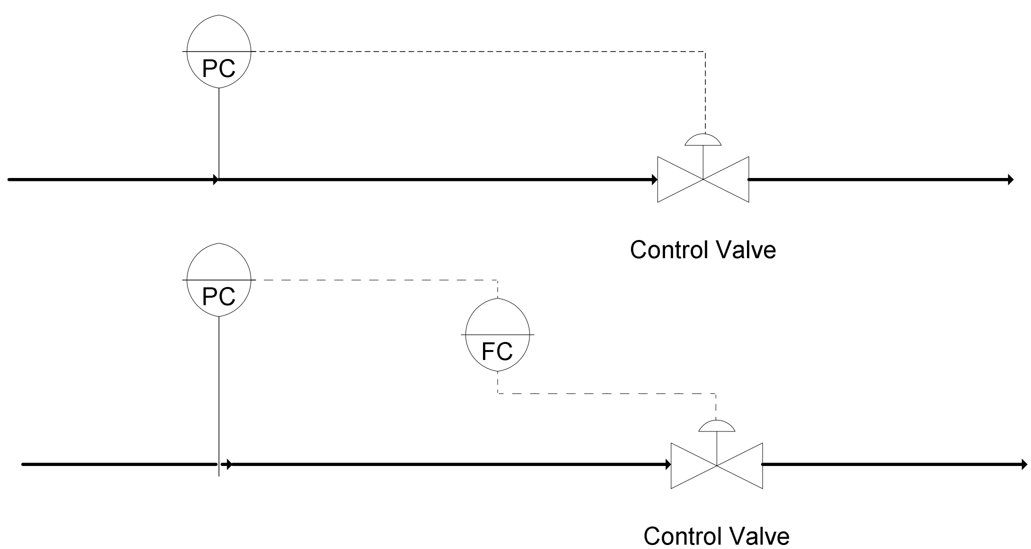

Figure 11: Pressure Control

4.3.4 Level Control

Level controllers are used in tanks and vessels as shown in Figure 12. Level controllers may have different objectives such as maintaining tank levels or reducing system disturbances. A level controller is either used directly to control a valve or interconnected to a flow controller that is used to control the valve.

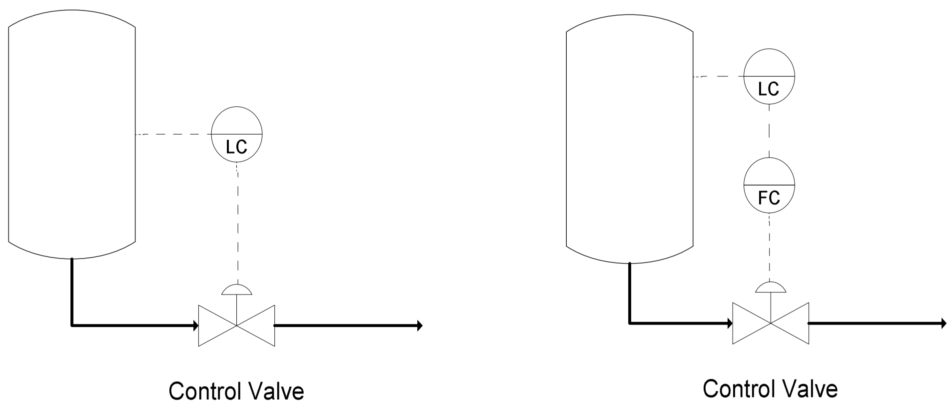

Figure 12: Level Control

4.3.5 Quality Control

Quality controllers are used to ensure the purity of the final product in a plant. These are usually inferred measurements by using temperature measurements which are simpler, faster, and reliable. Two main methods for quality control are usually used; the single quality control and the double quality control. The first one monitors the quality of the main product (Top or Bottom) most commonly the top product is monitored and the bottom product is further processed down stream. Double quality control is mainly used for economical reasons to maintain a balance between the energy consumption versus product loss and increasing the throughput versus stabilizing downstream units.

4.4 Heat Exchangers

Heat exchangers operate under the basic principle that heat can be transferred from a hot material to a cold one. Thus exposing a cold liquid or gas to a hot one will increase the temperature of the first one and reduce the temperature of the second material.

4.5 Other Components

Other equipment and instruments that play an important role in the Deethanizer process are pumps, sensors, vessels and analysers.

4.6 Control Strategies

There are a number of strategies used to control distillation columns. Depending on the type of strategy used, controllers in the plant will have different objectives to meet. A two stage distillation column has five streams of flow as shown in Figure 8 thus it can have four degrees of freedom. The flow (F) is divided into overhead product (D) and bottom product (B). From the overhead a reflux line re-enters the system (L) and from the bottom a re-boiler line (G) re-enters the system.

4.6.1 D-G Control

In this control strategy the distillate (D) and re-boiler (G) are directly manipulated. This setup is used when there is a need to control the amount of distillate product produced by the unit. This could be due to limited downstream facilities for example. By controlling how much heat enters the system we manipulate the amount of top product leaving the unit.

4.6.2 L-B Control

In this case the reflux (L) and bottom (B) are directly controlled. In this case the limit is on the bottom product flow. Increasing the reflux would increase the amount of product flowing to the bottom of the column.

4.6.3 L-G Control

In this system we are controlling both the reflux (L) and the re-boiler (G). In this setup there are constraints on both top and bottom product flows. The system is controlled based on the quality requirements of the products.

4.7 Known Interactions and Problems

The control strategies of a distillation column are based on maintaining a level of good product quality. This quality is achieved by sustaining a balance between the upper and lower temperature profiles of the column. Since the top part of the column runs the cooling process and the bottom part runs the heating process; it is essential that we maintain a balance between both ends of the column.

4.7.1 Time Delay

The apparent time delay is considered a source of problem when the distillation column is taken as one unit. The differences between the top and bottom time delay dynamics is due to the presence of many trays in the column. Each tray adds to the dynamics of the process as it flows from the top to the bottom of the column.

4.7.2 Loop Interactions

Although each controller in the column has its own targets and objectives, they are not independent of each other. Controllers would most likely have conflicting objectives especially when the column is being controlled for top and bottom product quality.

4.7.3 External Disturbances

A distillation column usually is a part of a bigger production facility that receives its feedstock from upstream units and passes its products to storage or downstream units. Any changes or disturbances to these units mean that the column would need be adjusted to compensate for these changes.

Weather conditions also have considerable affect on the column performance; sudden changes in temperature can have a significant effect on reflux rate which will result in a change in the top and bottom separation rate.

4.7.4 Operational Constraints

Pressure is one of the most common constraints in a distillation column and safety measures are used to prevent explosions and ruptures. Energy transfer and fluid flow are other constraints that set limits on the vapour flow through the column. The more vapour we have going up the column the less fluid we have going down. Vapour flow can also be restricted by the amount of heat added to the system by the re-boiler and removed by the condenser. Changes in the feed quality also play a role that affects the temperature profiles of the column and may limit its range.

4.7.5 Conclusion

In this chapter the basics of the Deethanizer system were explained. From which we can see that the process is complex and requires a number of different interacting components to work properly. This level of complexity explains why a sound and efficient system is needed to constantly monitor the performance of such a system.

CHAPTER 5
DEETHANIZER SYSTEM ANALYSIS WITH CLPM INDICES

In this chapter the data collected from a gas processing plant is used to study the performance of the Deethanizer columns. The data was collected over a period of three days under normal operating conditions. The data was collected at one minute intervals with all the compression and averaging functions in the data historian suspended. For each of the Deethanizer systems a Dynamic Matrix Control (DMC) [72] generates the various set-points. The analysis has been conducted in two different phases; firstly an analysis of the performance of a single Deethanizer system was done. Secondly, a comparative analysis of three Deethanizer systems was done.

5.1 Deethanizer Control Analysis

In this section the performance of the controllers in a single Deethanizer system is analysed. The system is first analysed for oscillations and then analysis is carried out for each controller depending on its control objectives and goals.

5.1.1 Oscillation Analysis

5.1.1.1 Plant Wide Oscillations

The first step in the analysis is to find out if there are any oscillations that are affecting the entire plant. For this we use the Principal Component Analysis method to detect shared oscillations in the plant.

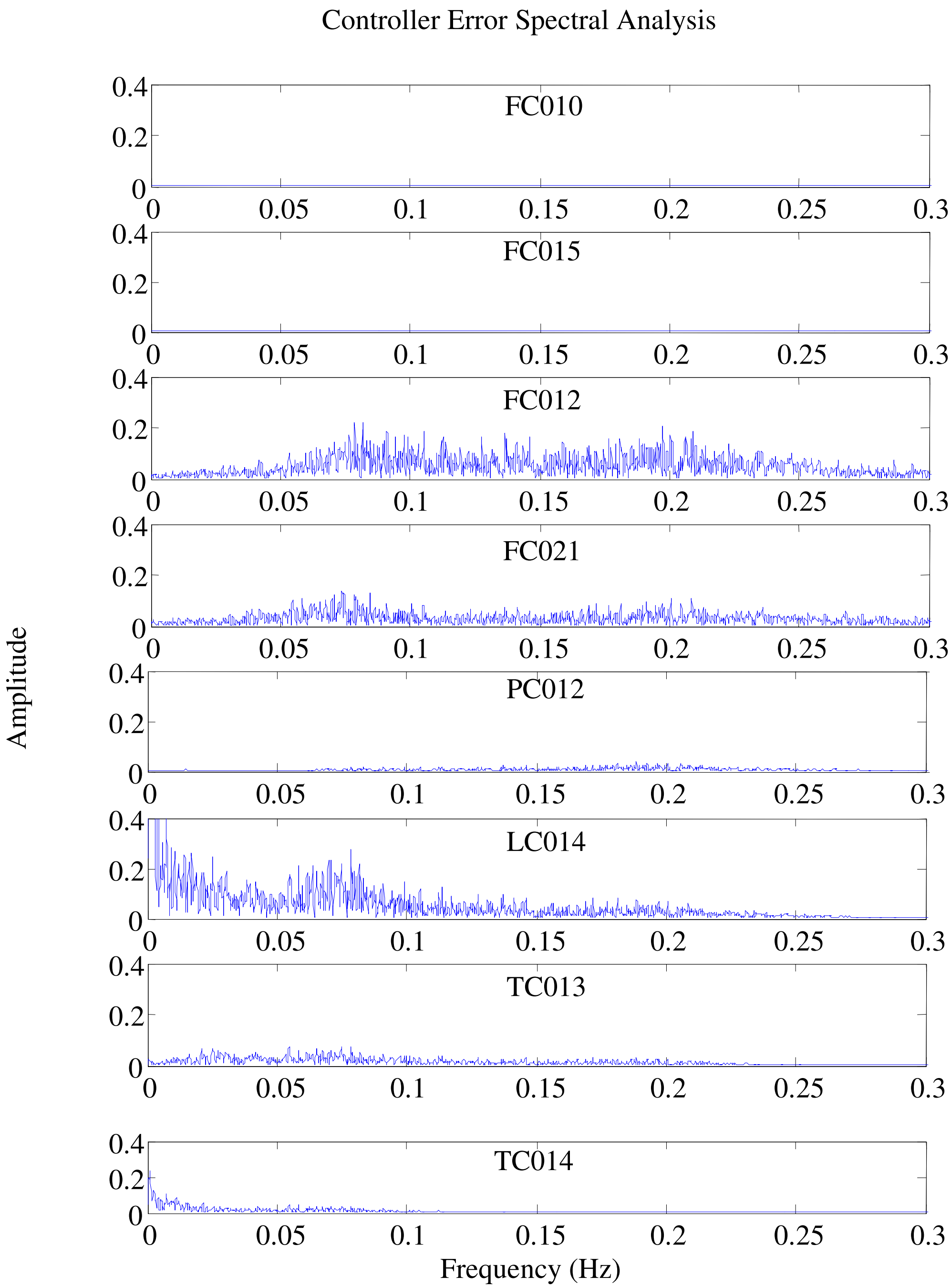

Figure 13: Spectral Analysis

As can be seen from the Spectral Analysis trends in Figure 13, the two steam flow controllers (FC012 and FC021) share the similar oscillations as well as the steam level controller (LC014). This makes sense since these controllers are interacting with each other very closely. It is also clear that the rest of the controllers do not share these oscillations so their performance can be assessed in isolation based on their specific objectives.

5.1.1.2 Control Loop Oscillations

From the previous section we can identify that FC012 and FC021 share similar oscillations and the signals seem to be identical through the entire frequency range. It is also clear from Figure 13 that the amplitude of FC012 is bigger than that of FC021 which could be an indication that FC012 is the source of the oscillation. We can also see some oscillations at the lower frequencies in the case of the level controller LC014. The next analysis step is to check whether these oscillations are from linear sources or not.

5.1.1.3 Oscillation Linearity Analysis

Higher order statistics [73] have been used to analyse the type of oscillations in these controllers. The results are described in Table 9.

Table 9: Oscillation Gaussianity and Linearity test

Controller	Gaussian	Non-Linear
FC012	No	Yes
FC021	Yes	Ignored
LC014	No	Yes

These results show that the oscillations present in FC012 and LC014 are the result of a nonlinear source. Thus further analysis into nonlinear sources such as valve problems need to be undertaken. As for FC021 it is most likely affected by a linear problem such as tight controller tuning or a result from the oscillation in FC012.

5.1.2 Temperature Control Analysis

The objective of TC013 controller is to maintain the temperature of the column. Thus it needs to reject disturbances that would affect the temperature of the column. For this we use the disturbance rejection performance measures.

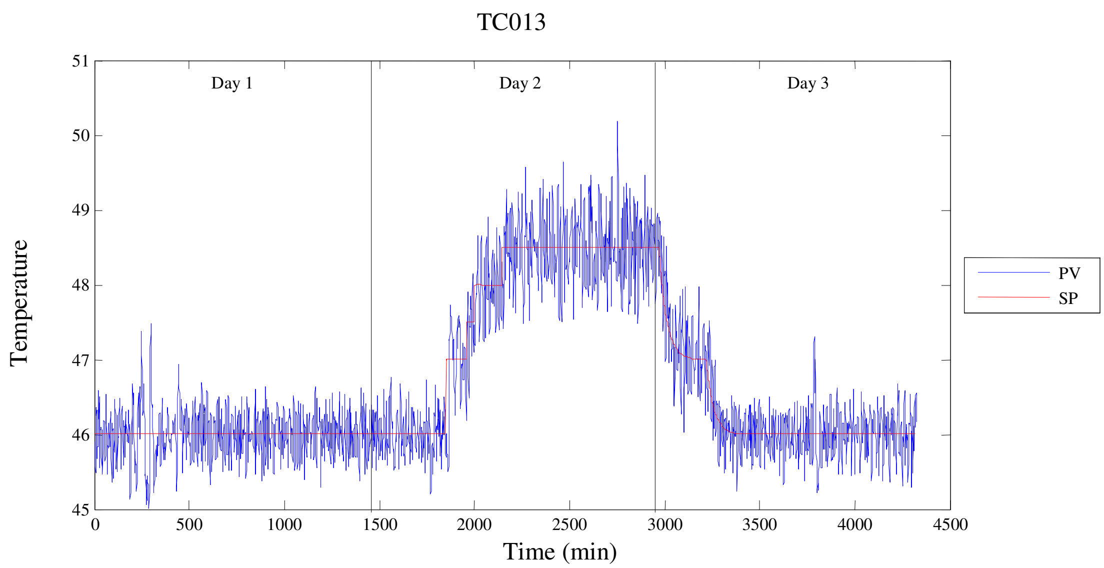

Figure 14: TC013 Data

Table 10: TC013 Index Analysis

	Day 1	Day 2	Day 3
SD	0.3993	0.6780	0.5198
Idle	-0.0516	0.1632	-0.4657
CLPA	0.876	0.844	0.799

As we can see from the data in Figure 14 and in Table 10 for the first day the controller was performing well closely tracking its set-point and successfully rejecting disturbances acting upon it. During the second day a change in the set-point caused a decline in the performance which is clearly evident from both performance indices since the SD and

Idle indices both increased. On the third day there was another set-point change which the controller was able to react very well.

5.1.3 Reflux Flow Analysis

This flow controller controls the amount of cold reflux entering the system thus it also plays a vital role in the temperature profile of the top of the column. For flow controllers we look for set-point control strategies.

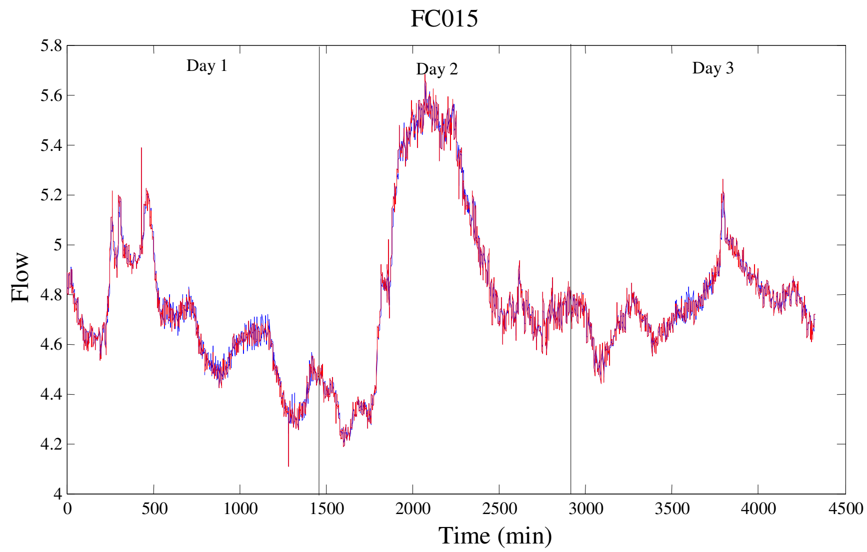

Figure 15: Reflux Flow Data

As we can see in Figure 15 the reflux flow set-point is constantly changing. Thus we will assess the performance of the controller using set-point change criteria as described in Table 11.

Table 11: Analysis of Reflux flow controller

	Day 1	Day 2	Day 3
AMP	**39.2**	**14.7**	**16.1**
SD	**0.3672**	**0.3786**	**0.2749**
ITAE	**2.74E+70**	**9.26E+70**	**7.81E+101**
CLPA	**0.1983**	**0.2573**	**0.2404**
Idle	**0.7896**	**0.6824**	**0.7617**

Based on this analysis we can see that the Reflux Flow controller has had high values of AMP index and a considerable amount of ITAE error. By looking at the results from the SD, CLPA and Idle indices we can see that the controller has maintained the same level of performance throughout the three days. The performance of the controller can be enhanced by improving the tuning of the controller.

5.1.4 Feed Flow Control Analysis

This controller manages how much feed comes into the system. It is also subjected to a constantly changing set-point as shown in Figure 16.

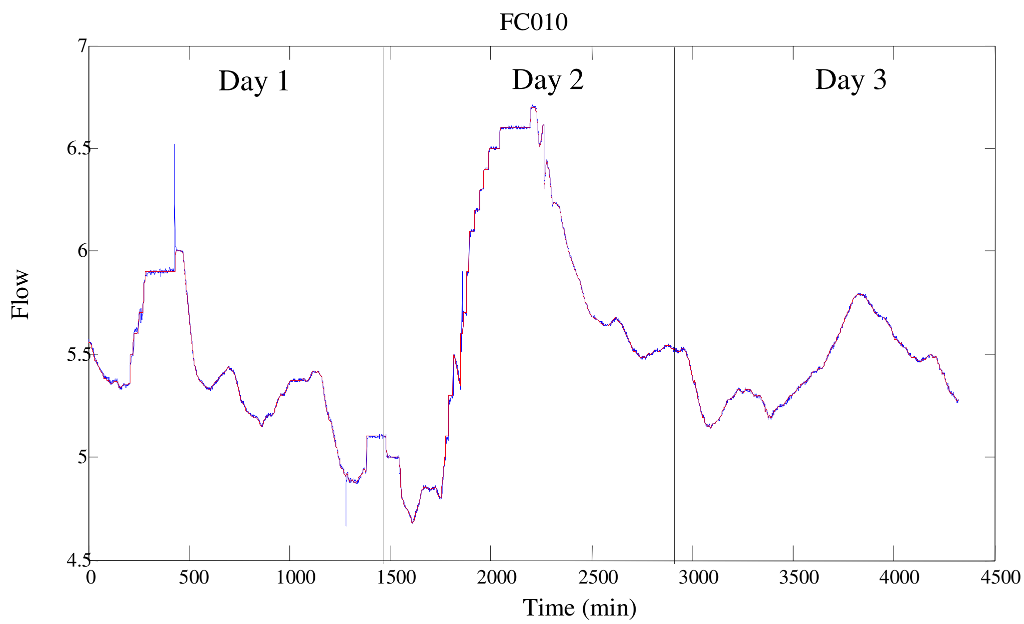

Figure 16: FC010 Feed Flow Data

Table 12: Feed flow Set-point Analysis

	Day 1	Day 2	Day 3
AMP	**0.1528**	**1.3028**	**1.3631**
SD	**0.2407**	**0.1178**	**0.0758**
ITAE	**4.96E+19**	**3.97E+03**	**2.17E+04**
CLPA	**-4.0412**	**-0.043**	**0.1491**
Idle	**0.2832**	**-0.043**	**0.1951**

As we can see from the analysis in Table 12 that this controller has been performing very well in keeping up with its set-point changes, and all of its performance indices seem to be holding within the same ranges. Except for negative values of the CLPA index which are more probably due to improper estimation of the time delay.

5.1.5 Pressure Control Analysis

This controller needs to reject disturbance and maintain a constant pressure on the top of the column.

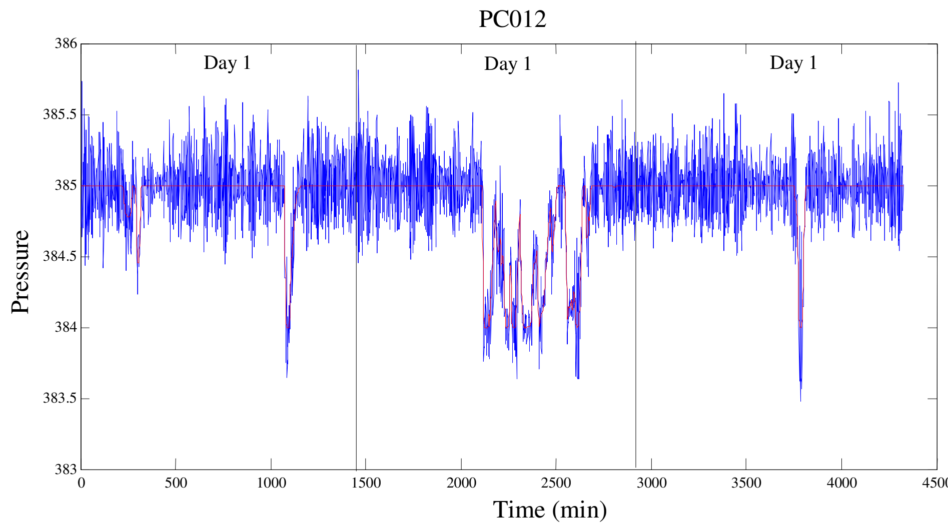

Figure 17: PC012 Pressure Data

As we can see from the data in Figure 17 during a disturbance the set-point is used to compensate for any changes in the system.

Table 13 : Pressure Control Analysis

	Day 1	Day 2	Day 3
SD	**0.0292**	**0.0375**	**0.0385**
Idle	**0.1354**	**0.1433**	**0.3586**
CLPA	**0.5645**	**0.3753**	**0.4805**

The analysis for this controller indicates that its performance is quite satisfactory in maintaining its control objectives. Table 13 indicates that the SD and Idle indices are within good performance regions. The CLPA index can be improved by working on decreasing the variance in the controller.

5.1.6 Tray 9 Temperature Control Analysis

This temperature controller is for maintaining the temperature of the bottom part of the column. Continuous set-point changes are made in order to adjust the columns temperature and maintain the required degree of evaporation from the column as shown in Figure 18.

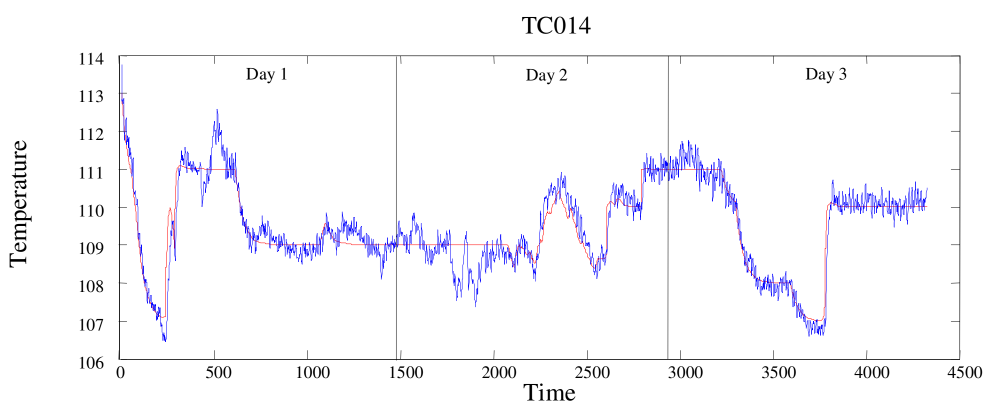

Figure 18: Tray 9 Temperature Data

Table 14: Tray 9 Temperature Control Analysis

	Day 1	Day 2	Day 3
AMP	0.051	0.3799	10.854
SD	0.4486	0.2975	0.19
ITAE	8.19E+09	1.32E+06	4.49E+07
CLPA	0.8835	0.9267	0.7938
Idle	0.0322	-0.0308	0.1162

Performance analysis results presented in Table 14 indicate that the controller was able to maintain good performance under different set-point changes. The CLPA index in this case is high but since we are more concerned about the controller being able to track set-point values the performance of the this controller is deemed satisfactory.

5.1.7 Steam Flow Controllers Analysis

In this setup we have two steam flow controllers connected to two heat exchangers on each side of the Deethanizer column. Their objective is to control how much steam flows to the system in order to heat up the bottom part of the column.

5.1.7.1 FC012 Analysis

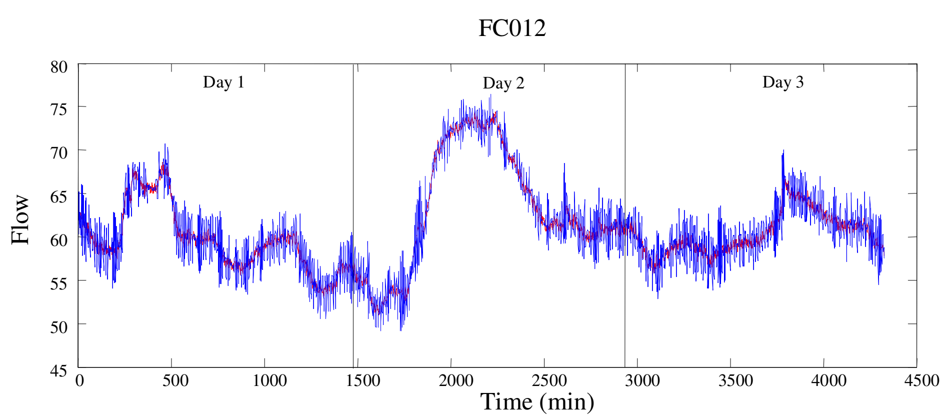

Figure 19: FC012 Steam Data

Table 15: FC012 Steam Control Analysis

	Day 1	Day 2	Day 3
AMP	**0.2697**	**3.4013**	**6.7383**
SD	**7.3947**	**1.6259**	**1.8341**
ITAE	**1.50**	**3.65E+17**	**1.87E+17**
CLPA	**0.3504**	**-1.9525**	**0.2923**
Idle	**0.0429**	**-0.1696**	**0.2687**

Knowing that this controller is oscillating Figure 19 can provide some understanding regarding the inconsistency of the analysis results in Table 15. Knowing that the oscillation is most likely due to a nonlinear source requires further analysis into the source of the problem. The valve is a very common source of oscillation in steam flow controllers and a valve sticking test should be done to confirm this finding. The oscillation in this controller needs to be addressed and then the performance analysis can be repeated to have a better view of the controller performance.

5.1.7.2 FC021 Analysis

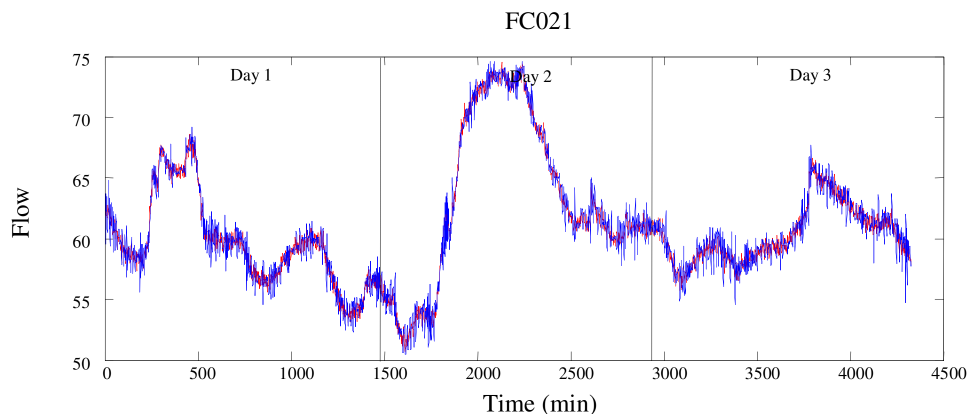

Figure 20: FC021 Steam Data

Table 16: FC021 Steam Control Analysis

	Day 1	Day 2	Day 3
AMP	0.4005	12.6416	2.1336
SD	2.2142	0.9964	1.0302
ITAE	2.52E+05	2.79E+13	6.21E+04
CLPA	0.1371	0.0648	0.0962
Idle	-0.0251	-0.0564	0.0437

This controller is also subjected to an oscillating signal as seen in Figure 20 but the oscillation analysis indicates that it is not as strong as in the case of FC012 and it is most likely due to an external oscillation. Nevertheless, the performance shown in Table 16 of this controller needs to be also reassessed after the oscillation problem has been dealt with.

5.1.8 Level Control Analysis

The objective of this controller is to maintain a constant level and smooth the process of any disturbances in the signal as shown in Figure 21.

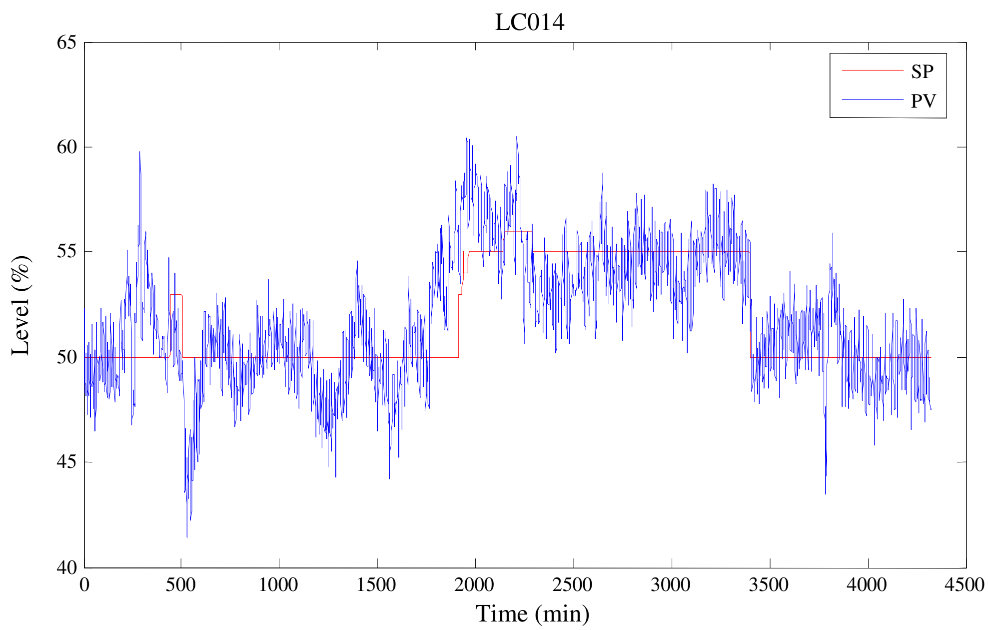

Figure 21: LC014 Level Data

Table 17: LC014 level Control Analysis

	Day 1	Day 2	Day 3
SD	**6.3151**	**3.6204**	**2.5434**
Idle	**-0.1507**	**-0.2959**	**0.1153**
CLPA	**0.9083**	**0.8687**	**0.9018**

This controller has also an oscillation that needs to be addressed before a meaningful analysis can be obtained from the performance indices in Table 17.

5.1.9 System Performance

The analysis of the performance of the controllers in this system has revealed the following areas of concern:

- An oscillation is present in the lower section of the deethanizer system. This oscillation is most likely due to a problem with FC012. Though this oscillation has an affect on the performance of the system, it does not have a significant impact on the quality of the top product which is the main concern in this systems control scheme.
- The performance of the top temperature and reflux controllers need to be improved. The reflux flow controller is showing problems keeping with set-point changes. And the top temperature controller is also exhibiting problems with maintaining the temperature of the top section of the column. These two controllers have great influence in determining the quality of the final overhead product.

5.2 System Analysis Comparison

This section compares the controller performance of three Deethanizer systems running in the same plant. Each system receives its controller set-points from its own DMC controller. All three systems share a common feed stock source. The data was collected over a period of three days of normal operations. The data historians were configured not to compress or average the collected data. The comparison looks at the performance of similar controllers at each plant.

5.2.1 Oscillation Analysis

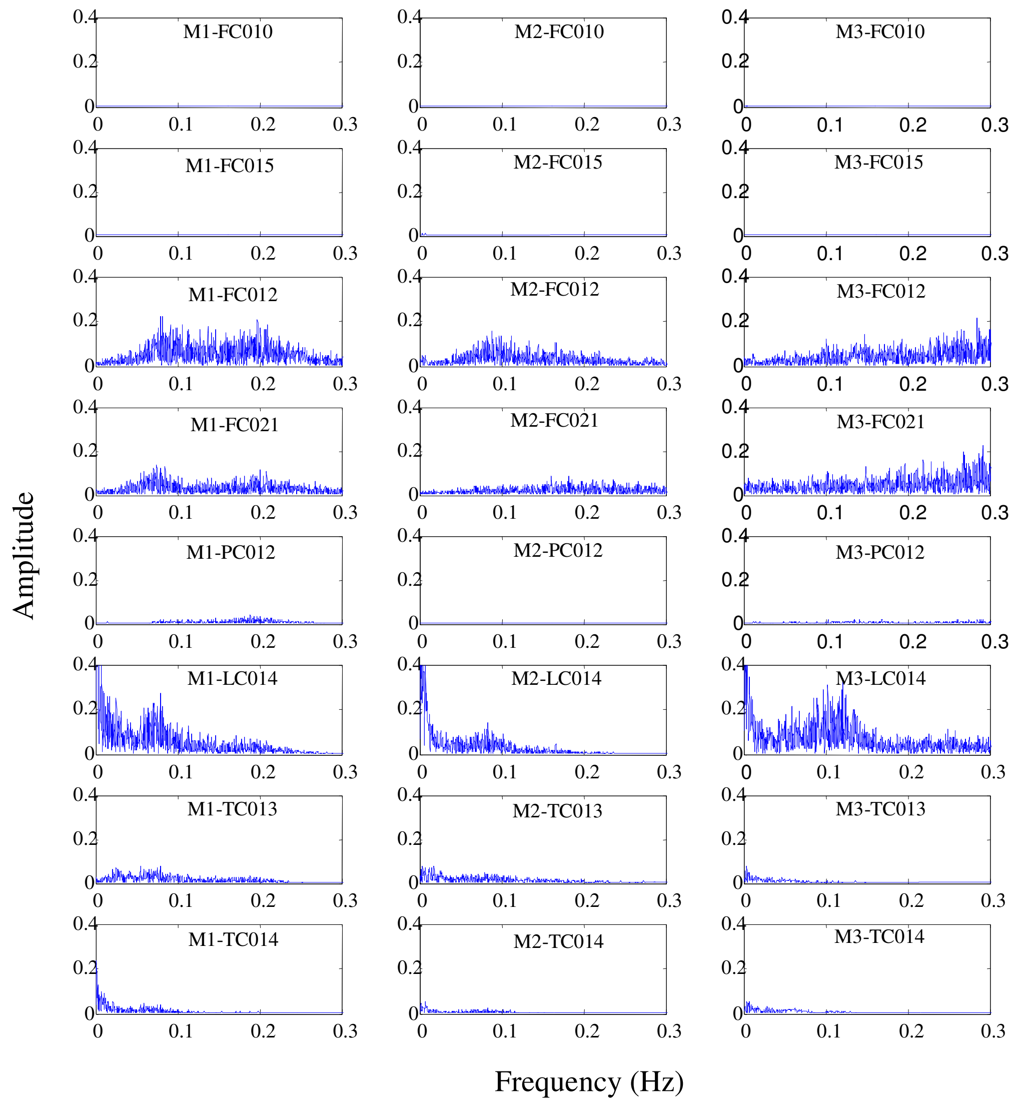

Figure 22: Spectral Analysis Comparison

The oscillation analysis of the three systems in Figure 22 shows that the same controllers are oscillating in all three plants. The noticeable difference is that M2-LC014 is only showing oscillations at frequencies around 0.1 Hz, M1-LC014 is up to around 0.2 Hz, whereas M3-LC014 is showing oscillations all the way up to 0.3 Hz. That means that M3-LC014 is given more freedom to oscillate than the other two controllers. It is also shown that the TC013 and TC014 controllers in all three plants appear to have an oscillation signal with very low amplitudes but these oscillations are stronger in M1 and M2 than they are in M3.

Further analysis into the nature of the oscillations in Table 18 indicates that except for M1-FC012 and M1-LC014 the sources of the oscillations in the controllers seam to be from linear sources. That is to say that the most probable cause of the oscillations is either tuning or controller interactions.

Table 18: Oscillation Gaussianity and Linearity Comparison

M1			M2			M3		
Controller	Gaussian	Non-Linear	Controller	Gaussian	Non-Linear	Controller	Gaussian	Non-Linear
FC012	No	Yes	FC012	No	No	FC012	Yes	Ignored
FC021	Yes	Ignored	FC021	Yes	Ignored	FC021	Yes	Ignored
LC014	No	Yes	LC014	No	No	LC014	Yes	Ignored
TC013	Yes	Ignored	TC013	Yes	Ignored	TC013	Yes	Ignored
TC014	No	No	TC014	No	No	TC014	No	No

5.2.2 Temperature Control Analysis

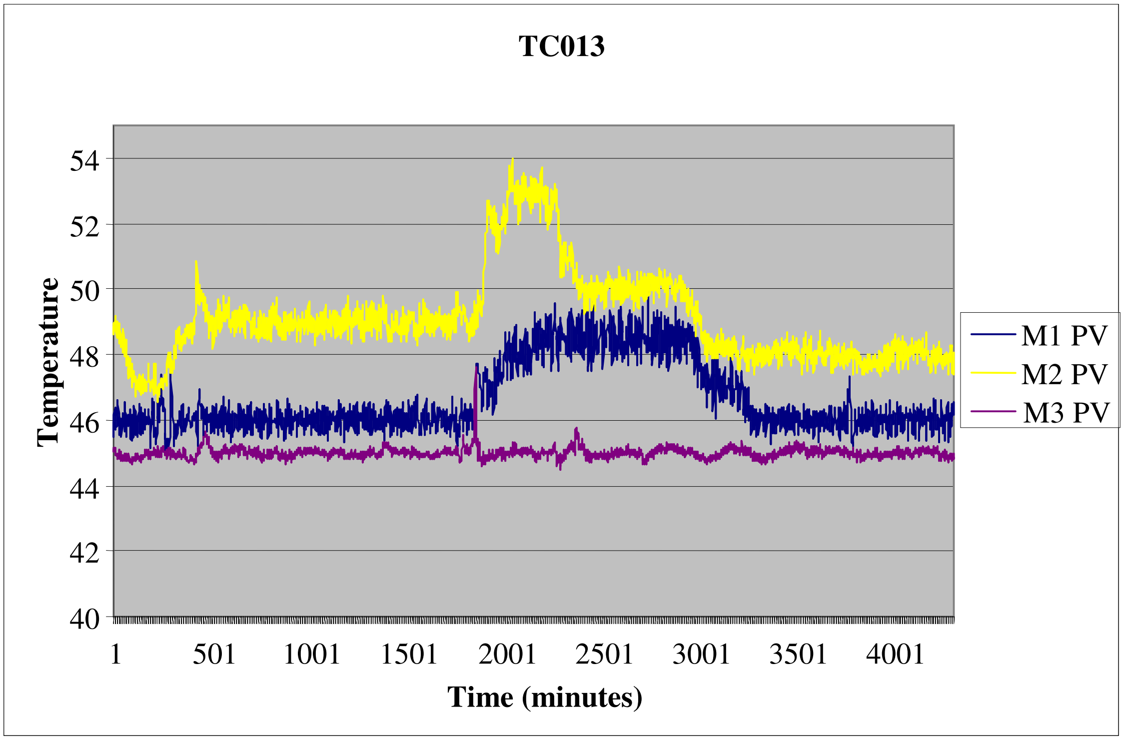

Figure 23: TC013 Plant Data Comparison

Table 19 : Column Top Temperature Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-tc013	0.532367	-0.11803	0.839733	1.4083
M2-tc013	0.510967	0.025633	0.683733	8.894133
M3-tc013	0.239767	0.032733	0.657767	0.0221

The analysis results of the data in Figure 23 are shown in Table 19. These controllers are normally not subjected to any set-point changes, which is the case except for the period in the middle where both M1 and M2 have a set-point change. The analysis shows that M3 has the best overall control of the process. M1 and M2 both show problems with SD performance. M1 is having a CLPA index which indicates difficulty in minimizing the variance of the signal. M2 is showing a higher AMP index resulting from incapability to respond properly to set-point changes.

5.2.3 Reflux Flow Analysis

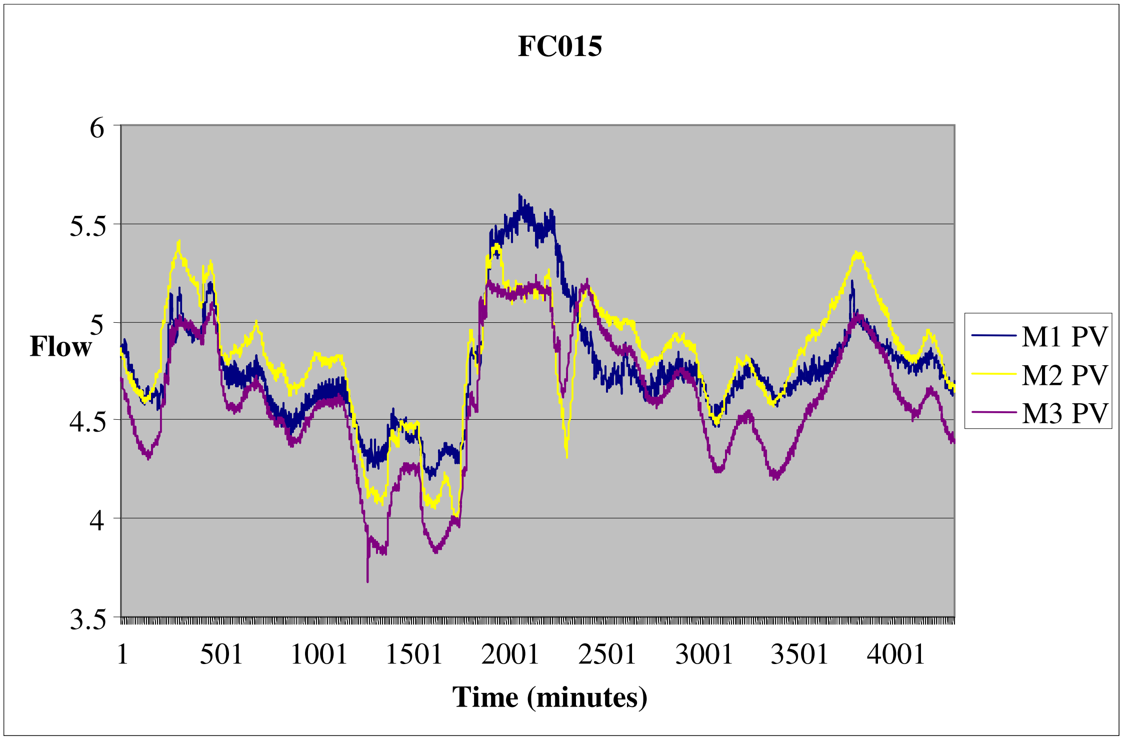

Figure 24: FC015 Plant Data Comparison

Table 20: Reflux Flow Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-fc015	**0.340233**	**0.744567**	**0.232**	**16.79727**
M2-fc015	**0.409467**	**0.142333**	**0.3474**	**18.9648**
M3-fc015	**0.229633**	**0.2213**	**-0.3309**	**7.633667**

The reflux flow data is shown in Figure 24. Here the set-point was constantly changing to adjust the temperature of the column. The analysis as shown in Table 20 indicates a better overall performance by the M3 controller. M1 shows a better performance over M2 in the indices except for the Idle index. M3 is showing a negative CLPA index indicating a need to re-evaluate the time delay estimation used.

5.2.4 Feed Flow Analysis

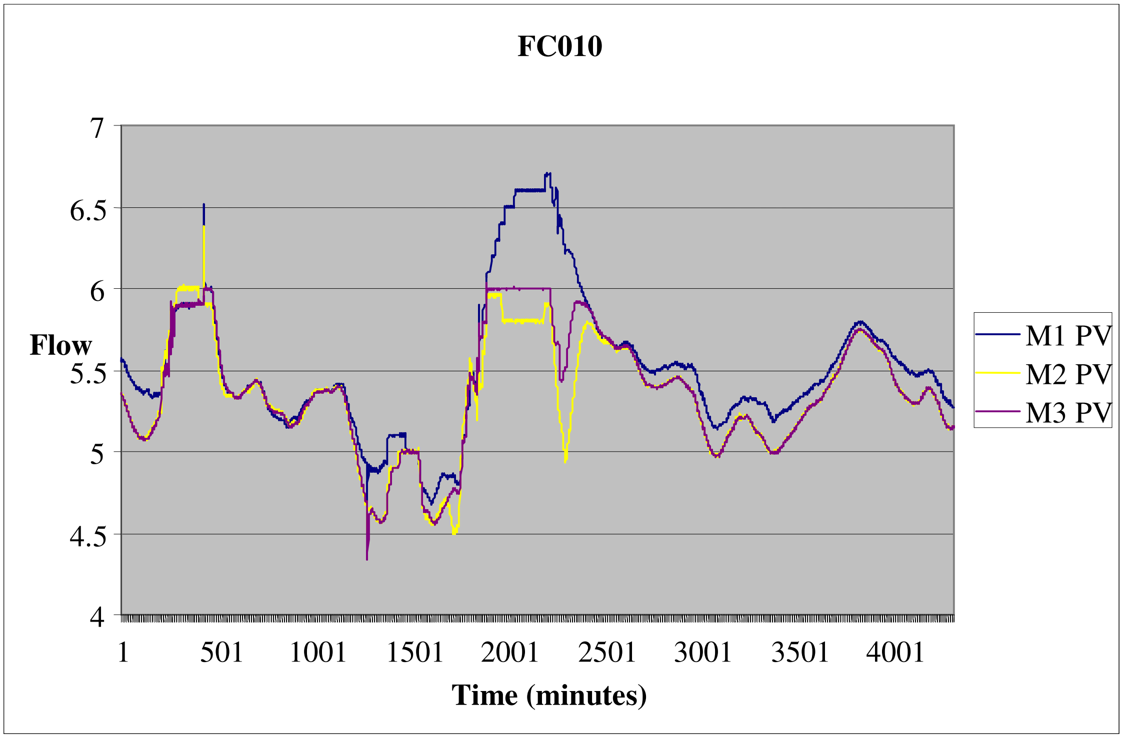

Figure 25: FC010 Plant Data Comparison

Table 21: Feed Flow Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-fc010	0.144767	0.1451	-1.91337	1.195067
M2-fc010	0.1021	0.4724	0	8.760633
M3-fc010	0.154867	0.2543	-3.5703	7.9409

The feed flow into each system is shown in Figure 25. The analysis results in Table 21 indicate a similar performance for each system except for a slightly worse performance by M2 in the Idle and AMP indices. The negative values of CLPA index indicate that the controllers are exhibiting a time delay that is smaller then the used estimate.

5.2.5 Pressure Control Analysis

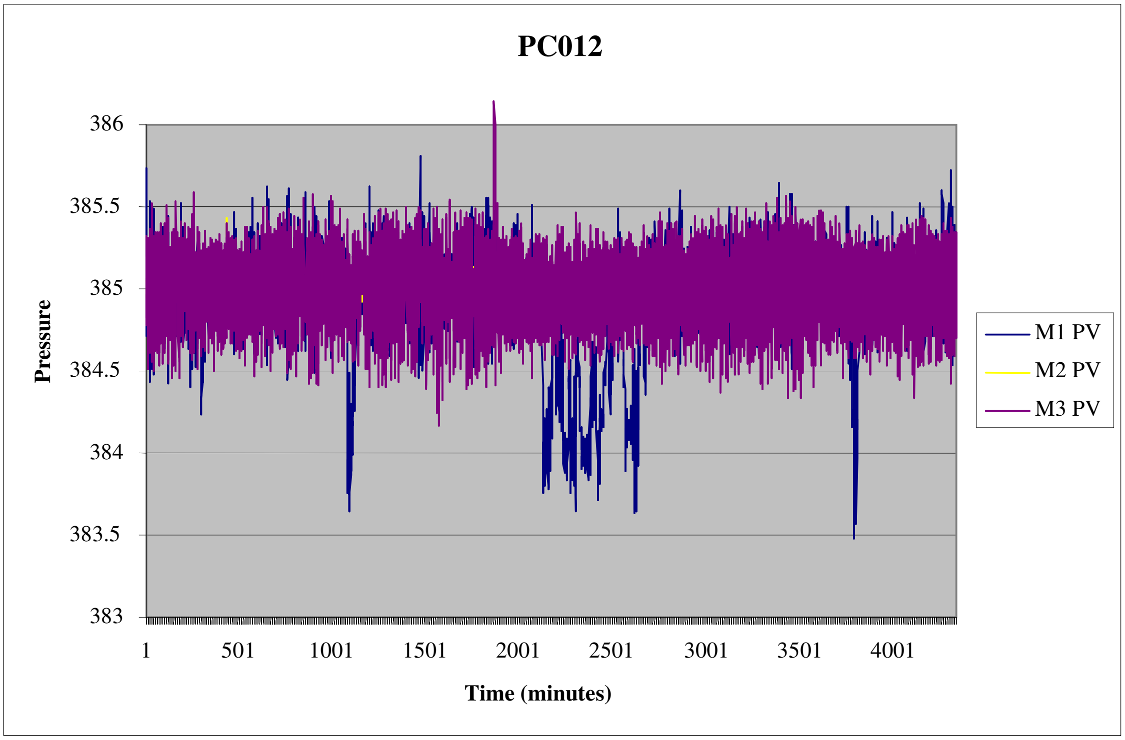

Figure 26: PC012 Plant Data Comparison

Table 22: Pressure Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-pc012	**0.035067**	**0.212433**	**0.473433**	**2.3653**
M2-pc012	**0.0093**	**0.013333**	**0.019367**	**0.566533**
M3-pc012	**0.054433**	**0**	**0.0408**	**0**

All three controllers in Figure 26 appear to be performing similarly except for M1 which seems to be having some problems in maintaining the pressure at the set-point Table 22.

5.2.6 Tray 9 Temperature Control Analysis

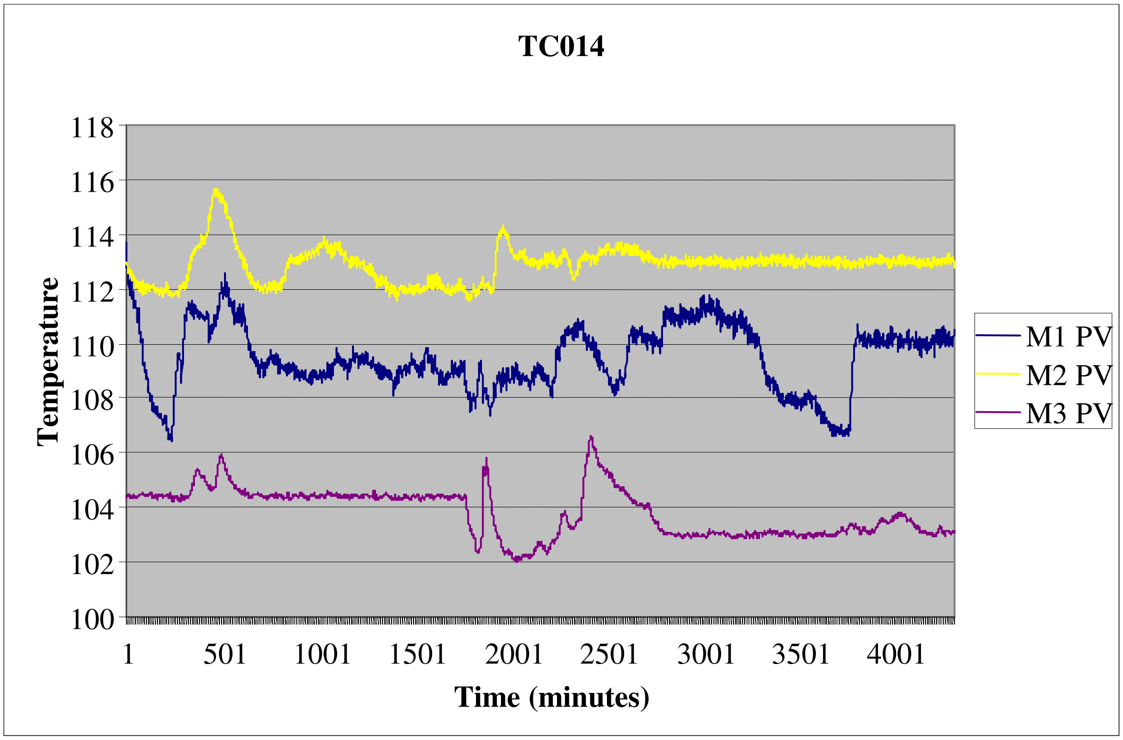

Figure 27: TC014 Plant Data Comparison

Table 23: Tray 9 Temperature Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-tc014	**0.312033**	**0.0392**	**0.868**	**4.094667**
M2-tc014	**0.100133**	**0.0078**	**0.873867**	**5.044267**
M3-tc014	**0.0768**	**0.1318**	**-1.2327**	**6.4842**

The temperature profile at this level is shown in Figure 27. As previously discussed the better the control over the temperature, the better would be the product specifications. M1 and M2 are having problems maintaining a low CLPA index in Table 23, whereas M3 appears to show very good control. The negative value of the M3 CLPA index is most likely a result of an actual time delay smaller than the used estimation.

5.2.7 Steam Flow Control Analysis

5.2.7.1 FC012 Analysis

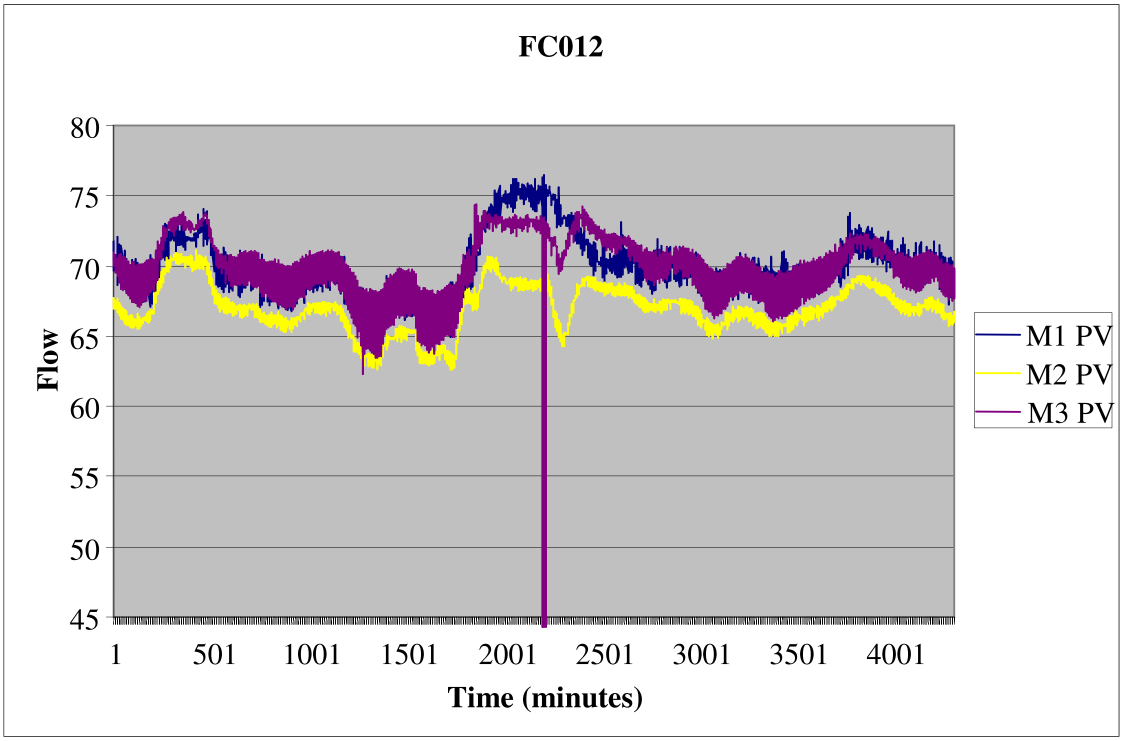

Figure 28: FC012 Plant Data Comparison

Table 24: FC012 Analysis Comparison

	SD	Idle	CLPA	AMP
M1-fc012	**3.618233**	**0.047333**	**-1.5101**	**8.3272**
M2-fc012	**1.100933**	**0.032833**	**0.142133**	**18.54147**
M3-fc012	**2.754033**	**0.304667**	**0.4625**	**8.497167**

The data in Figure 28 shows M3 has been experiencing stronger oscillations than M1 and M2. The analysis results in Table 24 need to be re-evaluated after the oscillations in the controllers are resolved.

5.2.7.2 FC021 Analysis

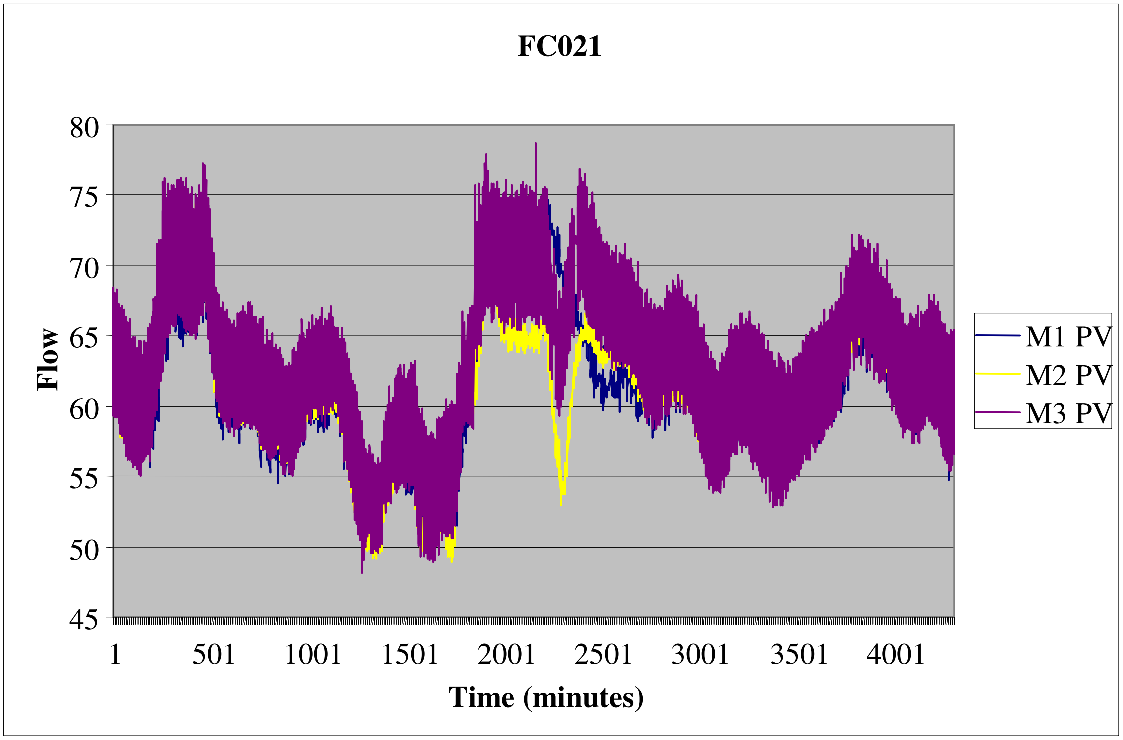

Figure 29: FC021 Plant Data Comparison

Table 25: FC021 Analysis Comparison

	SD	Idle	CLPA	AMP
M1-fc021	**1.4136**	**-0.0126**	**0.099367**	**6.9893**
M2-fc021	**0.820133**	**0.014733**	**0.006767**	**4.095833**
M3-fc021	**4.660867**	**0.4422**	**0.465133**	**11.4053**

Similarly, FC021 is showing high oscillations for M3 in Figure 29. Table 25 shows the performance analysis of the controllers but they need to be reassessed after removing the oscillations from the controllers.

5.2.8 Level Control Analysis

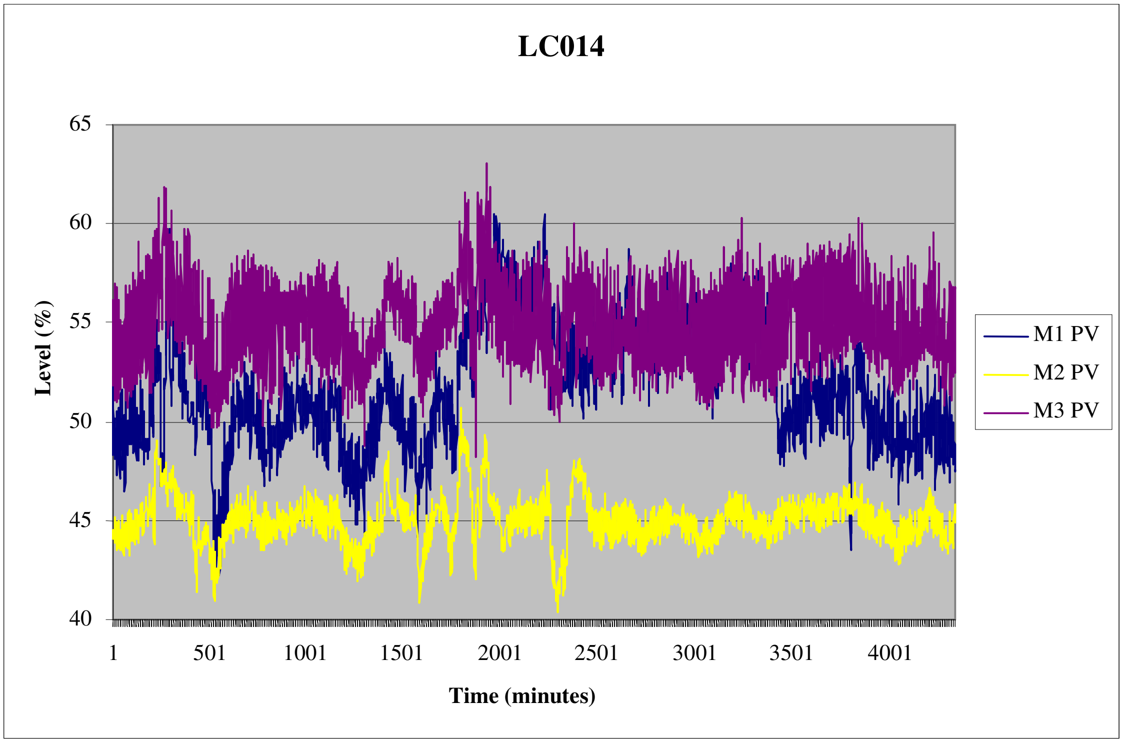

Figure 30: LC014 Plant Data Comparison

Table 26: Level Control Analysis Comparison

	SD	Idle	CLPA	AMP
M1-lc014	**4.159633**	**-0.11043**	**0.9729**	**1.665633**
M2-lc014	**1.957367**	**0**	**0.9672**	**0**
M3-lc014	**3.066467**	**0**	**0.5675**	**0**

The level control in Figure 30 shows that M2 was closely controlling the level around the set-point, whereas M1 and M3 are showing loose control which is also indicated in the analysis results in Table 26.

5.2.9 Performance Analysis Comparison

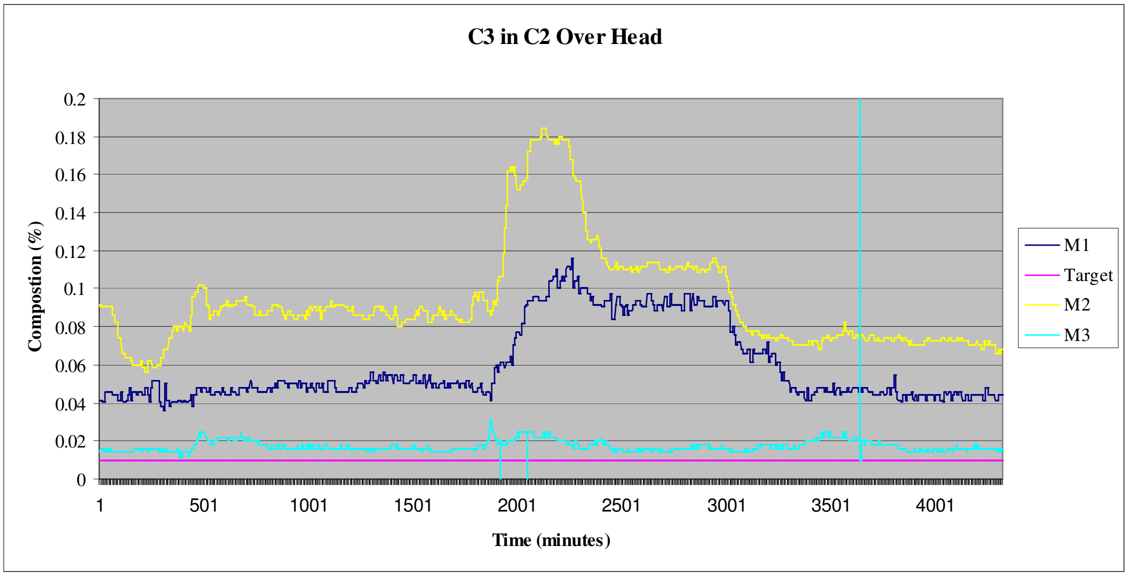

Figure 31: Top product specification Comparison

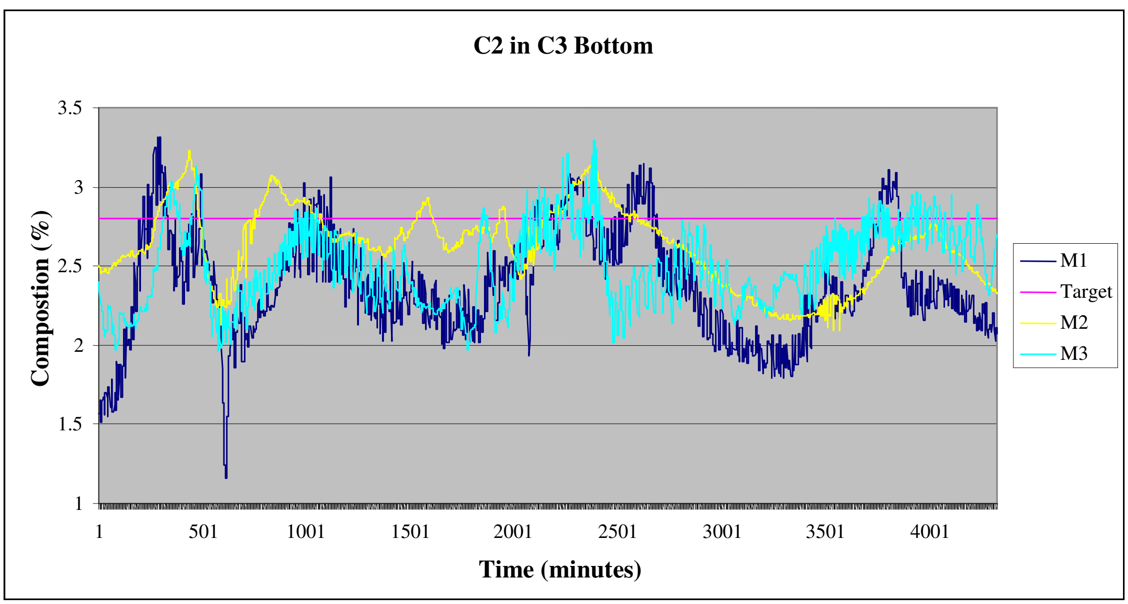

Figure 32: Bottom product specification Comparison

The trends in Figure 31 and 32 show the results of the top and bottom product specifications of each plant for the three day period. As we can see in Figure 31 M3 is producing a top product which is very close to the target specifications followed by M1 and M2. Figure 32 indicates that the product quality for M2 is controlled better than that for M1 and M3 with less variation in the quality and closer control near the target specification.

Going back to the control objectives for these systems we know that the top product quality is the main objective in this system. The bottom product quality can be sacrificed for a better top product quality.

The analysis results indicate that M3 was maintaining a better control on the top of the column by achieving smooth temperature control at TC013 and TC014 on one hand allowing slightly looser control on the bottom steam flow controllers FC012 and FC021 and level controller LC014. This gives the system enough flexibility to deal with disturbances with out affecting the top product quality.

On the other hand, M2 was achieving a better control on FC012 and FC021 and LC014 and less satisfactory control on TC013 and TC014 when compared with the other two plants. This resulted in M2 having the worst top product quality, since its controllers are not configured to cope with system disturbances at the bottom of the column. This configuration leaves the system to respond to problems at the top of the column which is affecting the quality of the top product.

5.3 Conclusion

In case I the performance evaluation of the controllers in the Deethanizer system showed that the values change from day to day. These changes depend on the different factors acting on the controller during these days. Nevertheless, the performance of a controller can be determined when we take into account the values of the different performance indices into account.

In case II the analysis of three similar systems showed that it is not enough for a controller to have good results when it comes to the values of the performance indices but also these values must agree with the control objectives of the system.

From the analysis done in this chapter we can conclude the following:

- A clear understanding of the entire system is critical during the analysis of the performance of the control loops in the system.
- In order to make a reasonable assessment of the performance of control loops one must identify the goals and objectives of each controller in the system.
- An understanding of the Control loop interactions in a system is very important to assess the performance.
- Oscillations play a major role in affecting the performance of control loops in process plants.
- Combining the analysis results from different performance indices provides a clear and more reliable assessment of the performance of control loops in the system.

CHAPTER 6
CONCLUSION AND FUTURE RESEARCH

6.1 Conclusion of Control Loop Performance Monitoring in Manufacturing Systems

This thesis looked at current performance monitoring methods that sort controllers based on a common performance measure. Though effective this approach depends largely on the users understanding of the unit and its operation to decide whether the level of controller performance is appropriate or not. With diminishing numbers of experienced personnel in the plants this task becomes harder to maintain and depend on for an effective control loop performance monitoring. One of the main factors affecting implementation of control loop performance monitoring techniques in operating plants is the ease of applying a monitoring system to a plant with hundreds of controllers.

Plants are usually divided into smaller operational units making up the whole plant. Thus, by looking at each unit individually and having a limited number of performance measurement options such as Set-point tracking, Steady State operation, and Disturbance rejection the added setup work is justified by the value gained from such a setting. This kind of performance monitoring will provide the end user with a clear understanding of the units operation based on the control objectives set forth for the unit. It also provides a better appreciation of which controllers are having problems with their control objectives.

In this thesis control loop performance monitoring was considered by looking at control objectives of individual SISO controllers in an operational unit. This approach provides an insight into the effectiveness of each controller in the unit control scheme. Controller performance was looked at from a functional stand point. Controllers that were steadily subjected to set-point changes were required to use measures that indicate their effectiveness in following those changes with minimal disturbance to the plant. On the other hand, controllers that required maintaining a steady state operation also needed to show the ability to stay around those operational states. Finally, controllers having to deal with disturbance rejection and minimizing the affects that these disturbances might have on the operation and performance of the unit also needed to be evaluated.

Combining the different performance analysis measurements with clear understanding of the control objectives of the plant is considered a key in accurately assessing the performance of control loops in that plant.

6.2 Thesis Contribution

The contributions of this thesis are:

- An intensive review of the literature is presented. This review includes all the developments made in the area of control loop performance monitoring in the last decade.
- The steps required to calculate performance monitoring indices are outlined and applied to a Deethanizer system.
- Using operational data collected from a Saudi Aramco, Gas plant Deethanizer system the performance of various control loops were analysed, and poor performing control loops were identified.
- Highlighted the following issues:
    - Control loop oscillations are one of the most common problems in the process control industry.
    - Oscillations in control loops need to be identified and resolved before a meaningful performance assessment can be made.
    - Control loops are used to satisfy different goals and objectives thus different performance measures need to be used accordingly.
    - In order to obtain an accurate control performance assessment one must have clear understanding of the process plant and its control scheme.

6.3 For Future Studies

In the oil and gas industry some units such as fractionation, boilers, heat exchangers, etc., are commonly found in every plant. These units are usually operating with a specific control scheme to meet particular product requirements. Developing unit specific performance monitoring applications that use techniques easily adjusted to meet individual differences would be of significant value to the industry.

6.4 Recommendation for Future Research

Areas that would attract further research in this field would be:

- Time delay estimation

Accurate online estimation of time delay is very important in providing performance measurement results that correctly describe the behaviour of the controllers.

- Performance measures for controllers under APC

Most SISO controllers operate under more advanced control systems such as MIMO, MPC, and DMC. The effect of using these different controllers and how that changes the dynamics of performance measurement for SISO controllers is worth studying.

- Controller interactions

With plants having hundreds of controllers further research into the interactions different systems have is important. These interactions play an important role in the performance of the control system.

- Oscillation analysis

Further analysis in the area of identifying sources of oscillation is required. Degrees of oscillation acceptable for Level controllers for example need to be identified.

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NOMENCLATURE AND ACRONYMS

I_p	=	Harris Index
$y(t)$	=	Output function
d	=	Dead-time (time delay)
A,B,C	=	Polynomial functions
$e(t)$.	=	Noise function
q^{-1}	=	Backward shift operator
q	=	Forward shift operator
h_0	=	
$u(t)$	=	input function
$\eta(b)$	=	Normalized performance index
N	=	Number of data points collected
d_1	=	Difference between set-point and process variable
d_2	=	Difference between two consecutive process variables
S	=	Process Variance
r	=	Watchdog index
a	=	Oscillation amplitude
T_i	=	Integral time
T_{sup}	=	Supervision time
IAE_{lim}	=	Integral of Absolute Error limit
$\eta(k)$	=	Extended horizon performance index
Ts	=	Dimensionless settling time index
t_s	=	settling time
r_o	=	size of set-point step changes
I_i	=	Idle index
t_{pos}	=	Time control in positive time
t_{neg}	=	Time control in negative time
K	=	Degrees of freedom
I_{mod}	=	Modified performance index
$y_{pv,\max/\min}$	=	Maximum and minimum values of the process variable

Δy_{sp} = magnitude of the set-point change

Symbols

σ_y^2 = Variance of output signal

σ_{MV}^2 = Variance of output signal under MV control

σ_e^2 = Variance of noise signal

ω = Ultimate frequency

θ_a = Apparent time delay

u = Location of pole

v = Disturbance

σ_{mod}^2 = Variance based on modified MV

γ = Forgetting factor

τ = Estimate of the time constant of the process

$\Re$ = Decay ratio

Acronyms

ACF = Auto-covariance function

AMP = Amplitude overshoot size

APC = Advanced Process Control

AR = Auto-regressive

ARMA= Auto-regressive moving average

CE = Control error

CLP = Closed Loop Potential index

CLPA = Control Loop Performance Assessment

CLPM = Control Loop Performance Monitoring

DCS = Distributed Control System

DMC = Dynamic Matrix Control

DFT = Discrete Foriear Transform

FC = Flow control

GMV = Generalized Minimum Variance index

GPC	=	Generalized Predictive Control benchmark
IAE	=	Integral of Absolute Error
ITAE	=	Integral of the Time weighted Absolute Error
LC	=	Level control
MA	=	Moving average
MIMO	=	Multi Input Multi Output
MPC	=	Model Predictive Control
MSE	=	Mean Square Error
MVC	=	Minimum Variance Control
M1	=	Deethanizer system plant 1
M2	=	Deethanizer system plant 2
M3	=	Deethanizer system plant 3
NFI	=	Non Gaussian index
NLI	=	Non linearity index
OP	=	Output
P	=	Proportional control
PC	=	Pressure control
PCA	=	Principal Component Analysis
PE	=	Permanent error
PI	=	Proportional and Integral Control
PID	=	Proportional, Integral and Derivative Control
PSCI	=	Power spectral correlation index
PV	=	Process Variable
RPM	=	Relative Performance Monitor
SISO	=	Single Input Single Output
SP	=	Set-point
SPD	=	Index of rise time
TC	=	Temperature control
TIME	=	Index of settling time

WEBLINKS

This page is for future referencing through the internet that has related information with the studies conducted in this thesis. The list is arranged in alphabetical order for easy referencing. Reader may read each link with the main subject followed by the brief description of the link and the web address.

1. ExperTune Library:

Link: http://www.expertune.com/articles.html

2. New Castle University:

Link: http://csd.newcastle.edu.au/index.html

3. Tennessee Eastman Challenge Archive:

Link: http://depts.washington.edu/control/LARRY/TE/download.html

4. University of Edinburgh Control HyperCourse

Link: http://eweb.chemeng.ed.ac.uk/courses/control/restricted/course/index.html

5. University of Cambridge Control Engineering Virtual Library

Link: http://www-control.eng.cam.ac.uk/extras/Virtual_Library/Control_VL.html

6. One Smart Click

Ink: http://www.onesmartclick.com/engineering/chemical-process-control.html

7. University of NewCastle Upon Tyne

Link: http://lorien.ncl.ac.uk/ming/Dept/Swot/connotes.htm

APPENDIX I

A. Distributed Control System (DCS)

The term Distributed Control System (DCS) is used to describe industrial and civil engineering applications that monitor and control equipment distributed in a plant with remote human intervention.

These systems are normally made up of field instruments that are digitally connected through a series of computer or electrical buses to multiplexer/demultiplexers and analog to digital converters and finally to the Human-Machine Interface (HMI). The term DCS describes the network of sensors, controllers, operator terminals and actuators that are used to control a process.

These systems have a wide range of applications in different industrial applications such as electrical power grids, electrical generation plants, environmental control systems, traffic signals, water managements systems, refining and chemical plants, and pharmaceutical manufacturing. [http://en.wikipedia.org/wiki/Distributed_control_system]

As an example, a typical Honeywell DCS system in a processing plant would have the following components: Operator-Machine interface known as the Global User Station (GUS), Process Historian (PHD) or History Module (HM), Application Processing Platform (APP), Network Interface Model (NIM), Local Control Network Extension (LCNE), and Network Gateway (NG).

A brief description of each component follows:

Global User Station (GUS):

The Global User Station is the latest version of TPS system man/machine interface. This Microsoft NT based workstation provides a Native Window through which information access is available from the entire system. Process data is accessed at the LCN level and below. Information is made equally available from the data that is resident in LCN nodes as well as data resident in process-connected devices. Plantwide information is made available through its connection to the Plant Information Network (PIN).

History Module (HM) / Process Historian (PHD):

The History Module (HM) provides mass storage of data on hard disk media. It is available with redundant hard disk drives and allows users to store and quickly access large blocks of data. Some examples of the types of data that can be stored and accessed are

- History of
    - Process alarms
    - Operator changes
    - Operator messages
    - System status changes
    - System errors
    - System maintenance recommendations
- Continuous process history to support logs and trends
- System rues of all types such as. load images and the data required to load nodes
- Checkpoint data for maintaining an up to date copy of the database in the event the node or device is taken out of service
- On process maintenance information and analysis

The Application Module (AM) permits the implementation of more complex control calculations and strategies that are possible when using only process-connected devices. A set of standard advanced control algorithms is included. Custom algorithms and control strategies can be developed by using a process-engineer-oriented Control Language (CL/AM).

The Process Manager (PM) provides a complete range of data acquisition and control capabilities, including digital inputs and outputs, analog inputs and outputs, and up to 160 regulatory control loops. The number and types of control functions to be implemented, along with the PM processing rate, are configurable by the user. Custom control strategies can be developed by using a process engineer oriented control language (CUPM). Peer-to-peer communications with other devices on the UCN is possible.

The Advanced Process Manager (APM) provides the functions of the Process Manager, plus

- millisecond sequence of events,
- device control point for process area motor control,
- array point for mapping variables to a serial interface device,
- increased memory, and
- time and string variable support for CL programs.

Software release R500 supports the High Performance Process Manager (HPM), which provides the functions of the Advanced Process Manager, plus

- Increase of processing units (2.5 X APM)
- Maximum number of points increase
- Point mix and scan rate change without reload

Network Interface Model (NIM):

The Network Interface Module (NIM) is a node on the LCN that interconnects the UCN with the LCN. It converts the transmission technique and protocol of the LCN to the transmission technique and protocol of the UCN. A NIM almost always has a redundant partner.

Network Gateway (NG):

The Network Gateway provides the capability for file and point access between multiple LCNs. Note that the LCNs

- Can be geographically separated.
- Provide current data.
- Allow inter network control by way of the Application Module.

The LCNs are connected through a dedicated Plant Information Network that consists of the necessary hardware, such as modems and connection devices.

Hiway Gateway (HG)

The Hiway Gateway (HG) is a node on the LCN that interconnects the Data Hiway and LCN. It makes the transition from the transmission technique and protocol of the LCN to the transmission technique and protocol of the Hiway. It also provides other functions such as polling, alarm scanning, and time synchronization for Hiway-based devices.

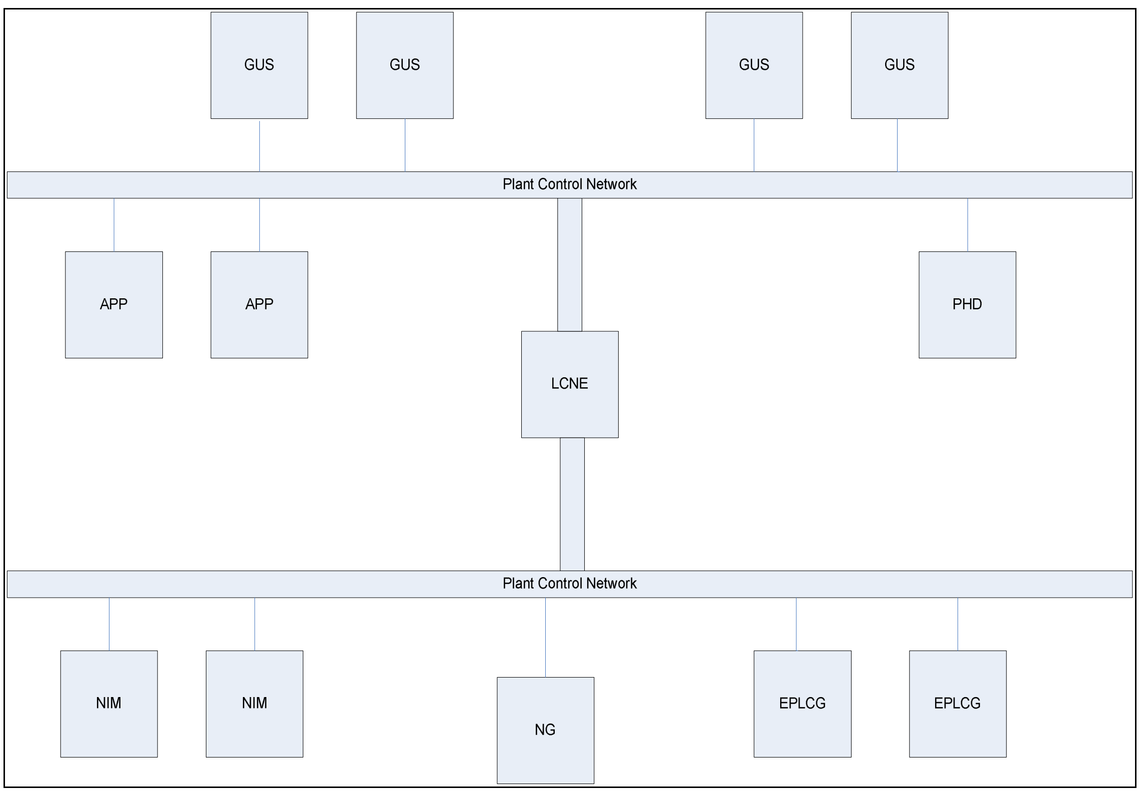

Figure 33: Typical Honeywell Plant Control Network

Figure (31) shows the Plant Control Network with most of the components usually used in a process control plant.

References:

- *TPS System GUS/LCN Implementation*, vol. Partition AC_ME 861 to 868. Phoenix, AZ: Honeywell, 2002.

APPENDIX II

A. Matlab code

The Matlab toolboxes and applications used in this thesis are listed below.

1. "Higher-Order Spectral Analysis Toolbox" United Signals & Systems (US&S), Inc., Version 2.0.3 (R12 compliant) 27 Dec 2000

2. Spectral analysis:[74]

```
function q = specwelch(x,dt,w,nsg,pnv,pc,g,n)
% Period spectrum using Welch's method
%
% USAGE:
%   q = specwelch(x,dt,w,nsg,pnv,pc,g,n)
%   [psdf,f] = specwelch(x,dt,w,nsg,pnv,pc,g,n)
%
% DESCRIPTION:
%   Calculates the period spectrum for x
%   using the simple Welch's method.
%
% INPUT VARIABLES:
%   x - Time series, [vector]
%   dt - Sampling Rate, [scalar]
%   w - Window, one of:
%       'hanning', 'hamming', 'boxcar'
%   nsg - Number of Segments (>=1)
%   pnv - Percentage Noverlap of Segments (0-100)
%   pc - Cut-Off period(s), used for filtering
%   g - Type of filter, 'high', 'low' or 'stop'
%   n - Number of coefficients to use in
%   the Butterworth filter
%
% OUTPUT VARIABLES:
%   q - structure with the following fields:
%       xp - detrended x
%       f = Frequencies
%       T - Periods
%       m - Magnitude
%       a - Amplitude
%       s - Power spectrum, Sxx(w)
%       psd - Power Spectral Density, Pxx(T)
%
%Copy-Left, Alejandro Sanchez-Barba, 2005

if nargin<2
   dt = 1;
end
if nargin<3
   w = 'boxcar';
end
if nargin<4
```

```
    nsg = 6;
end
if nargin<5
    pnv = 50; %Percent
end
if nargin<7 & nargin>5
    g = 'low';
end
if nargin<8 & nargin>5
    n = 5;
end

%******** IMPORTANT *********
pnv = pnv/100;

if nargin==0
    dt = 1/100;
    t=0:dt:250;
    sr = 2*randn(size(t)); %white noise
    s1 = 4*sin(2*pi*t*1);
    s2 = 2*sin(2*pi*t/4);
    s3 = 1*sin(t*2*pi/10);
    s4 = 3*sin(t*2*pi/20);
    s5 = -0.05*t;
    s0 = 5;
    x = s0 + s1 + s2 + s3 + s4 + s5 + sr;
    x(1000:6000) = NaN;
    w = 'hanning';

    specwelch(x,dt,w);
    return
end

isf = isfinite(x);

if nargout==0
    close all
    t = dt*(0:(length(x)-1));
    subplot(4,1,1)
    plot(t,x,'b')
    hold on
    t = t(isf);
end

x = x(isf);
x = x(:);
N = sum(isf);

%Calculate number of Segments
% nsg = (N-nv)./(L-nv); nv = pnv*L;
L = ceil(N/(nsg - nsg*pnv + pnv));
nv = floor(pnv*L); %Check- L*nsg - nv*(nsg-1)

%Butterworth Filter
if exist('pc')
    [b1,b2] = butter(n,1/pc*2*dt,g); %fc/nyquist = fc*2*dt
    x = filtfilt(b1,b2,x);
```

```
    xf = x;
end

if nargout==0
    plot(t,x,'r')
    axis tight
    set(gca,'xlim',[t(1),t(end)])
end

q.xp = x; %save before applying window

ind = 1; %startint index
for j=1:nsg
    switch j
        case 1
            q = spectral(x(ind:ind+L-1),dt,w);
            a = zeros(size(q.a));
            m = a;  s = a;  psdw = a;
            psdf = a;   psd = a;
        case nsg
            q = spectral(x(ind:end),dt,w);
        otherwise
            q = spectral(x(ind:ind+L-1),dt,w);
    end %switch
    psdf = psdf + q.psdf;
    a = a + q.a;
    psd = psd + q.psd;
    ind = ind + L - nv; %new index
end %for

% Average the sum of the periodograms
a = a/nsg;
m = m/nsg;
s = s/nsg;
psdw = psdw/nsg;
psdf = psdf/nsg;
psd = psd/nsg;

f = q.f;
T = 1./f;

if nargout==1
    %Collect variables
    varargout{1}.f = f;
    varargout{1}.T = T;
    varargout{1}.m = m;
    varargout{1}.a = a;
    varargout{1}.s = s;
    varargout{1}.psdw = psdw;
    varargout{1}.psdf = psdf;
    varargout{1}.psd = psd;
end
if nargout==2
    varargout{1} = psdf;
    varargout[74] = f;
end

if nargout==0
```

```
    subplot(4,1,2)
    semilogx(T,a)
    set(gca,'xlim',[T(end),T(1)])
    set(gca,'xticklabel',get(gca,'xtick'))
    xlabel('Period')
    ylabel('Amplitude')

    subplot(4,1,3)
    loglog(f,psdf)
    axis tight
    set(gca,'xticklabel',get(gca,'xtick'))
    xlabel('Period')
    ylabel('PSD(T)')

    %Filter or window
    subplot(4,1,4)
    if exist('pc')
        H = freqz(b1,b2,f*pi*2*dt);
        semilogx(T,abs(H),'b');
        axis tight
        set(gca,'xticklabel',get(gca,'xtick'))
        xlabel('Period')
        ylabel('Filter Response')
    else
        win = eval([w,'(',num2str(N),')']);
        plot(win)
        set(gca,'xticklabel',get(gca,'xtick'))
        xlabel('Period')
        ylabel('window')
        axis tight
    end
end

return
```

3. Indices:

Performance measures:

```
%This function will calculate the performance measures for
%a controller. Depending on the type of control the performance
%measure will differ. Some are for steady state operations,
%set-point change, and disturbance rejection.

function [H_index,N_index,AMP,ITAE,IAE,ISE,os,st,tu,rt,SD]=performance(pv_data,sp_data,time_delay)
pv=detrend(pv_data);
sp=detrend(sp_data);
size=length(pv);

for i=1 :time_delay
    td(i)=0;
end
% Harris Index Calculation
op_mod=armax(pv,[12 12]);
[q,r]=deconv([op_mod.C td],op_mod.A);
```

```
% Minimum Variance
mv=sum(q.^2);

% Data Variance
v=mse(pv);

H_index=mv/v;

% The normalized Index
N_index=1-(v/mv);

io_mod=armax([sp,pv],[12 12 12 time_delay]);

% Amplitude index
s_data=step(io_mod);
s_max=max(s_data);
s_min=min(s_data);
AMP=s_max-s_min;


% ITAE
% Integral of Time multiplied by Absolute Error

time = 0:1:size;
[y,t]=step(io_mod,time);

for i=1:size
   erro(i)=(abs(1-y(i)))*t(i);
end

ITAE = sum(erro);

% IAE
% Integral of Absolute Magnitude of the Error

for i=1:size
   errox(i)=1-y(i);
end

IAE =sum(abs(errox));

% ISE
% Integral of the Square of the Error

for i=1:size
   errov(i)=1-y(i);
end
errov=errov*errov';
ISE =sum(errov);

% MSE
% Mean of the Square of the Error

% for i=1:size
%    erron(i)=1-y(i);
% end
```

```
% error_sq =erron*erron';
%
% MSE=error_sq/max(size(erron));

% This function will find the step response results
[Response,Time] = step(io_mod);
[ResponseMax,IndexMax]=max(Response);
FinalValue = Response(end);
TimeLow = interp1q(Response(1:IndexMax),Time(1:IndexMax),0.1*FinalValue);
TimeHigh = interp1q(Response(1:IndexMax),Time(1:IndexMax),0.9*FinalValue);
% tu the time constant
tu= interp1q(Response(1:IndexMax),Time(1:IndexMax),0.632*FinalValue);
% rt the rise time
rt = TimeHigh - TimeLow;
k = length(Time);
while (k>0)&(0.02>abs((FinalValue - Response(k))/FinalValue));
   k = k - 1;
   end

% st the settling time
st = Time(k);
% os the percent over shoot
os = 100*(max(Response)-FinalValue)/FinalValue;

% Standard Variation Index
er=abs(pv_data-sp_data);
ser=sum(er);
x=ser/(size-1);
SD=((x)/mean(pv_data))*100;

subplot(3,1,1);plot(sp_data)
subplot(3,1,2);plot(step(io_mod))
subplot(3,1,3);plot(impulse(io_mod))
end
```