

Performance Assessment and Root Cause Analysis of Multivariable PID Control Loops

by

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**Performance Assessment and Root Cause Analysis of Multivariable PID
Control Loops**

Koç University

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To my family...

ABSTRACT

Industrial processes are controlled with different types of controllers. Among those, PID controllers are very popular. These controllers manipulate the process inputs to keep the process stable, to reject disturbances and to regulate the process outputs at the desired set-points. PID loops include different digital and mechanical hardware. In general, control engineers at the plants are responsible for the maintenance and performance of these loops. Nevertheless, with the increasing number of the control loops at the plants, diagnosis of each loop becomes tedious.

Control Loop Performance Monitoring (CPM) philosophy aims to solve this problem. Incorporating basic to advanced algorithms, CPM tries to deliver the most accurate assessment of control loops discovering the underlying causes for performance degradation. While doing that, CPM also does not manipulate the processes, instead it analyzes the already generated data. These analyses can be listed as performance assessment, oscillation detection, non-linearity detection, stiction detection and quantification, controller tuning assessment and root cause analysis.

In this study, each component building the CPM philosophy is examined. The methods for each analysis component are selected based on industrial popularity. The methods are described and their strengths and weaknesses are discussed extensively. The analysis starts with the assessment of control loop performances in terms of both stochastic and deterministic techniques. Then, a common problem, oscillation, is explained and the possible methods to detect oscillations in control loops are discussed. After that, non-linearities which are the reasons behind the oscillations are discussed. Then, stiction problem which is the most frequent cause of non-linearities in control valves is described. Later, multivariable PID controllers are assessed to detect the root causes. Finally, the examined methods are connected in a single algorithm

aiming to detect the root cause of performance degradation. The examined methods and the overall algorithm were tested in a plant of TÜPRAŞ İzmit Refinery. The advantages and disadvantages of the methods examined are explained.

The analysis showed that 47% of the loops have acceptable performance. The reasons of performance degradation were found out as oscillations, stiction and tuning problem. Finally, the root cause analysis shows that oscillations propagate and affect the other loops. 4 possible candidates for plant-wide disturbance are detected in the plant.

ÖZETÇE

Endüstriyel prosesler farklı tiplerdeki kontrolörler ile kontrol edilmektedir. Bunlar arasında, PID kontrolörler en yaygın olanlarıdır. Bu kontrolörler, prosesleri istikrarlı tutmak, bozucu etmenleri bertaraf etmek ve proses çıktılarının istenilen değere gelmesini sağlamak amacıyla proses girdilerini değiştirmektedirler. PID döngüler, dijital ve mekanik donanımlar içermektedir. Genellikle, fabrikalardaki kontrol mühendisleri bu döngülerin bakımından ve performansından sorumludur. Ancak, fabrikalarda artan kontrol döngüsü sayısı ile birlikte, döngülerin tek tek teşhis edilmesi meşakkatli bir hal almaktadır.

Kontrol Döngüsü Performans Takibi (CPM) felsefesi bu problemi çözmeyi amaçlar. Bünyesinde basitten gelişmiş algoritmaları barındırarak CPM, performans kaybının ardındaki nedenleri ortaya çıkartan en doğru performans değerlendirmesini yapmaya çalışır. Bunu yaparken CPM prosesi değiştirmez, aksine daha önce yaratılmış verileri analiz eder. Bu analizler; performans değerlendirme, salınım tespiti, doğrusalsızlık tespiti, vana aşınım tespiti ve ölçümü, kontrolör ayarlama değerlendirmesi ve kök neden analizi olarak sıralanabilir.

Bu çalışmada, CPM felsefesini oluşturan her bileşen incelenmektedir. Analiz bileşenlerini oluşturan metotlar, endüstriyel rağbetlerine göre seçilmiştir. Metotlar açıklanmış, zayıf ve güçlü yanları geniş ölçüde tartışılmıştır. Analiz, kontrol döngülerinin hem stokastik hem deterministik değerlendirmesi ile başlamaktadır. Daha sonra, yaygın bir problem olan salınım açıklanmış, salınımların tespit edilmesi için kullanılan muhtemel metotlar tartışılmıştır. Ardından, salınımların arkasındaki nedenlerden olan doğrusalsızlıklar tartışılmıştır. Daha sonra, kontrol vanalarındaki en yaygın doğrusalsızlık nedeni olan vana aşınım problemi ele alınmıştır. Ardından, çok değişkenli PID kontrolörler kök nedenlerin tespiti amacıyla değerlendirilmiştir. Son

olarak, incelenen metotlar, performans kaybına neden olan kök nedenlerin bulunması amacıyla tek bir algorithmada bağlanmıştır. İncelenen metotlar ve tüm algoritma TÜPRAŞ İzmit Rafinerisi'ndeki bir fabrikada test edilmiştir. Metotların avantajları ve dezavantajları açıklanmıştır.

Analizler, döngülerin % 47'sinin kabul edilebilir performansa sahip olduğunu göstermiştir. Kötü performansın nedenleri, salınımlar, vana aşınımı ve kontrolör ayarı olarak tespit edilmiştir. Çalışma sonunda kök neden analizi, salınımların yayıldığını ve diğer döngüleri de etkilediğini göstermektedir. Fabrikada, 4 adet olası fabrika geneli bozucu etmen adayı tespit edilmiştir.

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NOMENCLATURE

Abbreviations

<i>A/D</i>	Analog to Digital Converter
<i>ACF</i>	Auto-correlation Function
<i>AR</i>	Auto-Regressive
<i>AR – LS</i>	AR Model Least-Square Approach
<i>CE</i>	Control Error
<i>CPI</i>	Controller Performance Index
<i>CPM</i>	Control Loop Performance Monitoring
<i>D/A</i>	Digital to Analog Converter
<i>DCS</i>	Distributed Control System
<i>DFA</i>	Detrended Fluctuation Analysis
<i>DFT</i>	Discrete Fourier Transform
<i>DR</i>	Decay Ratio in SP response
<i>FCOR</i>	Filtering and Correlation Analysis
<i>FFT</i>	Fast Fourier Transform
<i>I/O</i>	Input-Output
<i>IAE</i>	Integral Absolute Error
<i>IFFT</i>	Inverse Fast Fourier Transform
<i>IRAI</i>	Impulse-Response Area Index
<i>IT</i>	Inner Triangle of the Principal Domain
<i>KPI</i>	Key Performance Indicator
<i>LTi</i>	Linear Time-Invariant

<i>MA</i>	Moving Average
<i>MIMO</i>	Multiple-Input Multiple-Output
<i>MPC</i>	Model Predictive Control
<i>MV</i>	Manipulated Variable (Actual valve position)
<i>MVC</i>	Minimum Variance Control
<i>NGI</i>	Non-Gaussianity Index
<i>NLI</i>	Non-linearity Index
<i>NPI</i>	Non-predictability Index
<i>OCI</i>	Oscillation Contribution Index
<i>OLE</i>	Object Linking and Embedding
<i>OP</i>	Controller Output
<i>OPC</i>	OLE for Process Control
<i>OS</i>	Overshoot
<i>OT</i>	Outer Triangle of the Principal Domain
<i>PDF</i>	Probability Density Function
<i>PEM</i>	Prediction Error Minimization
<i>PFD</i>	Process Flow Diagram
<i>PID</i>	Proportional-Derivative-Integral
<i>PO</i>	Period of Oscillation in SP response
<i>PSD</i>	Power Spectral Density
<i>PV</i>	Process Variable
<i>QR</i>	QR Decomposition
<i>RT</i>	Rise Time
<i>RTO</i>	Real Time Optimization
<i>SID</i>	Subspace Identification
<i>SISO</i>	Single-Input Single-Output

SNR	Signal-to-noise Ratio
SP	Set-point
ST	Settling Time
SVD	Singular Value Decomposition

Greek Letters

α_i	AR model coefficient at lag i
β	Optimum scaling vector
η	Low-pass filter constant
κ	Correction factor in bicoherence estimation
$\lambda(\omega)$	Largest portion of signal at frequency ω
μ_e	Mean of control error
ω	Frequency
ρ_k	Auto-correlation coefficient at lag k
$\rho_{y,\varepsilon}$	Cross-correlation coefficient between process output and disturbance
σ	Standard deviation
$\sigma_{\hat{bic}^2}$	Standard deviation of squared bicoherence
σ_{CE}	Standard deviation of control error
σ_{OP}	Standard deviation of controller output
σ_{resid}	Variance of residuals
$\varepsilon(t)$	Zero-mean white noise

Roman Notations

$\# \{.\}$	Counting operator
$\bar{T}_p$	Mean period of oscillation
$\hat{bic}^2$	Estimate of squared bicoherence
$\overline{\hat{bic}^2}$	Mean of squared bicoherence
$\overline{MSE}_{sin}$	Average MSE for all sinusoidal sections

$\overline{MSE}_{tri}$	Average MSE for all triangular sections
a	First distance in decay ratio method
A_i	Positive areas in Forsman-Stattin method
A_{sin}	Amplitude of sinusoid
a_{tri}	Triangular parameter
$AmpFactor$	Amplification factor
b	Second distance in decay ratio method
B_i	Negative areas in Forsman-Stattin method
b_{tri}	Triangular parameter
c_{cL}^z	Critical values of χ^2 at cL
cL	Confidence level
dof	Degree of freedom
$e(t), e_t$	Control error in terms of time(t)
$E\{.\}$	Expectation operator
$e_f(t)$	Filtered error at time t
f_s	Sampling frequency
G_ε	Disturbance transfer function
G_p	Process transfer function
h	Forsman-Stattin index
h_A	Number of the positive areas in Forsman-Stattin method
h_B	Number of the negative areas in Forsman-Stattin method
h_j	MA filter coefficient for PSD smoothing
K	Number of segments in bicoherence estimation
k	Dead time
K_d	Derivative action
K_i	Integral action

K_p	Proportional action
$kurt_{CE}$	Kurtosis of control error
L	Number of the frequency pairs in the principal domain
L_{maj}	Length of major axis of ellipse
L_{min}	Length of minor axis of ellipse
M	Segment length in bicoherence estimation
m	AR model order
$ManTime$	Time range in which controller in manual
$MSE(,)$	Mean-squared error operator
MSE_{sin}	Mean squared error for sinusoidal fitting
MSE_{tri}	Mean squared error for triangular fitting
N	Number of elements
n	Data length
n_A	Order of polynomial A of ARMAX model
n_B	Order of polynomial B of ARMAX model
n_C	Order of polynomial C of ARMAX model
N_{zc}	Number of zero-crossings
$ncyc_{sin}$	Number of sinusoidal cycles
$OCI_i(\omega)$	Oscillation contribution index for variable i at frequency ω
OP_{fs}	Filtered and cropped OP
P_X	PSD matrix for X matrix
PV_{fs}	Filtered and cropped PV
q^{-k}	Backward shift operator
R	Decay ratio
$r(t)$	Set-point
R_{devn}	Standard deviation ratio

reg	Regularity
$S_{j,sin}$	Sinusoidal signal
$S_{j,tri}$	Triangular signal
$SatTime$	Time range in which output in saturation
SI_{cf}	Stiction index obtained by curve-fitting analysis
$skew_{CE}$	Skewness of control error
$sup\{.\}$	Supremum operator
$TestStat_i(\omega)$	χ^2 test statistic for variable i at frequency ω
Tp_n	Estimated single period
Ts	Sampling interval
$u(t)$	Controller output / Process input
V_X	Covariance matrix for X matrix
$valve_{rev}$	Valve reversal
$valve_{trav}$	Valve travel
$X(f_1)$	DFT of time series signal at frequency f_1
X^*	Conjugate of X
X_ω	Fourier transform at frequency ω

Chapter 1

INTRODUCTION

The increasing importance of safety, energy efficiency, resource utilization and profitability has led to increase significance of process control recently [Seborg et al., 2010]. Moreover, the expanding complexity of industrial processes combined with several requirements such as better quality and greater flexibility has further reinforced that significance [Rao, 1993]. Today, process control can be considered as an integration tool which connects the systems of real-time information management and regulatory functions [Romagnoli and Palazoglu, 2005]. These systems cover many sub-systems such as engineering stations, control cabinets, control boards, data historians, OPCs, PIDs, transmitters, actuators, valves and so on. All these systems come together to control the processes automatically with respect to some desired operating conditions represented by process variable (PV) and set-point (SP). These set-points may come from different sources. Some of them may be intelligent sources (e.g. RTO) or some economical optimization systems (e.g. plant planning) or directly humans (e.g. operators). Having these, process control systems can also be considered as a translation tool to convert the economical expectations to the plant operations. The needs and the effects of process control systems to economical expectations have been discussed extensively in [Ordys et al., 2006] and [Romagnoli and Palazoglu, 2005].

With the advances in computer sciences and electronics, the aim of process control systems has evolved to full automatic systems with as little user intervention as possible. Although in the past, the objective was to control only the operational parameters, today advanced optimization and control systems have been developed to control the processes in the most economic and safest way. Among those, the

model predictive controllers (MPCs) and the real time optimizers (RTOs) are the most popular ones. Figure 1.1 shows the state-of-art process control systems hierarchy. Processes to be controlled are at the bottom of the hierarchy. The system

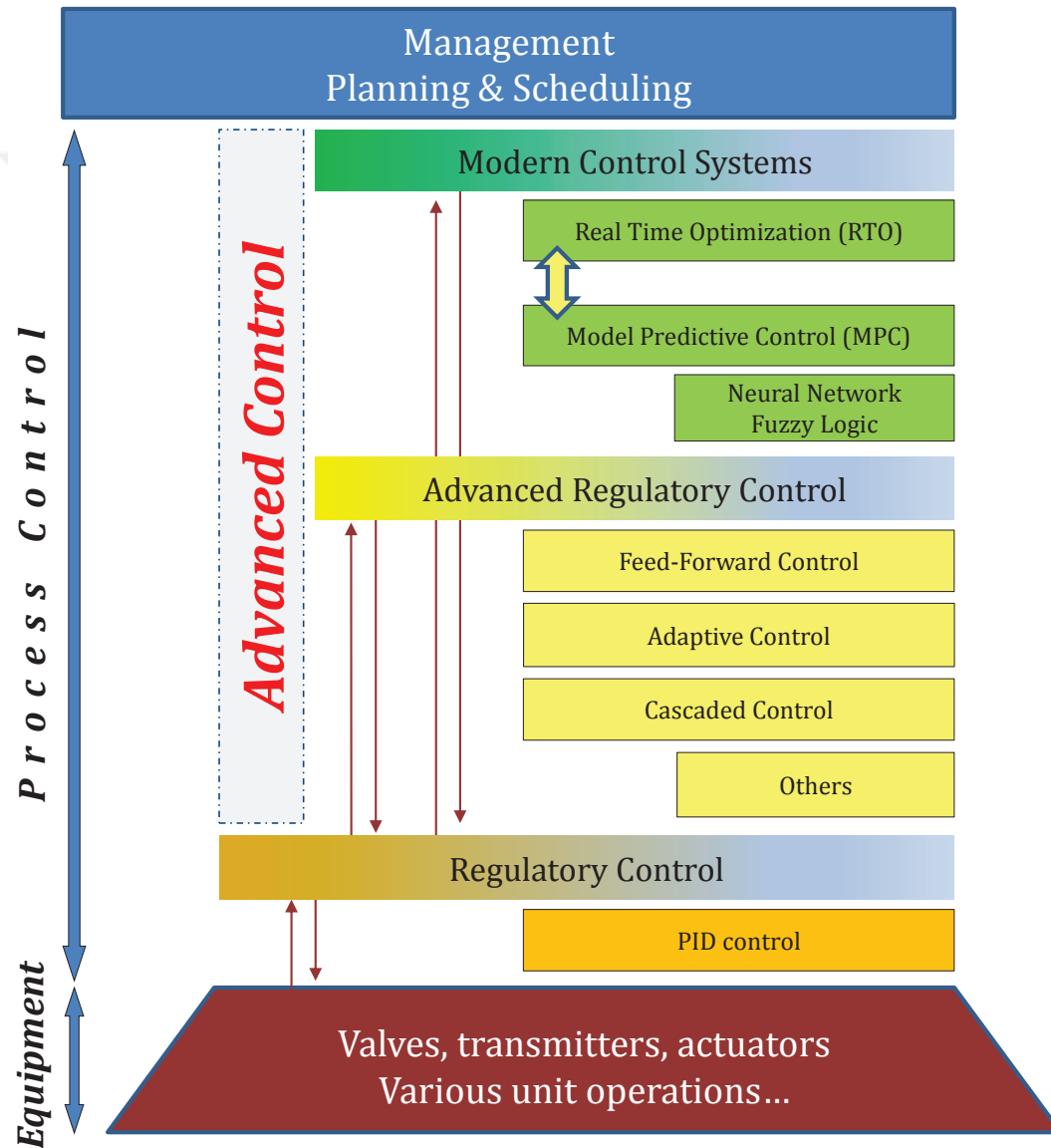


Figure 1.1: State-of-Art Control Hierarchy

directly in touch with the process is the first level of control named "*regulatory control*" which describes the regulation of essential process variables such as levels, flows, pressures and temperatures, whereas the next level up in the hierarchy "*advanced*

regulatory control” tries to minimize the constraints introduced by regulatory control such as non-linearities and large dead times [Wade, 2004]. On the upper level, *modern control systems*” are placed to optimize the processes with the ability of handling MIMO systems and the non-linear systems [Love, 2007]. Finally, on the top, there is the management division associated with the planning and scheduling activities.

The efficient operation of the hierarchy requires that the communication between the regulatory control and the process remains healthy. Furthermore, any problem with the regulatory control causes a decrease in the benefits of both the advanced regulatory control and the modern control systems. This fact puts a great constraint on the operability of the processes. As a result, an assessment methodology to analyze the performance of control systems is required.

Therefore, this thesis addresses the methods to assess the control loop performance and diagnose the poorly performing control loops in order to find the root causes for PID type of controllers. Additionally, plant-wide root cause analysis is also discussed. Chapter 1 is organized as follows. In 1.1, a brief introduction is given for control loops. In 1.2, frequent problems faced in the control loops are discussed and finally in 1.3, the needs of control loop performance monitoring (CPM) tools are discussed.

1.1 Control Loops

The control loops are used to keep the process variables at the desired conditions. For that purpose, each loop has different elements such as a controller, a control element, a process and a sensor. The controller tries to reduce control error (CE) which is calculated by taking the difference of the set-point (SP) and the measured process variable (PV). In order to do that, the controller sends the output signal (OP) to the control element. The control element moves and acts on the process with the manipulated variable (MV). The procedure is given in Figure 1.2.

For regulatory control purposes, PID type controllers are the most popular ones (approximately 95% of the industrial controllers) because of their simplicity, the ability to overcome offsets in steady-state conditions and the anticipation of the future

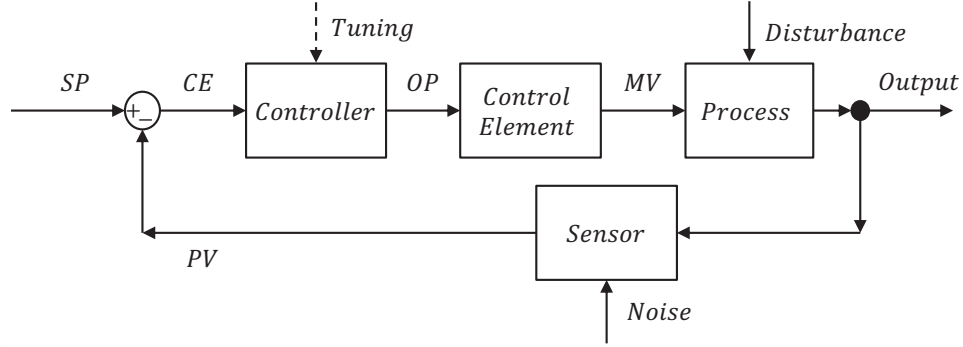


Figure 1.2: General Feedback Closed Loop Control System

behavior of the process [Åström and Hägglund, 1995]. In addition, they can be tuned according to needs by adjusting the parameters of proportional, integral and derivative. These features enhance the effectiveness of PID controllers in process control requirements [Visioli, 2006]. The controller output (OP) is calculated in PID controllers such that:

$$OP(t) = \left(K_p \times CE(t) \right) + \left(K_i \int_0^t CE(\tau) d\tau \right) + \left(K_d \times \frac{dCE(t)}{dt} \right) \quad (1.1)$$

In Figure 1.2, the input "Tuning" to the controller represents the parameters in Equation 1.1. Here, K_p represents proportional, K_i represents integral and K_d represents derivative actions. Via adjusting these parameters, one can adjust the behavior of the controller.

The sensor block in Figure 1.2 represents the measuring element. This can be a thermocouple to measure temperature or an orifice-type flow meter to measure flow-rate or any other measuring devices. These devices are under noise effect, which creates deviations on the measurement. In addition, the process experiences some disturbances. These might be measured or unmeasured disturbances. For example, a leakage on a pipe creates an unmeasured disturbance for the flow-rate. On the other hand, if a stream coming into a tank is measured but not controlled, the flow-rate of the stream is said to be a measured disturbance for the tank level.

1.2 Performance Issues in Control Loops

Figure 1.2 shows that a control loop consists of different elements. In addition, all these elements have different sub-parts. For example, the sensor block is composed of a physical measurement element and an A/D converter. Similarly, the control element block (mostly a control valve) is composed of an actuator, a spring and a diaphragm. Having that complexity, detection of a problem arising in a single sub-part can be tedious. Furthermore, in case of too many controllers in a single plant, diagnosing each loop one by one is not sustainable [Jelali, 2013].

In general, the process-control engineers are the responsible people for the control tasks in plants [Liptak and Eren, 2011]. They try to keep the controllers stable and healthy with maintenance activities. These activities cover basic monitoring, corrective maintenance and planned maintenance. The effects of maintenance on the control loop performance are given in Figure 1.3 [Morrison, 2001].

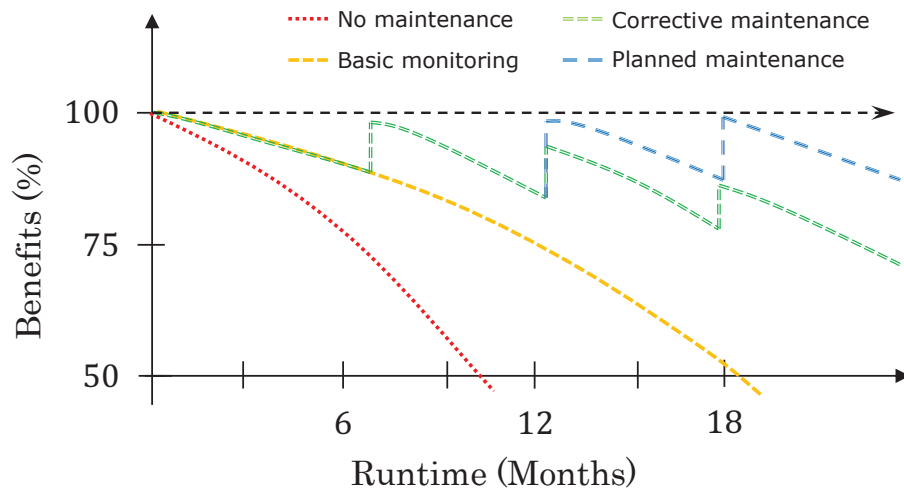


Figure 1.3: Effects of Maintenance Activities on Control Loop Performance

Figure 1.3 states that after the commissioning, the performance of controllers degrades over time. Even in the most optimistic case for the planned maintenance, poor performing controllers are let to work for months. The reasons for performance degradation are summarized as [Jelali, 2013]:

- Raw material (feed) changes
- Operating point/range changes
- Decreasing lifetime of plant equipment
- Process modifications, equipment upgrades
- Hardware or software failures
- Delays and constraints
- Non-linear process dynamics

Having these reasons, several surveys have been conducted to analyze the industrial controllers. Paulonis and Cox [2003] conducted a survey and analyzed 14000 PID controllers in 40 plants at 9 sites worldwide, all belonging to the Eastman Chemical Company. Among 9000 controllers having performance history, the researchers detected that 41% of the loops were below good performance. Another interesting survey covering different sectors has been done by Torres et al. [2006]. They audited on 700 control loops belonging to 12 different companies (petrochemical, pulp and paper, cement, chemical, steel and mining). For a period of almost 1 year, they found that 41% of the loops had oscillations due to tuning problems, coupling, disturbances and actuator problems. In addition, 24% of the loops had saturation problems. Desborough and Miller [2001] also showed that the control loop performance has not been as good as expected. They stated that only 32% of the globally audited 26000 PID control loops have excellent and acceptable performance.

Summarizing the results from the surveys suggests that, the typical problems in control loops are the following [Blevins, 2012]:

- Inappropriate controller tuning
- Inappropriate control structure design
- Control valve problems (corrosion, wear, stiction etc.)
- Process dynamics
- Sensor faults (connection and calibration problems, deposit formation)
- Changing process gains
- Interactions between loops

These problems have several fingerprints in the process data. Oscillations are the most eye-catching ones. Controller tuning problems, valve stictions, external disturbances and transmitter faults mostly show up as oscillations in the signals. Therefore, oscillation detection is one of the main analyses in CPM applications. After detecting the oscillation, further analyses are done to check non-linearities in loops. Control valve problems are the most frequent ones. The stiction in control valves produces limit cycles and can be detected by non-linearity analysis. If a significant non-linearity is detected, stiction is questioned with appropriate techniques. Those are discussed in 1.3 and extensively given in Chapter 3.

1.3 Control Loop Performance Monitoring Philosophy

Figure 1.3 shows that there are planned maintenance activities in plants to overcome the problems presented in 1.2. However, due to high number of control loops in plants and low resources (especially the process control engineers), planned maintenance activities have long periods. In addition, in these activities, usually all control loops in the plant are inspected without knowing whether they are poor or not. Different from the planned maintenance, the control engineers also try to correct the problems when the plant operators inform them. Even sometimes, poor performance is accepted by the plant operators [Jelali, 2013]. As a result, in most of the cases, the economic benefits are lost. Figure 1.4 represents the economic relation with the control systems. In addition, the objectives change according to the hierarchical levels. From the control engineers' point of view, the ability to hold the set-points and the adherence to control constraints are the main goals, whereas the process engineers mostly focus on stable operation within the limits. From the business side, all these aims are translated into the safety, quality, productivity, reliability and especially costs [Liptak and Eren, 2011]. Figure 1.4 shows that having efficient and healthy control systems forms the basis of all objectives. Therefore, continuous monitoring of the control systems is an essential requirement to satisfy these objectives.

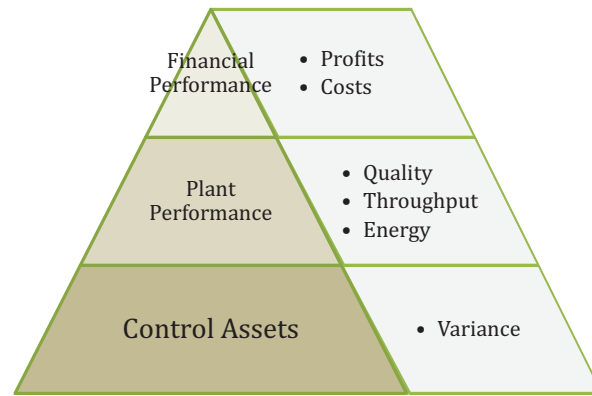


Figure 1.4: Relation of Control Assets to Economic Benefits

CPM covers the databases and both basic and advanced tools which are used to assess the performance of the control loops, keep track of their performance and analyze the loops further [Liptak and Eren, 2011]. The expected requirements from CPM tools were discussed by Hugo [2001]. In that sense, the analyses should be non-invasive. The tool should connect to either plant historian or OPC servers to gather and analyze the loop data and give some advices. In addition, it should be as automatic as possible. The users should not need to give too many inputs. Finally, the tool should give a detailed cause analysis ending with a suggestion or at least an indication of reason for poor performing loops. The possible benefits of such a tool have been discussed by Paulonis and Cox [2003]. They include the following but are not limited to:

- Ranked controllers with respect to their performances
- Instantly accessible information on wealth of controllers
- Continuous monitoring of control assets
- Automatic detection of loop problems
- Automatic notifications
- Comparison of control performance at different plants/sites

Having these capabilities, all the control assets can be monitored from a single screen

and sorted according to their performance rankings. As a result, the control engineers can pin point the problems within hundreds or even thousands of loops and investigate them before the problem propagates. In addition, the control engineers and maintenance engineers can plan periodic maintenances easily.

Figure 1.5 gives the fundamental elements of a CPM tool [Liptak and Eren, 2011].

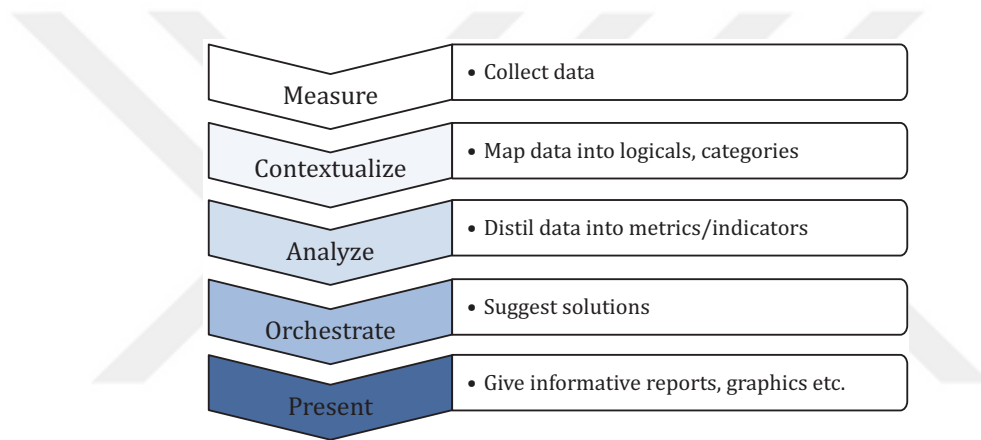


Figure 1.5: Fundamental Elements of a CPM tool

To elaborate, Jelali [2013] proposed the following stages for efficient CPM tools:

- **Assessment of performance:** Performances of all controllers are determined with a pre-defined benchmark point. Possible benchmarks are discussed and a popular benchmark MVC is given in details in Chapter 2.
- **Detection of poor performing loops:** Performances are ranked and poor performing loops are identified. Ranking can be based on benchmark indices, benchmark driven modified indices or user-defined indices.
- **Diagnostics for root causes:** Further analyses are done to unfold the root causes. Those include oscillation analysis, nonlinearity analysis and stiction analysis. Details are discussed in Chapters 3 and 4.
- **Improvement of performance/fixing problems:** Suggestions to improve performance are given. The plant personnel take the action.

Taking the algorithms proposed by Ordys et al. [2006] and Jelali [2013] as a basis, a modified complete algorithm is given in Figure 1.6.

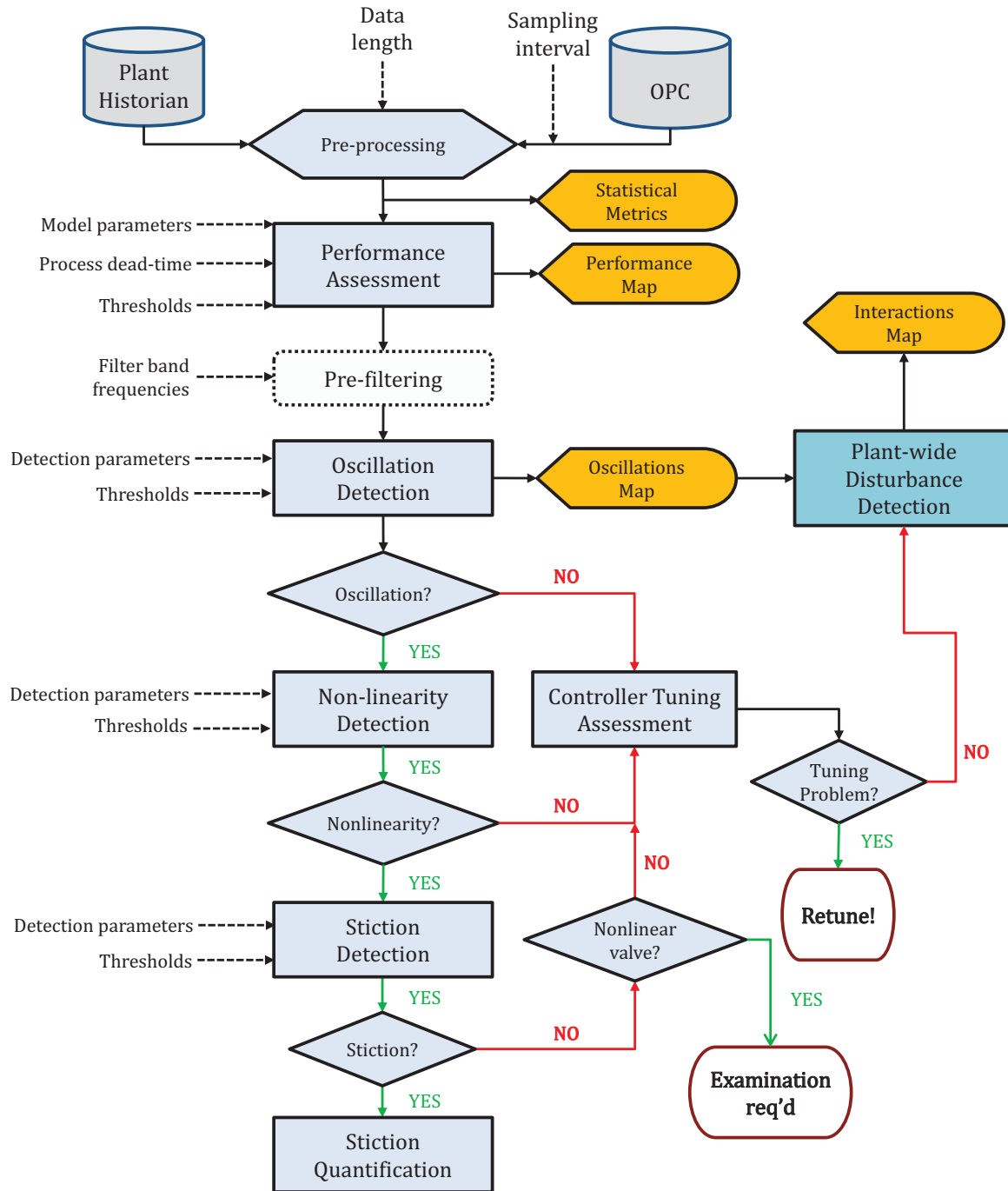


Figure 1.6: Overall Algorithm of CPM tool

Chapter 2

PERFORMANCE ASSESSMENT

2.1 Introduction

Industrial controllers often present operational problems. Poor performance combined with increasing number of control loops result in deteriorating product quality, safety problems and loss of profitability [Hoo et al., 2003]. Frequently, these problems cannot be easily corrected by the plant operators [Harris et al., 1999]. Therefore, researchers have tried to develop techniques to assess the performance of control systems. One of the leading studies defining minimum variance control (MVC) is done by Åström [1970]. Later, DeVries and Wu [1978] have discussed control performance assessment further. Afterwards, Harris [1989] showed that it is possible to determine performance of controllers with closed-loop data, with respect to the MVC benchmark. Later on, Shinskey [1990], Ender [1993] and Bialkowski [1993] brought the ideas into industrial applications. Kozub [1997] discussed the required features for online assessment algorithms. Later in the beginning of 2000s, several surveys were presented as discussed in 1.2. Performance assessment now forms the basis of complete performance monitoring tools. Efficient and realistic assessment of the controllers enables the control engineers and the plant personnel to assess how healthy the control system is.

In order to assess the performance of control systems, the main approach is to compare the current performance with a standard. To that end, selection of a benchmark point is an important step. Hugo [2001] summarizes the possible standards in increasing order with respect to their variances on process output:

- ***Perfect control:*** This benchmark requires zero variance on the output. In practice, it is hard to achieve since, due to disturbances and set-point changes, there is always a variance on the output.

- **Best possible non-linear control:** It is the theoretical controller which gives a lower bound on reducing variance than a linear controller. However, due to its complexity and difficulty in design, it is not used widely.
- **Minimum variance control:** MVC is a control scheme which declares to give minimum possible variance on the output. To that end, it tries to vanish CE completely by predicting the effects of disturbance. MVC is not used as a control strategy since, while trying to reduce the variance on the output, it introduces too much control effort, which may result in wear of control elements. However, its simplicity in calculation using closed-loop data with reasonable amount of user inputs makes it a widely accepted benchmark. Details are discussed in 2.3.
- **Best possible MPC control:** This benchmark compares the current performance with the best MPC controller design. Best possible MPC controller is obtained with a simplified step-disturbance model. It is more realistic since the theoretical response is not as tight as MVC.
- **Best possible PID control:** Most of the controllers in process industry are PID controllers. However, comparing to MPC controllers, they do not handle dead time compensation and constraints conveniently as in MPC.
- **Open loop control:** That benchmark is mostly used to determine the requirement of any control system. It enables to analyze the process economically, considering the costs for control systems and the cost of output variance.

Evaluation of controller performance can be basically divided into two categories as *stochastic* and *deterministic*. Stochastic evaluation mostly deals with the reduction of variance due to disturbances (introduced by noise effect), whereas deterministic evaluation tries to rate the responses in the presence of step changes in SP or PV, and parameters like settling time, rise time, overshoot and decay ratio.

Chapter 2 is organized as follows. First, in 2.2, simple statistical metrics and their relevance to control systems are discussed. Then, in 2.3, a stochastic assessment benchmark, MVC, is discussed extensively. In 2.4, autocorrelation test for performance assessment is given and in 2.5 deterministic assessment metrics are given.

2.2 Basic Statistical Analysis

Before going into the details of stochastic and deterministic performance assessment, it is beneficial to discuss some useful statistical metrics which are used to evaluate the performance of controllers. The reason of naming them as "*basic*" is their computational simplicity and reasonable user input requirements. Individually, they are not that much informative about the complex problems [Horch and Heiber, 2004]; on the other hand, they provide supportive information to other indices. However, calculating a single score of measure is usually not enough to interpret the problems in the loops. Rather, it is suggested monitoring their trends over time [Holstein, 2004]. Some useful statistical performance metrics are listed below:

- **Mean of control error (μ_e):**

Usually, it is expected to have zero mean for the control error. However, in practice, this is not possible due to either random or systematic variations. Too much deviation or offset from zero of that measure indicates loop problems.

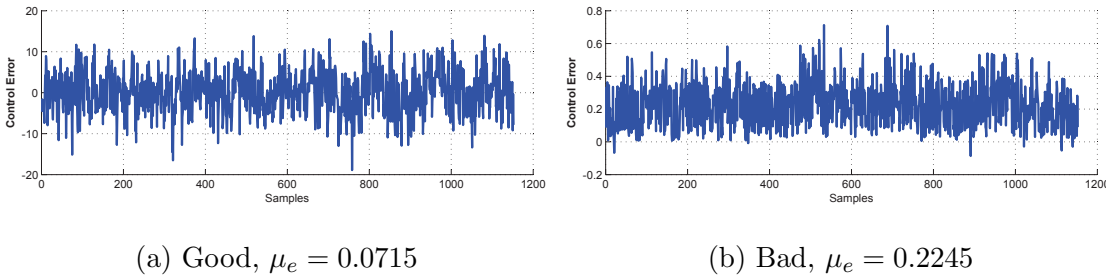


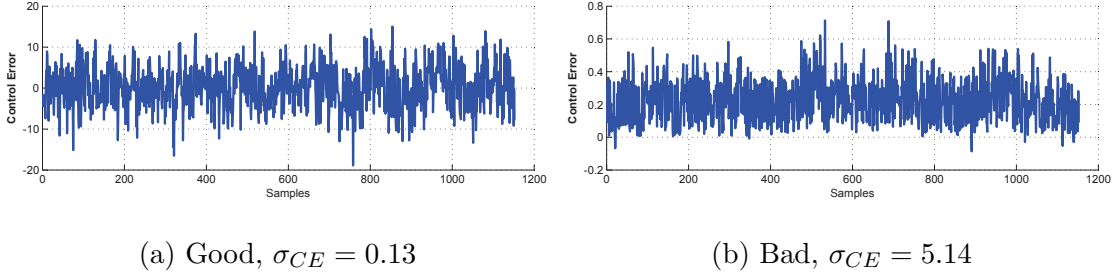
Figure 2.1: Examples for μ_e

- **Standard deviation of control error (σ_{CE}):**

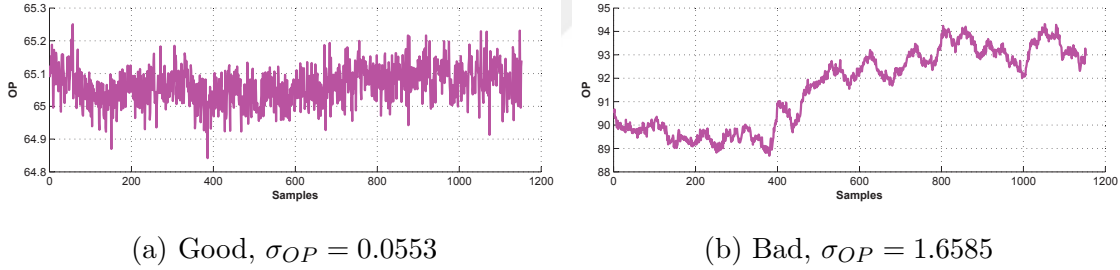
It is also an easy-to-measure metric to check the control loop anomalies. Like mean of control error, too much variation in standard deviation indicates poor control performance.

- **Standard deviation of controller output (σ_{OP}):**

Monitoring the behavior of control output is also an important measure, since

Figure 2.2: Examples for σ_{CE}

it indirectly indicates the actuator actions to control the system. Increasing standard deviation might indicate stiction or some other non-linearities in the control system.

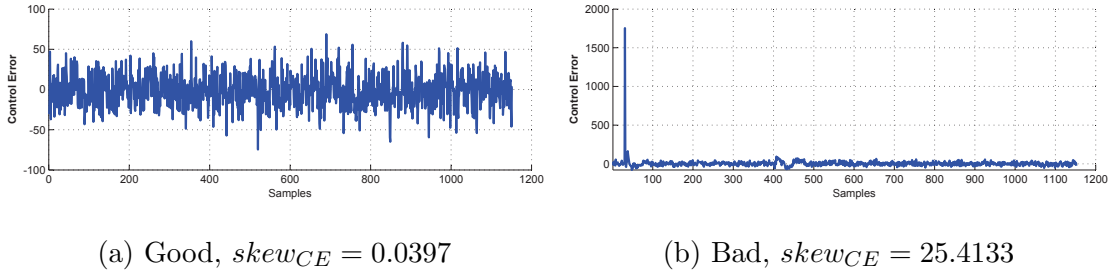
Figure 2.3: Examples for σ_{OP}

- **Skewness of control error ($skew_{CE}$):**

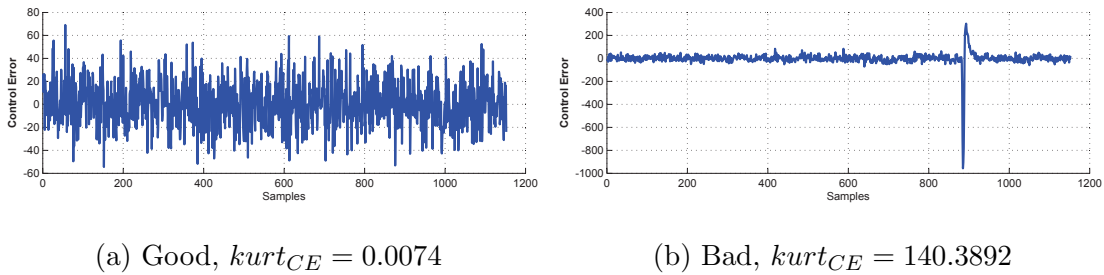
Skewness is a basic statistical measure of symmetry for histogram. For a uniform symmetric distribution, skewness is zero. For histograms skewed towards left, the metric gets positive values; whereas for histograms skewed towards right, the metric gets negative values. For well performing loops, one must expect almost zero skewness. Too much variation or too high values indicate either non-linearities (e.g. stiction) or drastic operator intervention [Gordon, 2006].

- **Kurtosis of control error ($kurt_{CE}$):**

Kurtosis, by definition, is the measure of the peakedness of the histogram [Awasthi, 2013]. There are different formulas to calculate kurtosis, but it is

Figure 2.4: Examples for $skew_{CE}$

better to use the difference from the normal distribution formula [Joreskog, 1999]. Normal distributions have a kurtosis value of 3. In order to see how the data is distributed compared to the normal one, the normal kurtosis value of 3 is subtracted from the calculated one. Excess kurtosis calculated in this fashion can indicate different types of problems. For example, sharper the peak of the distribution means higher the kurtosis value. Thus, higher values might indicate tight tuning or sensor faults (connection loss, deposit formation on the sensor etc.) [Gordon, 2006].

Figure 2.5: Examples for $kurt_{CE}$

- **Standard deviation ratio (R_{devn}):**

Another simple but informative statistical measure is the standard deviation ratio ($R_{devn} = \sigma_{CE}/\sigma_{OP}$) [Horch and Heiber, 2004]. This ratio simply implies how much of the control error variation is due to the deviation of control output. Similar to other indices, single values are not much informative; rather

it is suggested monitoring the trend. In addition, one can also normalize the standard deviation values with their loop ranges before calculating the ratio. It enables to compare different types of loops. Normalized values closer to one usually indicate good control. Decreasing values might indicate control valve stiction problem or sensor faults [Horch and Heiber, 2004].

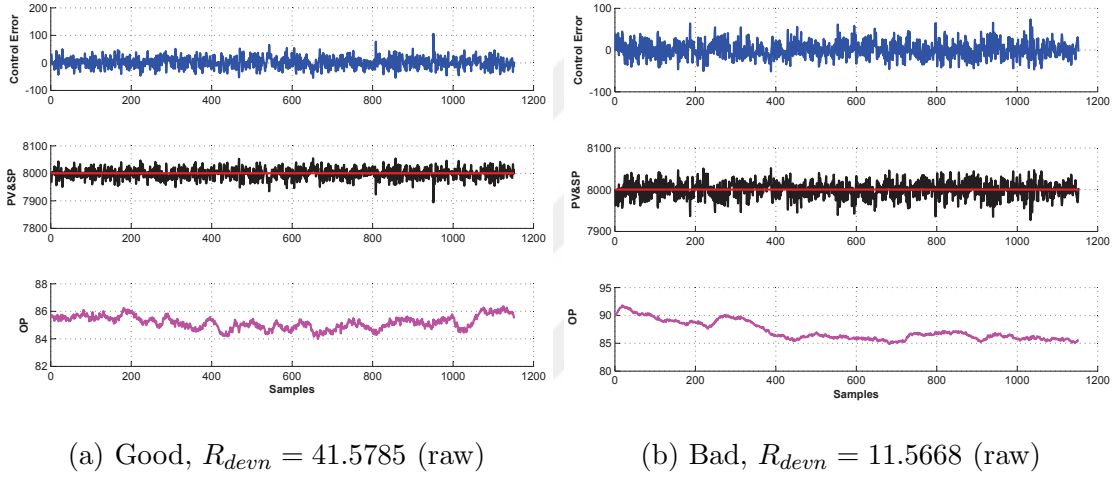


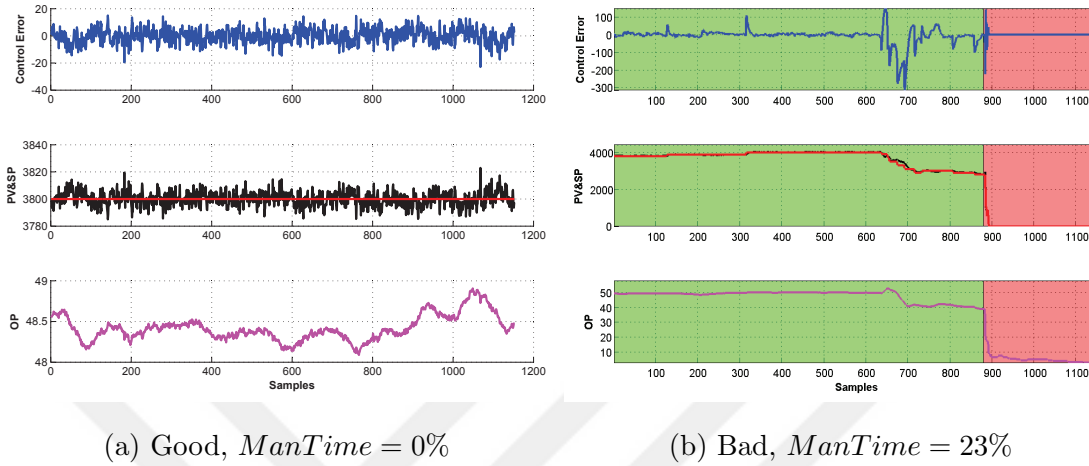
Figure 2.6: Examples for R_{devn}

- **Percent manual time (*ManTime*):**

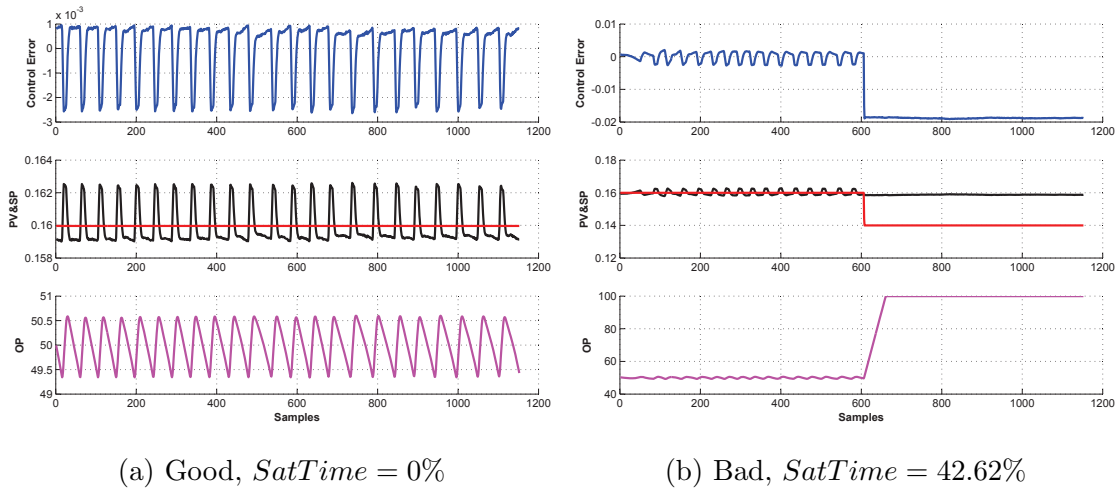
Even in a simple control system, all the controllers are expected to be in automatic mode. However, due to some problems, operators at the plant have a tendency to put the problematic controllers in manual mode. In order to see the controller service time, percent manual time is an important metric to monitor.

- **Percent saturation time (*SatTime*):**

Saturation is a frequent valve problem in control loops. It is a result of either inappropriate control valve sizing or infeasible control system structure. In case of saturation, the controller tries to open or close the valve but the valve is stuck at the limits. In modern DCS systems, generally those limits are set to 0 and 100 which are the physical limits as well. However, for some of the control

Figure 2.7: Examples for $ManTime$

loops at plants, the valve limits might be adjusted to different values for safety reasons. An example of such loop might be a reactor feed flow control loop since the space velocity puts a lower limit for reactors. In that case, the lower limit can be adjusted to higher values.

Figure 2.8: Examples for $SatTime$

- **Amplification factor ($AmpFactor$):**

Another simple but informative statistic is the amplification factor. It is sug-

gested using only for level and pressure loops [Longhi et al., 2012] due to their integrating nature; however, it might also be useful for other types of loops. This factor is basically calculated by taking the ratio of summation of controller output and IAE of control error ($AmpFactor = (\sum OP)/IAE$). For better representation, IAE can be converted in terms of percentage; so that, the obtained factor become bounded between zero and one. Decreasing values (or values greater than one for normalized version) indicate that loop has difficulty in disturbance rejection, whereas increasing values (or values less than one for normalized version) indicate vice versa [Longhi et al., 2012].

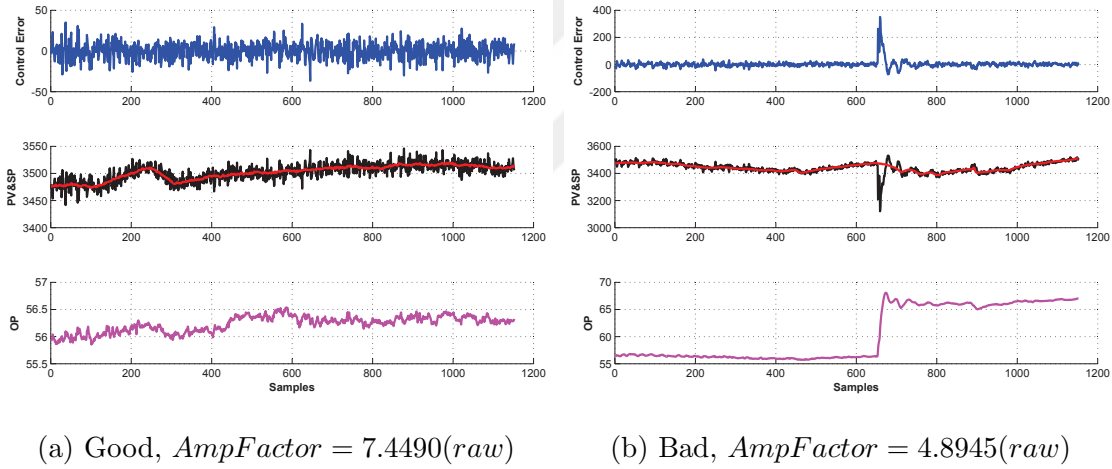


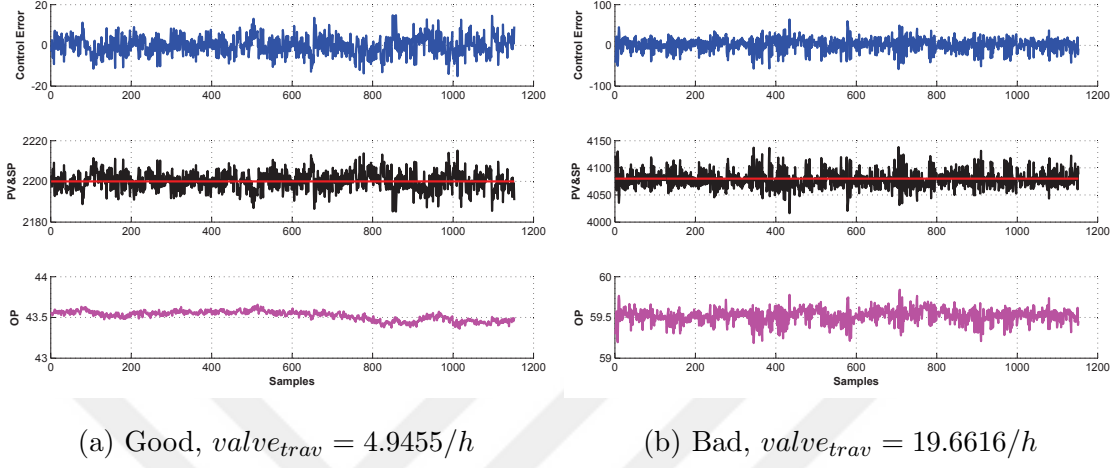
Figure 2.9: Examples for $AmpFactor$

- **Valve travel** ($valve_{trav}$):

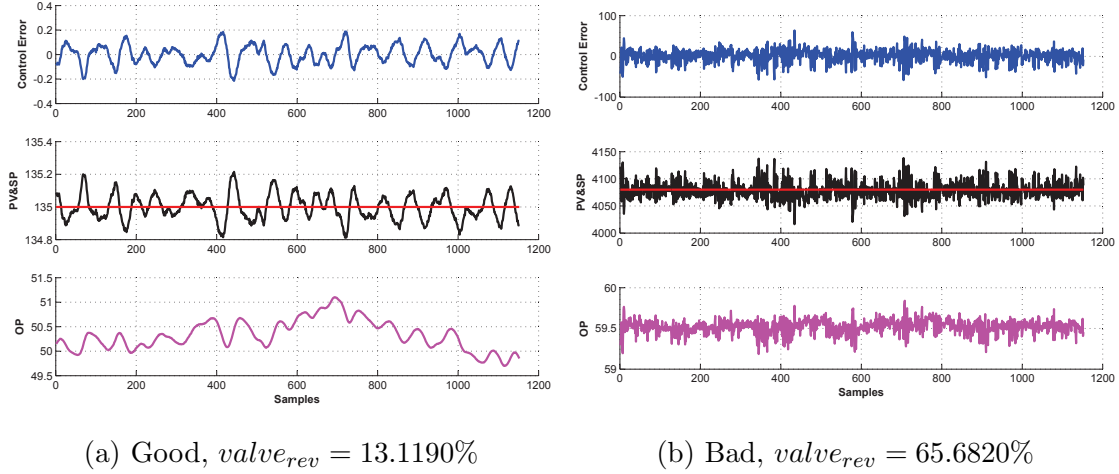
Valve travel is a simple metric to analyze control valve problems. Excessive valve movement causes mechanical wear and thus decreases the lifetime of actuator [ABB, 2010]. Differences between successive valve movements are summed and normalized (if required) in terms of desired time range. $(valve_{trav}(raw) = \sum_{t=1}^{N-1} (OP_{t+1} - OP_t))$

- **Valve reversal** ($valve_{rev}$):

Valve reversal is the number of direction changes the control valve makes. Too much direction change might indicate tight tuning, limit cycle or physical prob-

Figure 2.10: Examples for $valve_{trav}$

lems in the valve. One can normalize the raw value to monitor its trend easily [ABB, 2010].

Figure 2.11: Examples for $valve_{rev}$

2.3 Minimum Variance Control Benchmark

Two main objectives of the control systems are to solve regulator problem and servo problem [Seborg et al., 2010]. In cases where the quality variables are of special

interest, regulator problem becomes the main criterion. For such cases, the aim is to reduce the variations in the process output. Figure 2.12 indicates that decreasing the variation of process output enables to have narrower PDF. As a result, one can able to shift the process set-point to its constraint. At the end, performance is improved by reduction of cost or increase in throughput [Åström and Wittenmark, 2013].

One of the control strategies for that aim is Minimum Variance Control (MVC). It is introduced as an optimal solution which incorporates prediction of the effects of disturbance and calculation of optimum control signal for linear time-invariant (LTI) regulator problem [Åström, 1970].

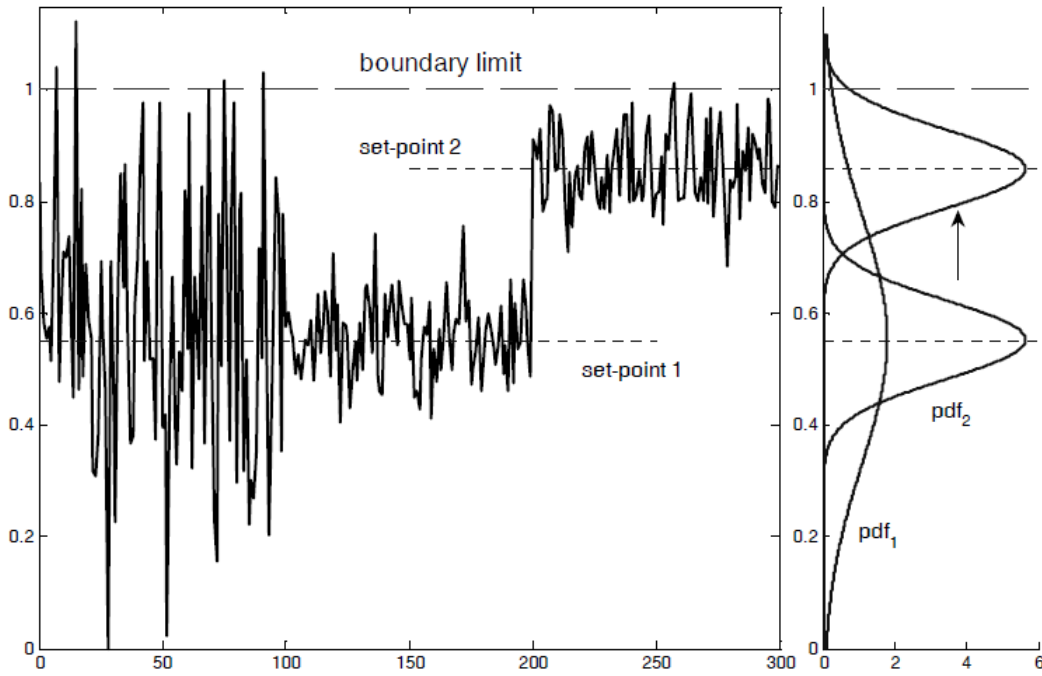


Figure 2.12: Variance Reduction in Control Systems

Therefore, it is better to start with derivation of MVC law and then move on to the benchmark. The generic stochastic feedback control loop is given in Figure 2.13. As described in Figure 2.13, the process model becomes:

$$A(q)y(t) = q^{-k}B(q)u(t) + C(q)\varepsilon(t) \quad (2.1)$$

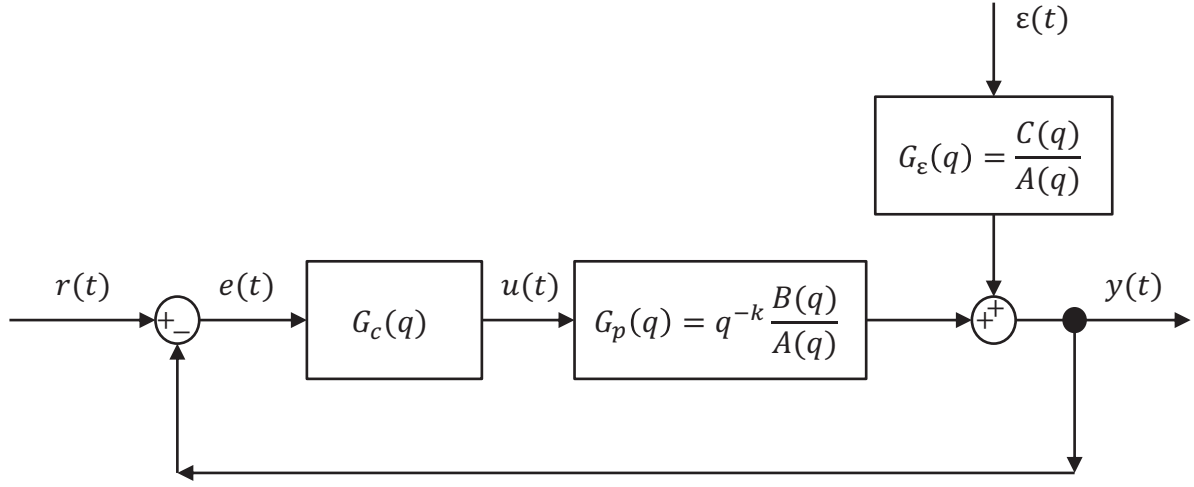


Figure 2.13: Generic Stochastic Feedback Control Loop

Here in Equation 2.1; $A(q)$, $B(q)$ and $C(q)$ are the polynomials of ARMAX structure type model [Ljung, 1999]. Polynomials can also be written as:

$$\begin{aligned}
 A(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + a_3 q^{-3} + \dots + a_{n_A} q^{-n_A} \\
 B(q) &= b_0 + b_1 q^{-1} + b_2 q^{-2} + b_3 q^{-3} + \dots + b_{n_B} q^{-n_B} \\
 C(q) &= 1 + c_1 q^{-1} + c_2 q^{-2} + c_3 q^{-3} + \dots + c_{n_C} q^{-n_C}
 \end{aligned} \tag{2.2}$$

Since no control action can affect the process before the dead-time, the output can be written as:

$$y(t+k) = \frac{B(q)}{A(q)}u(t) + \frac{C(q)}{A(q)}\varepsilon(t+k) \tag{2.3}$$

Then, disturbance effect can be divided into two different time spans as *past* and *future* with Diophantine equation as:

$$C(q) = A(q)F + q^{-k}G \tag{2.4}$$

Substituting Equation 2.4 into Equation 2.3:

$$y(t+k) = \frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t) + F\varepsilon(t+k) \tag{2.5}$$

From Equation 2.5, one can obtain k-step ahead prediction equation as:

$$y(t+k|t) = \frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t) \quad (2.6)$$

MVC derives the control law in which one can obtain the least possible process output variance such that:

$$\sigma_y^2 = E\{[y(t+k)]^2\} \quad (2.7)$$

Substituting Equation 2.5 into Equation 2.7;

$$\sigma_y^2 = E\{[y(t+k)]^2\} = E\left\{\left[\frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t)\right]^2\right\} + E\left\{\left[F\varepsilon(t+k)\right]^2\right\} \quad (2.8)$$

Then, Equation 2.8 can be divided into two terms as:

$$\begin{aligned} J_{MVC} &= E\left\{\left[F\varepsilon(t+k)\right]^2\right\} \\ J_0 &= E\left\{\left[\frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t)\right]^2\right\} \end{aligned} \quad (2.9)$$

Equation 2.9 states that, under MVC one can only play with the control action to decrease the variance of process output. Since the disturbance cannot be manipulated, one can write:

$$\frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t) = 0 \quad (2.10)$$

$$u(t) = -\frac{G}{B(q)F}y(t) \quad (2.11)$$

Substituting Equation 2.11 into Equation 2.5, one can obtain the output-disturbance relationship under MVC as:

$$y(t+k) = F\varepsilon(t+k) \quad (2.12)$$

Equation 2.12 states that under MVC, one can reduce the variance with control actions. However, there is more from disturbance effect and the variation is due

to that. Theoretically, MVC is not practical to use since generally it introduces too much control action to system and results in aggressive control which is not desired in real systems. However, MVC is a useful tool as a performance benchmark [Desborough and Harris, 1992].

The idea introduced by Åström [1970] was further developed by Harris [1989] showing that closed-loop data can be used to analyze the system with respect to MVC. Then, Desborough and Harris [1992] further developed the idea and introduced a normalized performance index bounded between zero and one (interval $[0,1]$). For that purpose, the variance of theoretical MVC and the variance of actual system is compared and controller performance index (or Harris index) obtained as:

$$CPI = \frac{\sigma_{MVC}^2}{\sigma_y^2} \quad (2.13)$$

CPI values closer to "1" indicates that the loop performance is close to that of MVC; whereas, values closer to "0" means that the performance is poor.

CPI is easy and practical to compute because, one only need the closed-loop data and known or estimated time delay (k) of the system [Jelali, 2013]. Equation 2.13 indicates that it is required to compute the variance of theoretical MVC (σ_{MVC}^2). It can be calculated in different ways; but the most practical and popular methods are AR-LS and FCOR algorithms. Other approaches are summarized in 2.3.3

It is highly suggested subtracting the set-point ($r(t)$) from the process output ($y(t)$) and obtain the control error ($e(t)$) and then remove the mean of control error (μ_e) before moving to assessment algorithms [Desborough and Harris, 1992]. Thus, in 2.3.1 and 2.3.2, $y(t)$ in equations represents the mean-centered control error.

2.3.1 AR-LS Algorithm

Since MVC benchmark is not achieved in real control systems, Equation 2.10 can be rewritten as:

$$\hat{y}(t) = \frac{B(q)F}{C(q)}u(t) + \frac{G}{C(q)}y(t) \neq 0 \quad (2.14)$$

Then it is obvious that, there is another non-zero term in MVC output-disturbance relationship. Thus Equation 2.12 can be rewritten as:

$$y(t+k) = F\varepsilon(t+k) + \hat{y}(t) \quad (2.15)$$

where $\hat{y}(t)$ is introduced as an additional term to account for Equation 2.14. Then, $\hat{y}(t)$ can be modelled with AR model so that [Desborough and Harris, 1992]:

$$y(t) = F\varepsilon(t) + \alpha_1 y(t-k) + \alpha_2 y(t-k-1) + \dots + \alpha_m y(t-k-m) \quad (2.16)$$

$$y(t) = F\varepsilon(t) + \sum_{i=1}^m \alpha_i y(t-k-i+1) \quad (2.17)$$

Then, AR model coefficients can be found via least-square fitting by constructing the following:

$$\mathbf{y} = \mathbf{X}\alpha + \mathbf{F}\varepsilon \quad (2.18)$$

where;

$$\mathbf{y} = \begin{bmatrix} y_n \\ y_{n-1} \\ \vdots \\ y_{k+m} \end{bmatrix} \quad \mathbf{X} = \begin{bmatrix} y_{n-k} & y_{n-k-1} & y_{n-k-2} & \dots & y_{n-k-m+1} \\ y_{n-k-1} & y_{n-k-2} & y_{n-k-3} & \dots & y_{n-k-m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_m & y_{m-1} & y_{m-2} & \dots & y_1 \end{bmatrix} \quad \alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_m \end{bmatrix} \quad (2.19)$$

From Equation 2.18 and Equation 2.19, AR model coefficients can be estimated via the least-square solution as:

$$\hat{\alpha} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad (2.20)$$

After estimating α , one can also estimate the variance of MVC (the residual variance) such that:

$$\hat{\sigma}_{MVC}^2 = J_{MVC} = \frac{1}{n-k-2m+1} (\mathbf{y} - \mathbf{X}\alpha)^T (\mathbf{y} - \mathbf{X}\alpha) \quad (2.21)$$

Moreover, the actual variance can be calculated by:

$$\hat{\sigma}_y^2 = J_0 = \frac{1}{n-k-m+1} \mathbf{y}^T \mathbf{y} \quad (2.22)$$

Finally, CPI is given by $CPI = \hat{\sigma}_{MVC}^2 / \hat{\sigma}_y^2$.

2.3.2 FCOR Algorithm

Another method to estimate CPI is proposed by Huang and Shah [1999]. The method filters the process output and correlates the residuals. Therefore, Equation 2.12 is represented by an infinite order moving average (MA) impulse response model:

$$y(t) = \left(\sum_{i=0}^{\infty} f_i q^{-i} \right) \varepsilon(t) \quad (2.23)$$

Equation 2.23 can be rewritten as an impulse response which consists of summation of feedback variant and feedback invariant terms such that:

$$y(t) = \underbrace{(f_0 + f_1 q^{-1} + f_2 q^{-2} + \dots + f_{k-1} q^{-(k-1)})}_{\text{feedback invariant}} \varepsilon(t) \quad (2.24)$$

$$+ \underbrace{(f_k q^{-k} + f_{k+1} q^{-(k+1)} + f_{k+2} q^{-(k+2)} + \dots)}_{\text{feedback variant}} \varepsilon(t) \quad (2.25)$$

As discussed previously in 2.3, under MVC, the variance only comes from feedback invariant part of the process. Thus, the variance of MVC can be written as:

$$\sigma_{MVC}^2 = \sum_{i=0}^{k-1} f_i^2 \sigma_{\varepsilon}^2 \quad (2.26)$$

Writing the feedback invariant portion of Equation 2.24 in open form and taking expectation of both sides yields:

$$\begin{aligned} r_{y,\varepsilon}(0) &= E[y(t)\varepsilon(t)] = f_0 \sigma_{\varepsilon}^2 \\ r_{y,\varepsilon}(1) &= E[y(t)\varepsilon(t-1)] = f_1 \sigma_{\varepsilon}^2 \\ r_{y,\varepsilon}(2) &= E[y(t)\varepsilon(t-2)] = f_2 \sigma_{\varepsilon}^2 \\ &\vdots \\ r_{y,\varepsilon}(k-1) &= E[y(t)\varepsilon(t-k+1)] = f_{k-1} \sigma_{\varepsilon}^2 \end{aligned} \quad (2.27)$$

Substituting Equation 2.27 into Equation 2.26 results:

$$\begin{aligned} \sigma_{MVC}^2 &= \left[\left(\frac{r_{y,\varepsilon}(0)}{\sigma_{\varepsilon}^2} \right)^2 + \left(\frac{r_{y,\varepsilon}(1)}{\sigma_{\varepsilon}^2} \right)^2 + \dots + \left(\frac{r_{y,\varepsilon}(k-1)}{\sigma_{\varepsilon}^2} \right)^2 \right] \sigma_{\varepsilon}^2 \\ &= \left[r_{y,\varepsilon}(0)^2 + r_{y,\varepsilon}(1)^2 + r_{y,\varepsilon}(2)^2 + \dots + r_{y,\varepsilon}(k-1)^2 \right] / \sigma_{\varepsilon}^2 \end{aligned} \quad (2.28)$$

Substituting Equation 2.28 into Equation 2.13, CPI can be estimated as:

$$\begin{aligned} CPI &= \left[r_{y,\varepsilon}(0)^2 + r_{y,\varepsilon}(1)^2 + r_{y,\varepsilon}(2)^2 + \dots + r_{y,\varepsilon}(k-1)^2 \right] / \sigma_\varepsilon^2 \sigma_y^2 \\ &= \rho_{y,\varepsilon}^2(0) + \rho_{y,\varepsilon}^2(1) + \rho_{y,\varepsilon}^2(2) + \dots + \rho_{y,\varepsilon}^2(k-1) \end{aligned} \quad (2.29)$$

Equation 2.29 states that one can easily obtain CPI by correlating the output and the disturbance noise. Proposed algorithm is given in Figure 2.14. Here the filter

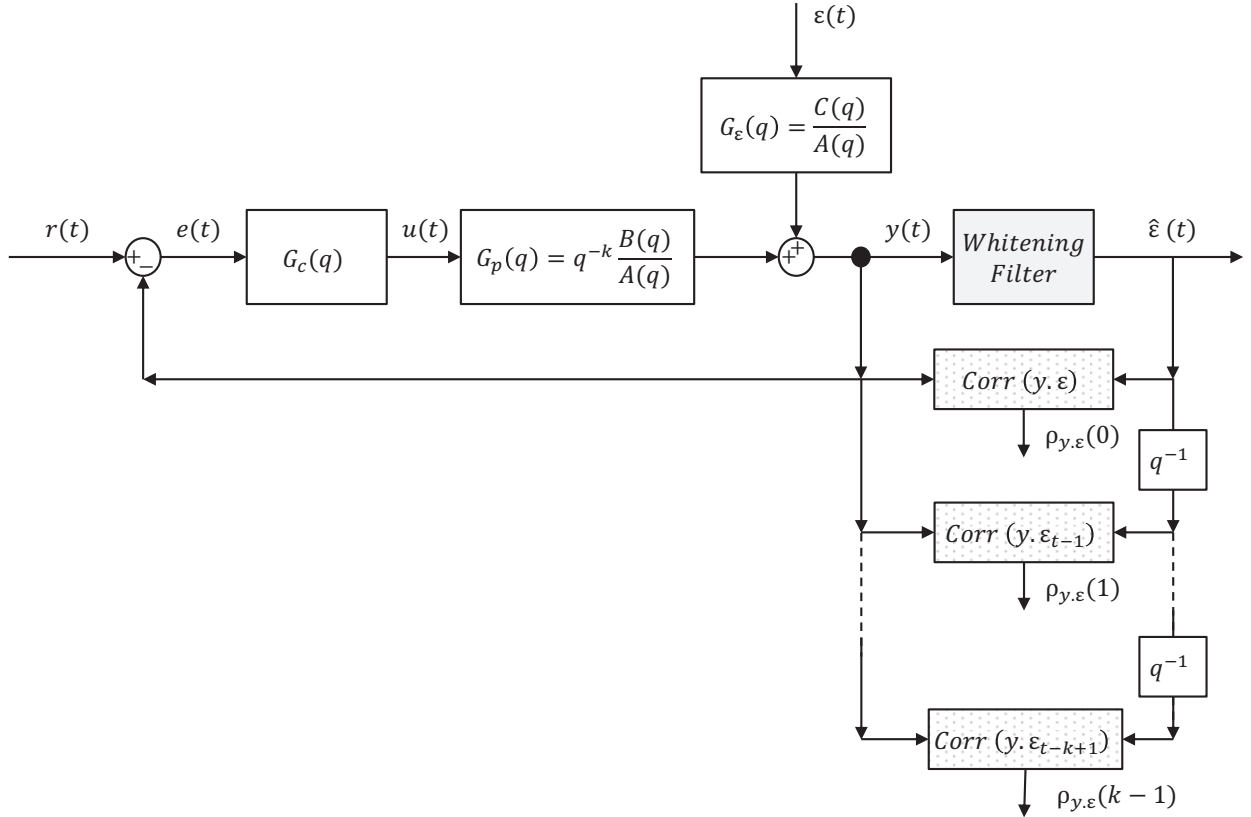


Figure 2.14: FCOR Algorithm Representation

represents the inverse of estimated process model [Soderstrom and Stoica, 1989] to estimate noise disturbance. Then, they are correlated with output to obtain theoretical MVC variance.

2.3.3 Other Modelling Approaches

As discussed in 2.3.1 and 2.3.2, AR-LS and FCOR algorithms are most popular algorithms in industrial applications. However, the modelling approaches are not limited to those. Models are used to estimate the disturbance transfer function. Sufficient fits to predictable components satisfy the basic requirements [Thornhill et al., 1999]; so that, model validation is not a primary requirement. Therefore, theoretically any modelling approach is useful. Jelali [2013] suggests using as simple models as possible for better computation time and less implementation effort. Among those, AR(X) type models are most useful ones. On the other hand, for complete performance assessment and root-cause analysis solutions (e.g. tuning advice feature), advanced modelling methods would be required. In that scope, subspace identification (SID) which makes use of state space models can be a good option to utilize. It has numerous advantages over classical methods [Favoreel et al., 2000]. In addition, SSARX is proved to be successful in closed-loop system identification [Jansson, 2003]. One of the proposed algorithms using SID is as follows [Huang and Kadali, 2008]:

- Collecting closed-loop data
- Applying SID methods (preferably SSARX or N4SID)
- Refining of model with PEM algorithm
- Estimating the impulse response of model (using Equation 2.26)
- Utilizing MVC benchmark (using Equation 2.13)

2.3.4 Concerns on Automatic Stochastic Performance Assessment

Assessment of control loop performance is an essential requirement for complete performance analysis solution. Although single performance score is not that much informative itself, continuous monitoring helps to prioritize problems [Kozub, 1997]. However, for typical process plants, number of control loops reaches to 2000-4000 [ABB, 2008]. Therefore, efficient assessment algorithms are crucial. In addition, automation capability should be high whereas the user input requirement (e.g. delay and model order) should be less [Hugo, 2001]. Moreover, set-points can change depending

on the operational conditions. Especially, in MPC controlled plants, the set-points change frequently to keep quality estimators at their desired values. Furthermore, properties of closed loop data are also important. The number of data points to be used and their sampling interval are important parameters to consider. Considering these, the main topics in automatic assessment are as follows:

- ***User input requirements (model order, m and delay, k):***

Hugo [2001] listed required features of performance assessment techniques. One of the requirements is less user input. Users should be able to analyze the loop with as less effort as possible. Among those requirements, *model order* (m) is an important one which affects the estimated CPI greatly. Thornhill et al. [1999] proposed using a fixed order of 30, whereas Desborough and Harris [1992] suggested trying from lower to higher orders. One can increase the order until CPI values do not change significantly. In addition to the model order, *process delay* (k) is an important parameter to choose since it directly affects the estimated CPI. As discussed in 2.3, no control action can affect the process before the time delay. Thornhill et al. [1999] approaches the issue as an engineering criterion rather than true process time delay. They state that the delay can be restated as a prediction horizon which is a time span of a controller to deal with the predictable component of control error. Since estimation of true time delay is a non-trivial study, several methods were discussed extensively [Björklund, 2003]. In addition, if there is no time delay for a discrete system, k should be selected as 1; since the output depends on the previous input, there exists one sample delay.

- ***Data properties (data length, n and sampling interval, T_s):***

Selection of closed-loop data is another important issue in assessment applications. Abnormal operational conditions such as calibration periods, trips, feed changes directly affect CPI estimation [Thornhill et al., 1999]. It is expected to have normal operational conditions while assessing the performance of controllers. In addition, *data length* (n) which will be used to assess the per-

formance of a certain time span has a significant effect on the statistical quality of CPI estimation. Statistical confidence analysis has been discussed previously by Desborough and Harris [1992]. They state that increasing data length decreases the error bands on CPI values and increases its statistical confidence. However, using too much data should be avoided since one exposes different process characteristics into single model estimation [Kozub, 1996]. Recommended data length is 1000-1500 [Thornhill et al., 1999; Jelali, 2013]. Another important aspect is the selection of the *sampling interval* (T_s). In theory, sampling interval is equal to that of controller sampling interval [Huang and Shah, 1999]. In most of the plants, other than embedded data historians in DCS systems, process variables are collected into separate historians. However, to avoid intensive I/O connections over OPCs, data is sampled lower than the controller sampling frequency. Selection of higher and lower sampling frequencies has been discussed extensively [Huang and Shah, 1999]. A good approach is to check the estimated impulse response of given data set. Thornhill et al. [1999] suggest changing sampling interval until impulse response becomes steady in 30 sampling intervals.

- ***Control modes:***

As discussed in 2.2, controllers at the plant are expected to be in automatic mode. However, in case of problems, operators might change the control mode to manual. Different DCS vendors have different options. In most of the cases, in manual mode, tracking option is enabled in which controller set-point (SP) tracks measured process value (PV). In such cases, automatic evaluation of controller performance will certainly fail, because the control error will be exactly zero and result in CPI values almost equal to one. One approach, which some commercial tools are believed to use, can trace the control mode and omit the samples in manual mode. However, if one fixes pre-defined data length, omission of some data points will reduce the data length. Since, the performance is expected to be monitored continuously, each analysis will have different time

span and result in inconsistency between CPI values. Moreover, simultaneous analysis of different control loops might not be easy. Another approach could be again omitting manual mode samples but joining the automatic mode samples successively until the pre-defined data length is satisfied. However, in such solution, different process dynamics might be accumulated in a single assessment period. To overcome the discussed problems, a useful solution is assessing the performance ignoring the control mode and then penalizing it with respect to percent manual mode. Longhi et al. [2012] suggested using a derived performance index called "*Grade*" and formulated as:

$$Grade = CPI \times \frac{(100 - \%ManTime)(100 - \%SatTime)}{100} \quad (2.30)$$

2.4 Autocorrelation Test

In 2.2 and 2.3, some performance metrics are presented and discussed. Other than those metrics, another way to check the performance is autocorrelation of control error [Huang and Shah, 1999]. In signal processing, ACF has a very wide range of applications but basically it is used to find periodic behaviors and regular patterns in signals [Williston, 2009]. ACF describes how much the data is related with its past samples. That nature of ACF enables to analyze controllers with respect to disturbances. As shown in Figure 2.15a, beyond a certain process time delay k , the correlation should decay [Jelali, 2013]. This means that, up to k , the controller should overcome disturbance effect. If so, one can say the controller is close to performance of MVC. On the other hand, Figure 2.15b shows a poor performing controller in which correlations are dominant in all lags. However, visual inspection of each controller in plant is non-trivial. Box and Jenkins [1976] proposed that at 95% confidence level, statistically ACF coefficients should lie between $[-2\sigma, 2\sigma]$. Having that, one can test what fraction of ACF coefficients is satisfying given confidence interval and obtain a metric.

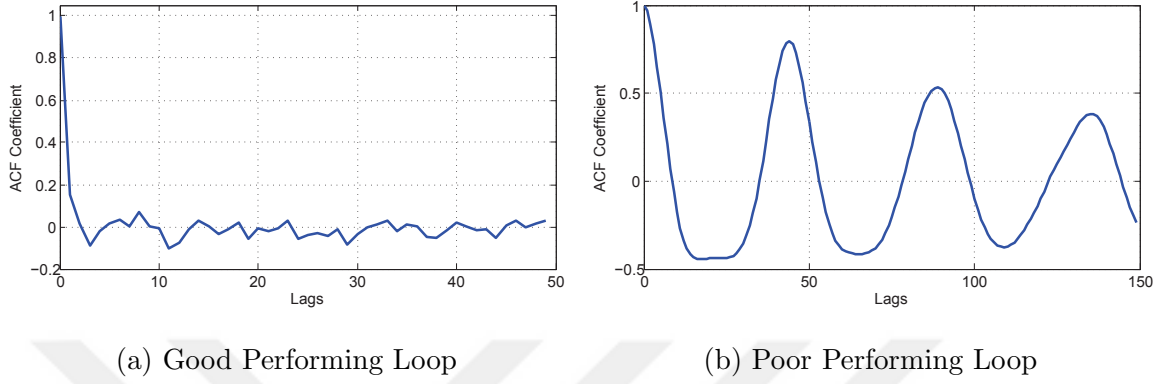


Figure 2.15: An Example of Autocorrelation Test

2.5 Deterministic Performance Assessment

Stochastic performance assessment techniques are useful solutions for the reduction of variances in desired locations. However, in some cases, the reduction in variance is not the single requirement. Rather, instantaneous behavior and responses to set-point changes and disturbance effects of some processes might be of interest. These include processes having frequent changes with respect to some references [Jelali, 2013]. In such cases, control engineers try to analyze the controllers either based on set-point response or disturbance rejection. Figure 2.16 represent typical response features and Table 2.1 gives the definitions of those metrics [Seborg et al., 2010].

However, in order to calculate the metrics given in Table 2.1, usually step-type SP response data is required, which may not be available. In addition, when automatic CPM algorithms are considered, plant tests are not desired. Therefore, analyses based on routine operating data are preferred. One of the studies has been discussed in [Goradia et al., 2005]. The method makes use of the closed loop impulse response features which are side-product of stochastic assessment techniques given in 2.3. In their study, Goradia et al. [2005] tried to characterize the impulse response features and produced typical responses as given in Figure 2.17. Goradia et al. [2005] proposed that if the estimated impulse response of the control loop is similar to one of them, adjust the tuning parameters accordingly. However, the method requires

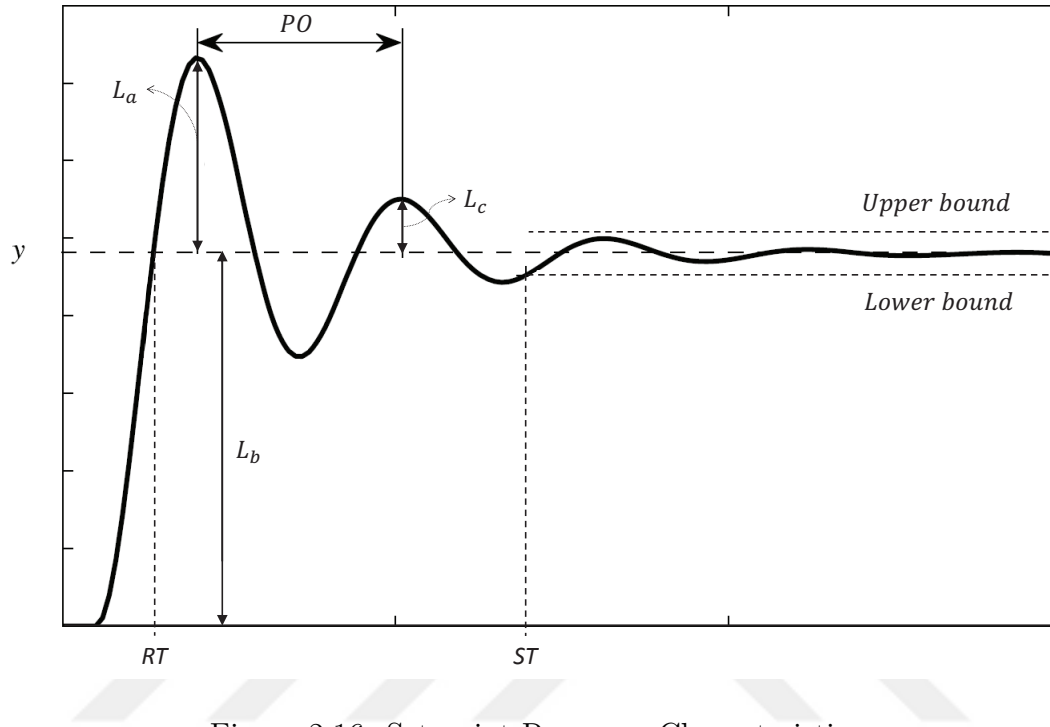


Figure 2.16: Set-point Response Characteristics

Table 2.1: Set-point Response Characteristics Metrics

Characteristic Feature	Definition
Rise time (RT)	The time when the process output reaches the steady state first. Usually, sluggish controllers generate too long rise times.
Settling time (ST)	The time when the process output starts to stabilize itself within pre-defined limits. Generally $\pm 5\%$ rule is used which results in $[0.95L_b - 1.05L_b]$. Too long settling time can mostly be fixed by appropriate tuning.
Overshoot (OS)	$OS = L_a/L_b$. Usually, higher overshoots are result of high gain controllers. It might be problematic in some loops (e.g tank level).
Decay ratio (DR)	$DR = L_c/L_a$. Represents how positive errors are dampened. Too high values are mostly due to aggressive controllers.
Period of oscillation (PO)	The time span between two successive peaks over the steady state line. Too high periods are usually result of sluggish controllers.

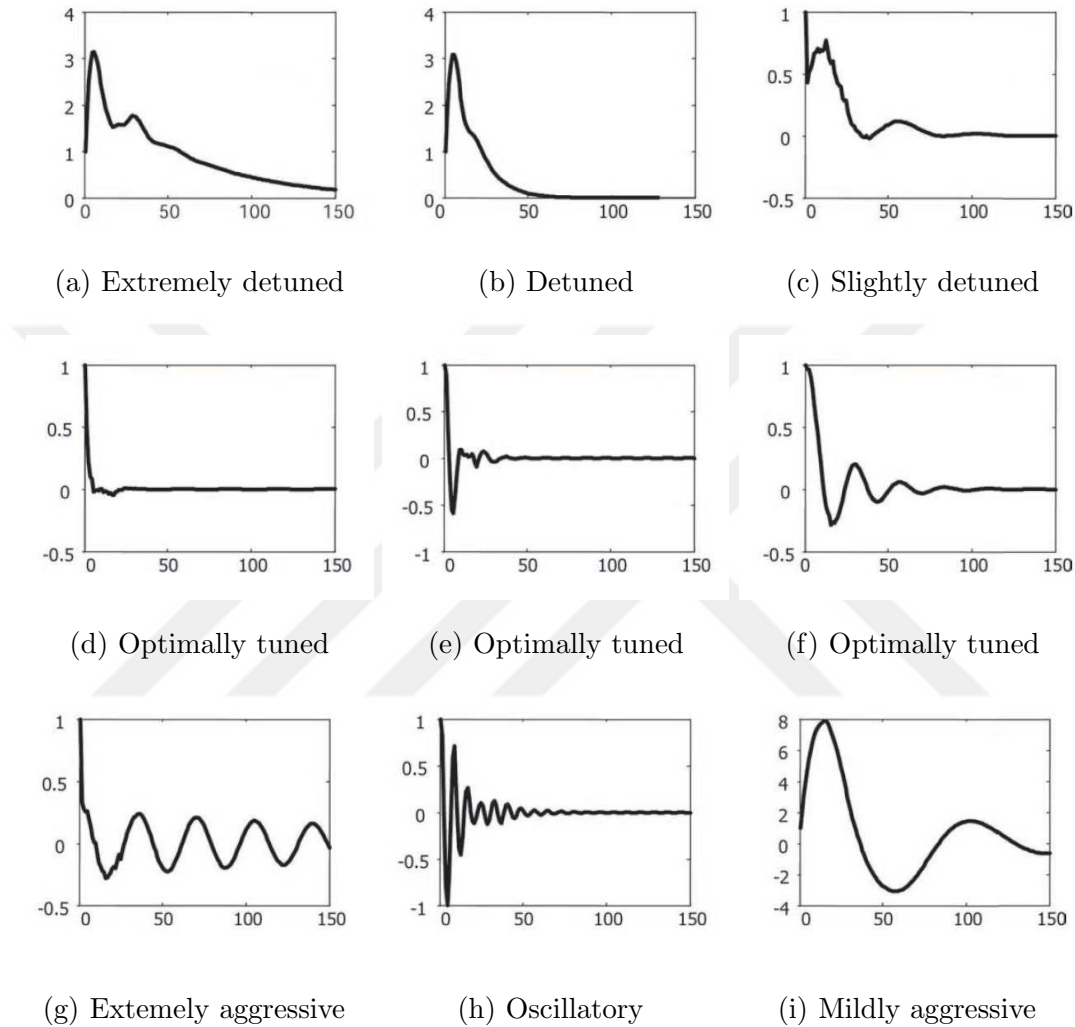


Figure 2.17: Standard Impulse Response Characteristics of Controllers

visual inspection and hard to automate. Therefore, Jelali [2013] have proposed a few modifications and end up with *impulse-response area index (IRAI)*, which gives an indication about the controller tuning.

First, typical nine characteristics proposed by Goradia et al. [2005] are reduced into three as *sluggish*, *optimally tuned* and *aggressive*. Second, the areas under the

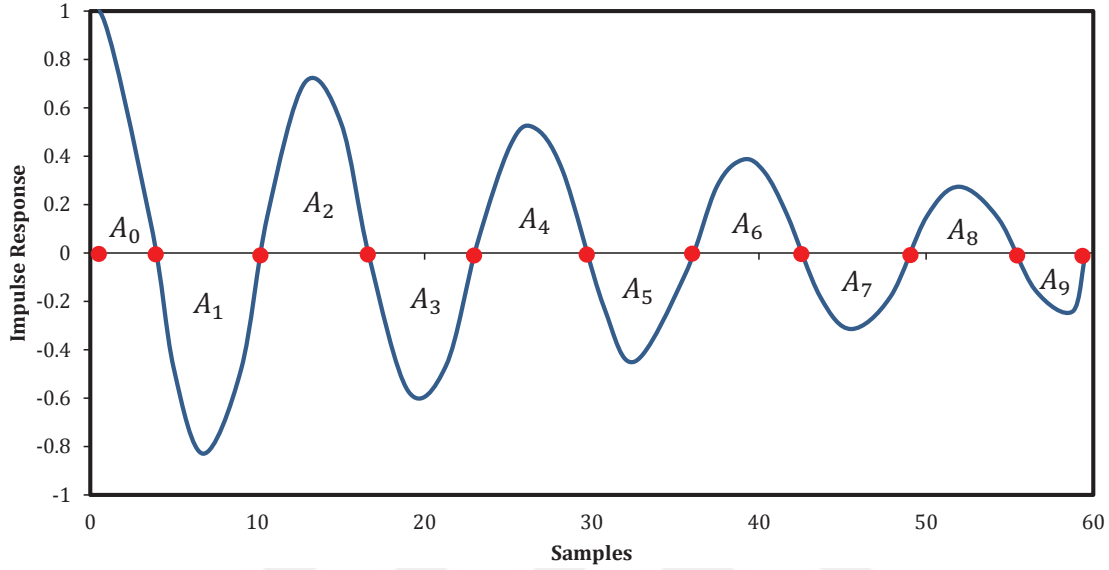


Figure 2.18: Schematic Representation of IRAI Method

impulse-response curve are utilized such that:

$$IRAI = \begin{cases} 1 & \text{for } n < 3 \\ \frac{\max(A_1, \dots, A_{N_{zc}-2})}{\sum_{i=1}^{N_{zc}-1} A_i} & \text{elsewhere} \end{cases} \quad (2.31)$$

Schematic representation of the method is given in Figure 2.18.

For Figure 2.18, IRAI is calculated as:

$$IRAI = \frac{\max(A_1, \dots, A_8)}{A_1 + A_2 + A_3 + \dots + A_9} \quad (2.32)$$

Jelali [2013] states that for $0 < IRAI < 0.35$, the loops are considered to be aggressive; whereas for $0.7 < IRAI < 1$, the loops are said to be sluggish. Values between $0.35 - 0.7$ show the optimum tuning.

Chapter 3

DETAILED DIAGNOSIS

3.1 Introduction

The frequent problems causing performance degradation in control loops are discussed in Chapter 1. However, in process industries, the number of control loops increase and visual inspection of loops becomes very tedious [Visioli and Zhong, 2011]. Therefore, detailed diagnosis of the control loops from routine operating data is an essential tool in CPM applications. Discussed problems can also be identified by plant tests. However, such tests require high amount of manpower. In addition, these may also result in some costs or even decrease in plant up-time. Since non-invasive methods are the most efficient ones [Jelali, 2013], only non-invasive methods are discussed in Chapter 3.

As given in Figure 1.6, detailed diagnosis is done after sorting out some of the operational problems with performance assessment methods. Here in Chapter 3, the methods and algorithms to detect causes of problems in control loops are given. The chapter starts with oscillation detection in 3.2. Then, the methods to detect non-linearities in control loops are discussed in 3.3 and the chapter ends with 3.4 explaining stiction detection and quantification methods.

3.2 Oscillation Detection

In signal processing, oscillation is defined as a signal which has a period and amplitude. In process control framework, oscillations in the control loops can be the signs of serious problems. The frequently faced problems are excessively high controller gains, static friction in control valves, oscillating disturbances or interactions [Jelali,

2013]. Moreover, oscillations often create plant-wide disturbances. Usually, these disturbances are not easily detectable by visual inspection. Sometimes, the oscillating loops are put in manual mode and taken out of operation even if they are realized [Ordys et al., 2006]. Such cases cause poor control performance and may end up with off-spec products, actuator wears or even unexpected shutdowns. The controllability and the operability of the process are also affected as well [Romagnoli and Palazoglu, 2005]. To overcome such problems, it is a crucial requirement to identify oscillating control loops and further diagnose their root causes. The required features of oscillation diagnosis can be summarized as [Ordys et al., 2006]:

- Reliable detection
- Reliable identification of root-cause
- Less user input requirement (even no requirement other than simple thresholds)
- Less data requirement for analysis
- Fast detection (especially for online applications)

Having these requirements, the researchers have studied and developed different methods. In the following parts, power spectrum analysis, regularity of time domain data, decay of auto-covariance function and regularity of auto-covariance function are discussed.

3.2.1 Power Spectrum Analysis

One of the most classical methods to identify oscillation is the power spectrum or the power spectral density (PSD). Power spectrum is mostly used to analyze the noise in a system as a signal processing application in the field of for example, electronic and communication systems [Howard, 2004]. Its wide use and simplicity to analyze make it a popular tool to identify the frequency components of signals.

PSD is simply based on Fourier transform, which states that any signal can be decomposed into an infinite sum of sine and cosine functions [Dyke, 2014]. Having that fact, a random signal can be separated into its frequency components. Then, one

can analyze the frequencies and their relative amplitudes in the signal. An example adopted from [Jiracek, 2012] represents the decomposition of a signal in Figure 3.1. It

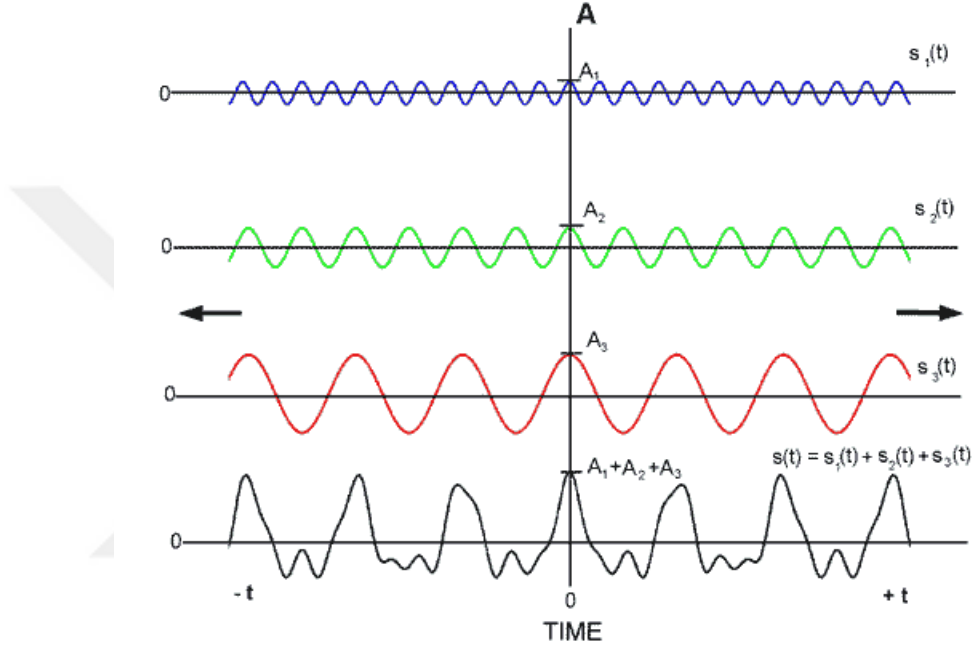


Figure 3.1: Basic Representation of Signal Decomposition

shows the signal at the bottom and its three components above. Each of those signals has different contributions in terms of frequency and amplitude. These contributions can be summarized in Figure 3.2 which shows the each frequency and the amplitude. PSD can be obtained in two ways, using either the discrete Fourier transform (DFT) of the time domain signal or Wiener-Khinchin theorem [Chatfield, 1989] which takes the Fourier transform of the ACF [Jelali and Huang, 2010]. Both methods give good estimates of the PSD. Once the PSD is calculated, the dominant frequencies can be analyzed. Fourier transform of discrete signal is given by:

$$X_{\omega} = \sum_{n=0}^{N-1} x_n \times \exp(-2\pi i \omega n / N) \quad (3.1)$$

There are several methods to estimate PSD from DFT. Those methods are discussed extensively in [Oppenheim and Schaffer, 2011; Press, 2007]. The other method which

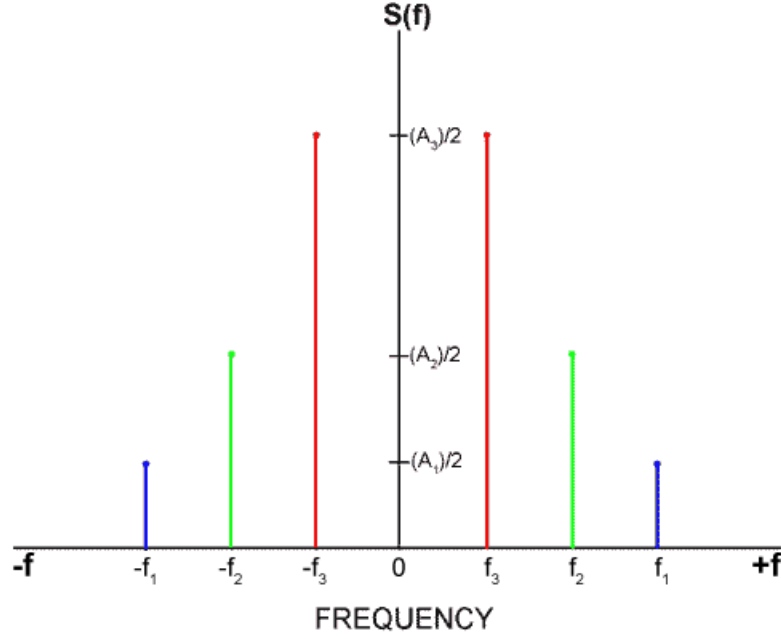


Figure 3.2: Basic Representation of Fourier Transform

is based on Wiener-Khinchin theorem makes use of ACF estimated as:

$$P_{\omega} = \sum_{k=0}^{N-1} \rho_k \times \exp(-2\pi i \omega k / N) \quad (3.2)$$

An example of signal is given in Figure 3.3 which represents time domain data and its PSD having two dominant frequencies.

The threshold for the relative power of oscillation depends on the application. Some of researchers suggest using 1% [Thornhill et al., 2003a], whereas some others 10% [Jelali and Huang, 2010]. However, it should be noted that each peak on the spectrum shows a regular systematic behavior and should be analyzed cautiously.

Power spectrum is a classical method to identify oscillations in control loops. However, it is difficult to automate it, since it requires visual inspection. In case of many control loops in a plant, it gets harder to analyze each.

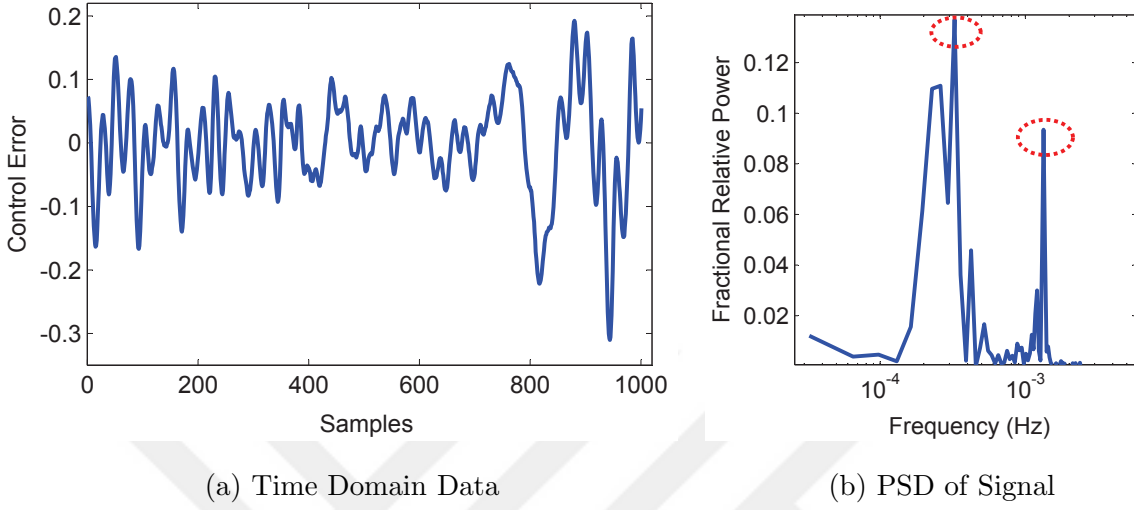


Figure 3.3: PSD Example of an Industrial Signal

3.2.2 Regularity of Time Domain Data

One of the basic methods to identify oscillation in a signal is to check its periodicity in the time domain. For that purpose, a popular integral absolute error criteria, IAE, has been suggested [Forsman and Stattin, 1999]. It has been stated that if the control error is periodic, then the positive and negative IAEs should be similar. Separating positive and negative IAEs makes asymmetrical oscillations to be identified. In that case, the areas can be calculated by Equation 3.3.

$$A_i = \int_{t_{2i}}^{t_{2i+1}} |e(t)| dt, \quad B_i = \int_{t_{2i+1}}^{t_{2i+2}} |e(t)| dt \quad (3.3)$$

Next, successive areas for both positive and negative ones are compared within certain limits. Number of the areas satisfying the pre-defined limits is calculated with Equations 3.4 and 3.5.

$$h_A = \# \left\{ i < \frac{N_{zc}}{2}; \quad \left(\alpha < \frac{A_{i+1}}{A_i} < \frac{1}{\alpha} \right) \wedge \left(\gamma < \frac{\delta_{i+1}}{\delta_i} < \frac{1}{\gamma} \right) \right\} \quad (3.4)$$

$$h_B = \# \left\{ i < \frac{N_{zc}}{2}; \quad \left(\alpha < \frac{B_{i+1}}{B_i} < \frac{1}{\alpha} \right) \wedge \left(\gamma < \frac{\varepsilon_{i+1}}{\varepsilon_i} < \frac{1}{\gamma} \right) \right\} \quad (3.5)$$

At the end, Forsman-Stattin index (h) becomes:

$$h = \frac{h_A + h_B}{N_{zc}} \quad (3.6)$$

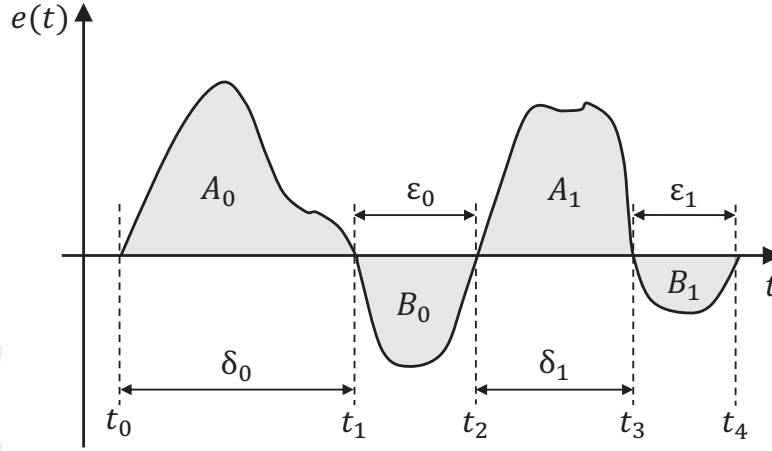


Figure 3.4: Representation of Forsman-Stattin method

where;

- White noise signal shows $h \approx 0.1$.
- Loops having $h > 0.4$ represent oscillating signal and requires closer analysis.
- Loops having $h > 0.8$ represent very distinct oscillation pattern.

The pre-defined limits to compare the successive areas are important parameters for the given method, since α represents the sensitivity for IAE and γ represents the sensitivity for zero-crossings. Forsman and Stattin [1999] suggest using $\alpha = 0.5 - 0.7$ and $\gamma = 0.7 - 0.8$. In addition, they state that in order to get better results, pre-filtering may require. In such cases, a trade-off exists between attenuating low frequency oscillations and high frequency noise. For practical purposes, a low-pass filter can be used [Jelali and Huang, 2010]:

$$e_f(t) = \eta \times e(t) + (1 - \eta) \times e_f(t) \quad (3.7)$$

Higher values ($\eta \rightarrow 1$) means detecting fast and small oscillations, whereas lower values ($\eta \rightarrow 0$) means more filtering and attenuation of high-frequency noise. Differing from simple low-pass filters, better smoothing filters can also be used. One of those filters is Savitzky-Golay filter. Savitzky-Golay filters apply polynomial fitting with a

predefined order to the given frame of data. These filters are generally used to smooth noisy signals without distorting the actual signal. The filters like simple averaging FIR filters are prone to filter the desired signal rather than the noise component [Orfanidis, 2010].

3.2.3 Decay of Auto-Covariance Function

Forsman-Stattin index is sensitive to noise and requires pre-filtering for better results. Unfortunately, this requirement makes the method harder to automate. To overcome such cases, Miao and Seborg [1999] have suggested using ACF of the control error signal. ACF of an oscillatory signal is also oscillatory with the same period. In addition, ACF provides somehow filtering, because ACF of the white noise is almost zero for the lags greater than zero [Jelali and Huang, 2010]. ACF of the control error can be estimated as:

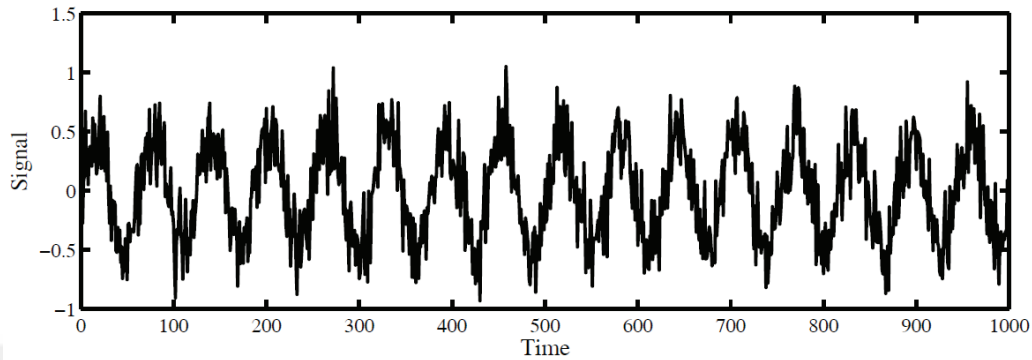
$$\rho_k = \frac{\sum_{t=1}^{N-k} (e_t - \mu_e)(e_{t+k} - \mu_e)}{\sum_{t=1}^N (e_t - \mu_e)^2} \quad (3.8)$$

In that manner, the proposed method does not require anything other than a simple threshold [Miao and Seborg, 1999]. To detect the oscillation in the signal, the decay of the ACF is calculated by comparing the relative distances of the ACF of the signal (see Figure 3.5). The relative distance is defined by $R = a/b$ where the distances a and b are defined as:

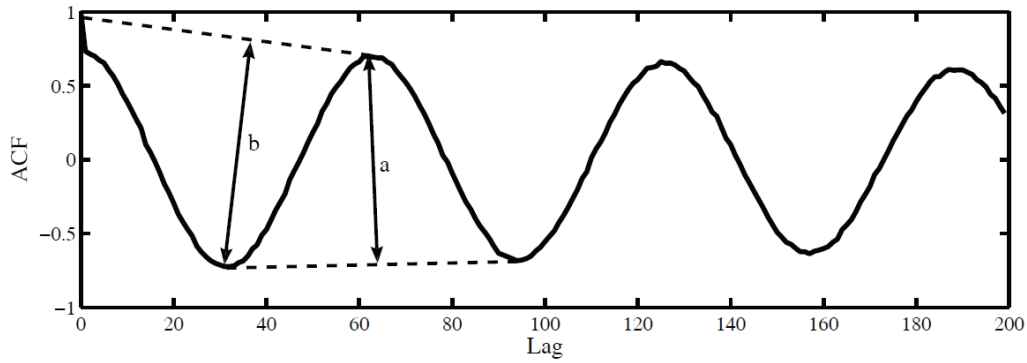
- b is the distance from the first minimum to the straight line connecting the zero-lag coefficient and the first maximum.
- a is the distance from the first maximum to the straight line connecting the first two minima.

Schematic representation of filtering effect of ACF and the decay ratio is given in Figure 3.5.

Miao and Seborg [1999] state that signals having $R > 0.5$ show excessively oscillatory behavior. In addition, as Figure 3.5 represents, the method requires at least



(a) An Oscillatory Signal



(b) ACF of the Signal

Figure 3.5: Decay Ratio Method

two minimum points and one maximum point, in other words 1.25 cycles in ACF. In the time domain, 1.25 cycles equal to five cycles since the maximum lag for ACF is selected as one quarter of the total data length [Box et al., 1994]. Thus, the method is able to detect the oscillations for the signals having at least five cycles in the time domain.

3.2.4 Regularity of Auto-Covariance Function

Decay of auto-covariance method is a powerful and easy to implement method to detect oscillations. However, characterization of the oscillation is a crucial requirement to further analyze the root of the oscillation. Since a single oscillation can affect the

other loops. Therefore, an extension analysis of ACF has been proposed. As presented in 3.2.3, the periods of oscillations are the same in both ACF and the time domain. By using that property, the period of oscillation can be determined in ACF [Thornhill et al., 2003a]. Finally, the regularity of zero-crossing points in ACF is analyzed with 3σ statistical test. Figure 3.6 gives the ACF of an oscillatory signal and its zero-crossing points. Remembering that a single sinusoid has three zero-crossings in

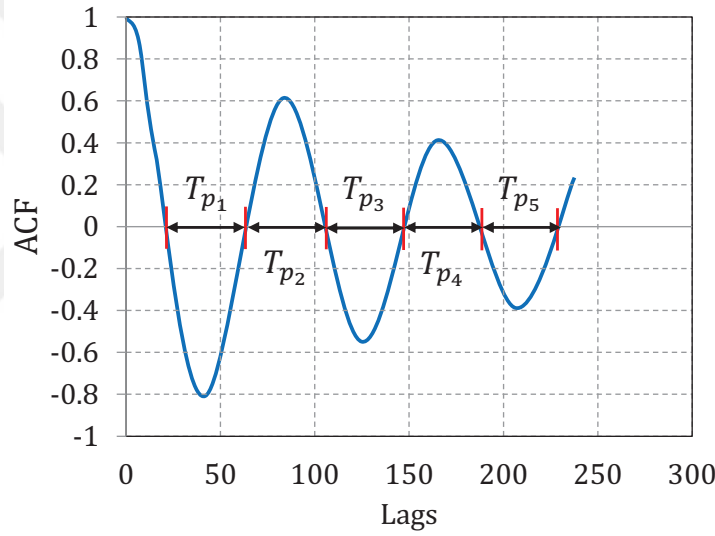


Figure 3.6: Regularity of ACF method

the time domain, two successive zero-crossings form a half-oscillation period. Thus, the mean oscillation period is calculated as:

$$\bar{T}_p = \frac{2}{N_{zc} - 1} \sum_{n=1}^{N_{zc}-1} T_{p_n} \quad (3.9)$$

Next, the standard deviation of oscillation periods is calculated as:

$$\sigma_{T_p} = 2 \times \sigma_{intervals} \quad (3.10)$$

Finally, the regularity of the ACF can be tested as:

$$reg = \frac{\bar{T}_p}{3 \times \sigma_{T_p}} \quad (3.11)$$

Thornhill et al. [2003a] state if $reg > 1$, the oscillation is regular with an average period of $\bar{T}_p$.

3.2.5 Summary of Oscillation Detection Methods

As discussed previously, the detection of oscillation in the control loops is an important aspect. Due to that fact, robust and widely applicable methods are required. The methods discussed above have some advantages and disadvantages. One of the most powerful methods is PSD. Since it is based on DFT of the signal, one can decompose the signal into its frequency components. A component forming the peak indicates a dominant frequency component in the signal. However, detection of those peaks requires visual inspection. In addition, for plants having high number of loops, visual inspection is difficult and hard to automate. An automatic method proposed by Forsman and Stattin [1999] is one of the methods which overcome that problem. In addition, it can handle asymmetrical oscillations. On the other hand, it is sensitive to noise in the signal. Since the method rely on finding zero-crossings over the control error, spurious zero-crossing points may lead wrong detections. In such cases, filtering may require. Forsman and Stattin [1999] have suggested using MA type of filter which is based on single tuning parameter. They have stated that, one can adjust the filtering parameter with respect to the noise. However, although Savitzky-Golay type of smoothing filters contains more parameters to select, they have better performance in smoothing. The time window of these filters should be chosen with respect to the process dynamics and the sampling interval. In general, 3rd order is sufficient for smoothing. Unfortunately, having those additional tools makes the method proposed by Forsman and Stattin [1999] loses robustness. Therefore, the researchers have headed towards more robust methods. Miao and Seborg [1999] have proposed using ACF instead of time domain data, since ACF eliminates the noise in the signal. In addition, the same period of the signal is preserved in the ACF. Miao and Seborg [1999] have analyzed the pattern of ACF and proposed a new index called *decay ratio* (R). The method can detect oscillations even in low SNR (signal-to-noise ratio). However, the characterization of the oscillations is also very important as well as detection. The method proposed by Thornhill et al. [2003a] overcomes that problem. It uses the regularity of ACF and ends up with both the

detection index (reg) and the average oscillation period ($\bar{T}_p$). However, the method may fail in multiple frequencies, since the regularity of ACF is lost when the signal have multiple frequency components.

When all these methods are examined, one can conclude that any of these methods are not superior to the others. One should choose one of them or a bunch of these considering their advantages and disadvantages. Table 3.1 summarizes all discussion above.

Table 3.1: Advantages and Disadvantages of Given Methods

Method	Advantages	Disadvantages
PSD	- Robust at multiple oscillations	- Visual inspection requirement
[Forsman and Stattin, 1999]	- Simple to calculate - Robust at asymmetrical oscillations	- Sensitivity to noise - Filtering requirement - No characterization
[Miao and Seborg, 1999]	- Robust to noise	- No characterization
[Thornhill et al., 2003a]	- Characterization of oscillation	- Sensitivity to multiple frequencies

3.3 Non-Linearity Analysis

Non-linearities pose severe problems, since the linear controllers cannot respond to non-linear behaviors well. Therefore, detection of the non-linearities in control loops is a vital part of the performance assessment.

There are different examples of non-linearities including multiple equilibrium points, periodic variations of state variables, limit cycles, frequency entrainment, and complex

dynamic behaviors [Sastry, 1999]. In the process control framework, one of the most important ones is the limit cycle. Problems such as stiction, hysteresis and dead-band in the actuators and sensors having faults are the most frequent candidates of the limit cycles [Jelali and Huang, 2010]. They do not show pure sinusoids but show periodicity. Therefore, the non-linear signals have harmonics [Thornhill, 2005]. Stiction-originated limit cycles are also called self-excited oscillations or self-generated cycles [Bakshi and Bakshi, 2008].

An important sign of non-linearity is the phase coupling which is a result of the interaction of different frequencies Thornhill [2005]. In that case, the first and second order statistical tools are deficient to interpret these systems and the higher order statistical tools such as bispectrum are needed. In the following sections, two useful methods to analyze non-linearities in the control loops are discussed.

3.3.1 Bispectral Analysis

One of the first studies to test the signals for non-linearity via bispectrum has been presented by Hinich [1982]. However, the analysis and usages of polyspectras can be celebrated back to Brillinger [1965], Ness [1966] and Rao and Gabr [1980]. In his study, Hinich [1982] has used the asymptotic features of bispectrum and proposed χ^2 test with 2-degrees-of-freedom. Then, Fackrell [1996] has used these advancements to analyze the speech signals. Although the spectral analysis had been used in several applications like radar signal analysis, mechanical machine condition monitoring and ocean wave analysis, Choudhury et al. [2004] were the first ones introducing those concepts into the process control framework. Having based on bispectrum of control error signal, they have proposed *NGI*(*non – Gaussianity*) and *NLI*(*non – linearity*) indices. The method estimates the frequency interactions over the principal domain of the normalized bispectrum and analyzes the smoothness and peakedness of the interaction surface. The normalized bispectrum is also called as *bicoherence* or *squared bicoherence*.

The bispectrum of two signals is given as:

$$B(f_1, f_2) = E\{X(f_1)X(f_2)X^*(f_1 + f_2)\} \quad (3.12)$$

Then, Equation 3.12 can be normalized to obtain squared bicoherence such that:

$$bic^2(f_1, f_2) = \frac{|B(f_1, f_2)|^2}{E\{|X(f_1)X(f_2)|^2\} E\{|X(f_1 + f_2)|^2\}} \quad (3.13)$$

Figure 3.7 shows the bicoherence of a generated signal given by Equation 3.14. As the figure indicates, frequency pair (0.12, 0.18) couples and creates a portion of the signal at 0.30.

$$y(t) = \sin(2\pi \times 0.12t + \pi/3) + \sin(2\pi \times 0.18t + \pi/12) + 0.1 \times \sin(2\pi \times 0.30t + 5\pi/12) \quad (3.14)$$

Estimation of bicoherence can be done in two ways: Indirect and direct methods.

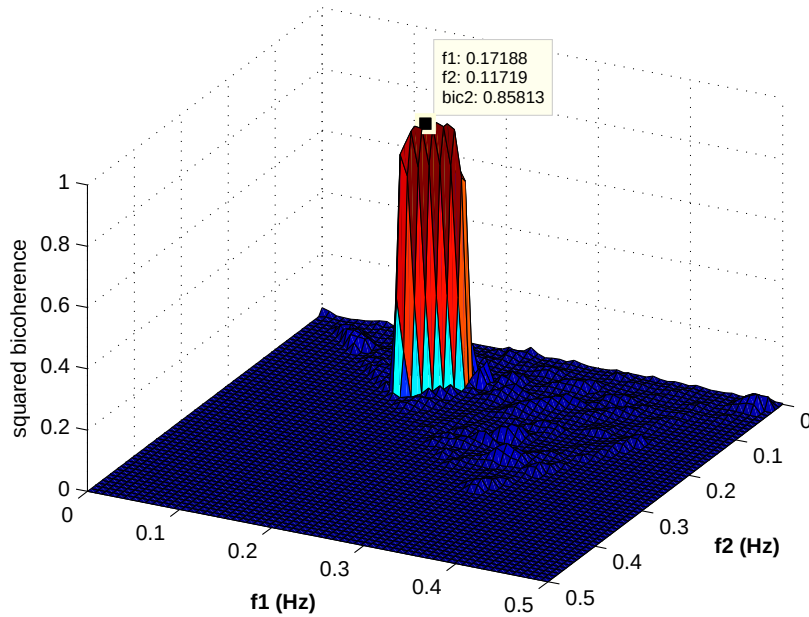


Figure 3.7: An Example for Non-linear Signal

The indirect method involves estimation of the cumulants and taking DFT of those; whereas, the direct method uses averaging of segments [Choudhury et al., 2008]. Here only the direct method is given. It is similar to the Welch periodogram [Welch, 1967] which applies averaging of several segments. The estimation procedure is as follows:

1. **Segmentation:** The signal $x(t)$ divided into K segments ($i = 1, 2, \dots, K$), each having data points of M . The segments should overlap.
2. **Detrending:** Mean of each segment is subtracted.
3. **Windowing:** A window function applied onto the detrended segments of data. The window function might be Hanning, Hamming, Blackman or any other.
4. **DFT:** Each segment is divided into its frequency components by DFT with a certain number of points. The estimates $(X_i(f))$ are obtained.
5. **Estimating raw spectral values:** Equation 3.13 applied to get raw spectral estimates.
6. **Averaging:** The raw estimates belonging to K segments are averaged. $\hat{b}ic^2(f_1, f_2)$ is calculated.

Choudhury et al. [2008] have discussed the estimation parameters (segment length, overlapping, window function and DFT points) extensively. First, they have suggested using as much data as possible (e.g. 4096); because, compared to power spectral estimates, the bispectral estimates have higher variance over a certain data points. In addition, to increase resolution, DFT points should also be high. They have recommended using DFT points equal to the segment length. Moreover, in order to avoid the spectral leakage phenomena, they have strongly suggested using window functions. The spectral leakage is a problem caused by overlapping of neighboring frequency channels. As a result, true amount of energy is spread onto other neighboring frequencies. Use of window function suppresses this affect and smooths the edge of segments. Finally, they have stated that SNR is the most affecting property of the raw signal. In case of higher power of noise (equivalent to lower SNR values), DFT points should be increased. Figure 3.8 adopted from [Choudhury et al., 2008] represents the effects of these parameters onto the bicoherence estimates. However, large

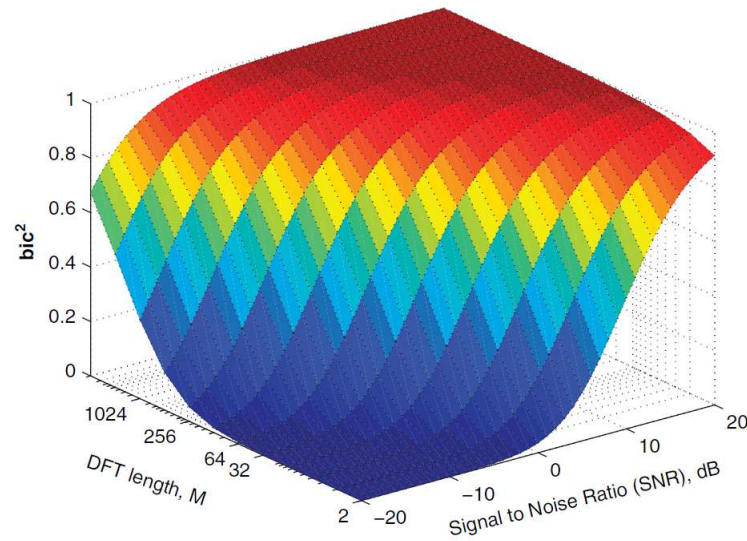


Figure 3.8: Effects of Bicoherence Estimation Parameters

data sets cannot be available. In addition, computation requirements may increase for increasing number of DFT points. Considering that, Choudhury et al. [2008] suggests some default parameters as given in Table 3.2.

Table 3.2: Suggested Default Parameters for Bicoherence Estimation

Parameter	Default
Data Length	At least 1024. 4096 is recommended.
Segment Length	64
Overlap	%50 (i.e 32 points for segment length of 64)
DFT points	128
Window Function	Hanning window

After estimating the bicoherence values, they are reduced into the principle domain; because, the discrete bispectrum has 12 planes of symmetries. The analysis of the results in only one plane is enough to interpret. The detailed extraction of the principal domain has been discussed in [Hinich, 1982; Hinich and Wolinsky, 1988]. Here, only the boundaries are given in Figure 3.9. IT represents inner and OT represents outer triangles respectively. Hinich and Wolinsky [1988] have recommended using OT to test whether signal has aliasing or not. Alternatively, one can only calculate the spectral values over the principal domain by meshing the domain, considering DFT points and boundaries cautiously.

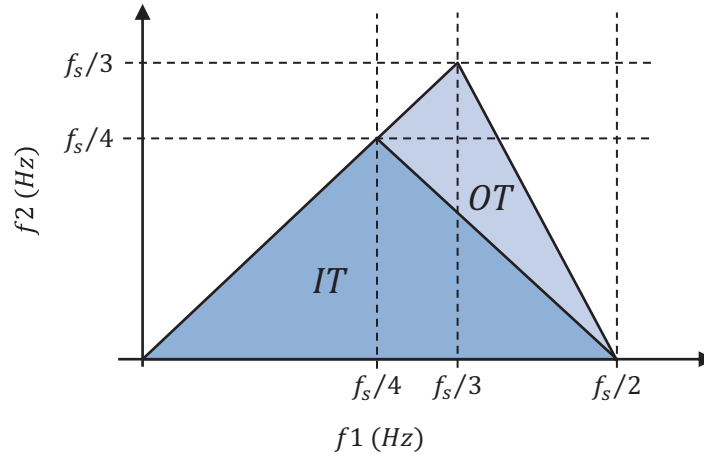


Figure 3.9: Principal Domain of Bispectrum

After estimating the bicoherence, one can analyze the non-linearity of signal. Distinct peaks in the bicoherence represent the phase coupling effect and result in non-linear signals. However, this requires visual inspection. As discussed earlier for other analysis, it is tedious to inspect all the loops. Choudhury et al. [2004] have suggested using two indices: NGI and NLI. These represent whether the bicoherence is non-Gaussian and non-linear or not. NGI is estimated by χ^2 test with null hypothesis of "the signal is Gaussian". For high number of bifrequencies over the principal domain,

Abramowitz and Stegun [1972] have proposed using χ^2 approximation such that:

$$c_{cL}^{\chi^2} = \frac{1}{2} \left(c_{cL}^z + \sqrt{2dof - 1} \right)^2 \quad (3.15)$$

The null hypothesis can be tested such that:

$$P \left(2KL \overline{\hat{b}\hat{c}^2} > c_{cL}^{\chi^2} \right) = cL \quad (3.16)$$

Then, the deviation of $\overline{\hat{b}\hat{c}^2}$ with respect to the critical value becomes NGI such that:

$$NGI = \overline{\hat{b}\hat{c}^2} - \overline{\hat{b}\hat{c}_{crit}^2} \quad (3.17)$$

where the critical value $\overline{\hat{b}\hat{c}_{crit}^2}$ is calculated as:

$$\overline{\hat{b}\hat{c}_{crit}^2} = \frac{1}{4KL} \left[c_{cL}^z + \sqrt{4L - 1} \right] \quad (3.18)$$

For the central distribution with $cL = 95\%$, $c_{cL}^z = 5.99$. Then, one can test the Gaussianity of the signal with given values. At the end, for $NGI \leq 0$, signals are Gaussian, whereas for $NGI > 0$, signals are non-Gaussian. Jelali [2013] states that if analysis ends with a Gaussian signal, it can be said that the signal generating process is linear. However, in practice, it might be difficult to obtain exact zero NGI for Gaussian signals. Therefore, Choudhury et al. [2004] have proposed that the values around 0.001 can be assumed to be zero.

In order to further analyze the bicoherence, another index proposed is NLI [Choudhury et al., 2004]. It is simply to check the flatness of the bicoherence surface. For $cL = 95\%$, NLI is defined as:

$$NLI = \left| \hat{b}\hat{c}_{max}^2 - \left(\overline{\hat{b}\hat{c}^2} + 2\sigma_{\hat{b}\hat{c}^2} \right) \right| \quad (3.19)$$

In ideal case, NLI is expected to be zero for the linear signals, resulting in a flat surface of bicoherence. The signals having $NLI > 0$ are said to be non-linear signals. However, similar to NGI, it might be difficult to obtain absolute zero for linear signals. Therefore, lower values (around 0.01) can be considered as linear [Choudhury et al., 2004].

In bispectral analysis, the signal is assumed to be stationary. Thus, the drifts and trends can affect the estimation. Choudhury et al. [2008] have proposed detrending the data first. Alternatively, a band pass filter can be used to eliminate certain frequencies. On the other hand, for an automatic solution, Nikias and Petropulu [1993] have suggested using only IT in the principal domain (Figure 3.9) to obtain the average bicoherence values.

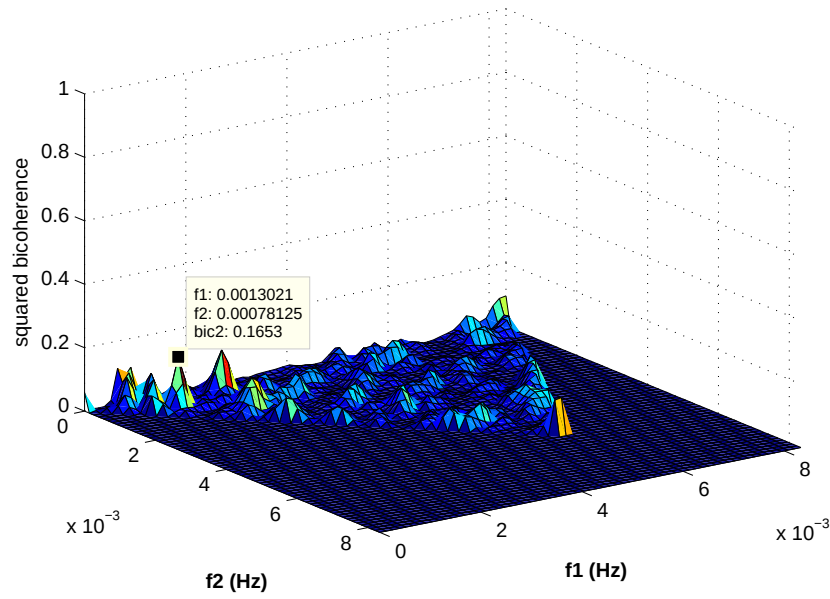
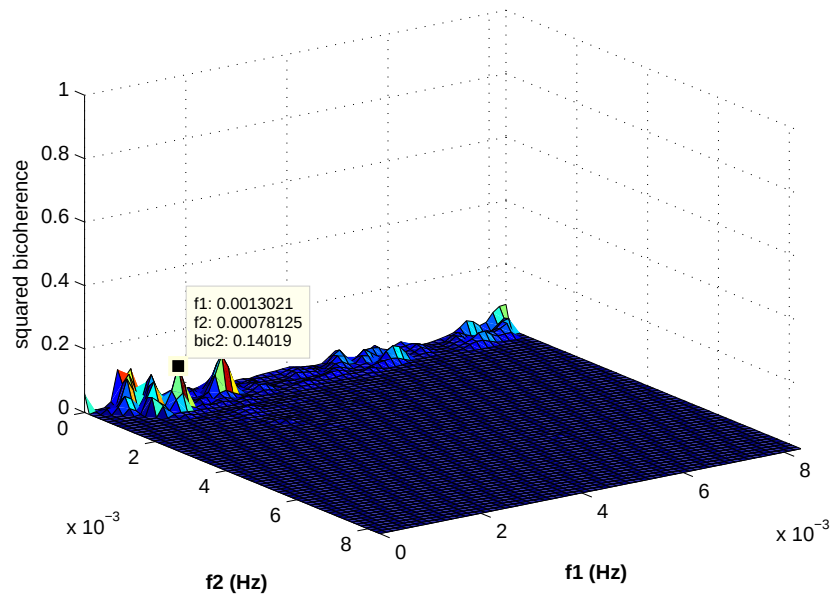
In addition to non-stationary data, spurious peaks in the principal domain should be handled carefully. Collis et al. [1998] have suggested using a correction factor κ into denominator of Equation 3.13 such that:

$$bic^2(f_1, f_2) = \frac{|B(f_1, f_2)|^2}{E\{|X(f_1)X(f_2)|^2\} E\{|X(f_1 + f_2)|^2\} + \kappa} \quad (3.20)$$

However, selecting a constant value for κ might cause over or under filtering of the bicoherence [Choudhury et al., 2006b]. In addition, the noise in the measurement and the selection of the bicoherence estimation parameters affect the variance and the number of spurious peaks. In order to make an automatic selection, Choudhury et al. [2006a] have suggested choosing 75 percentile of the denominator values (sorted in increasing order) of Equation 3.13. The effects of κ have been discussed extensively by Choudhury et al. [2008]. Figure 3.10 shows the effect of κ in the bicoherence estimation. As Figure 3.10b states, the frequency pair (0.0013021, 0.00078125) does not change for the filtered case of Figure 3.10a. Only maximum bicoherence value has been changed slightly from 0.1653 to 0.14019.

3.3.2 Surrogate Analysis

Another approach to analyze non-linearity of the time series data is the surrogate analysis. It is essentially based on destroying the phase coupling which is a result of the limit cycles as discussed in 3.3. In this analysis, the surrogate data is generated having the same power spectrum but the frequencies are randomized with certain methods [Thornhill, 2005]. Then, a pre-defined null hypothesis is tested with a discriminating statistical metric [Theiler et al., 1992]. The methods for generating surrogate data sets have been discussed extensively in [Theiler et al., 1992] which

(a) $\kappa = 0$ (b) $\kappa \neq 0$ Figure 3.10: Effect of κ in the Bicoherence Estimation

includes "random shuffle", "random phases" and "amplitude adjusted Fourier transform". In addition, they have discussed some applications covering fluid convection, EEG signals and sunspots.

Despite several applications, it was Thornhill [2005] first bringing the idea into the process control framework. She has proposed using the predictability of the time series data with respect to its surrogates. The mean square error (MSE) of both real time test data and its surrogates are calculated. The estimated values are tested with 3σ statistics and *NPI* (*non-predictability index*) is obtained. Thornhill [2005] has stated that if $NPI > 1$, the time series data is non-linear. Otherwise, the data is assumed to be linear.

Analysis procedure starts with generating the surrogate data sets. "Random phases" method has been explained as follows [Theiler et al., 1992]:

1. **Fourier Transform:** Fourier transform of the real time test data is obtained.

$$X = FFT(x) \quad (3.21)$$

2. **Phase Randomization:** The phases at all frequencies are randomized observing asymmetry around zero frequency. The Nyquist frequency should be carefully handled.

$$X_{surr} = \begin{cases} X(i), & i = 1 \\ X(i)e^{j\phi_{i-1}}, & i = 2, \dots, N/2 \\ X(i), & i = N/2 + 1 \\ X(i)e^{-j\phi_{N-i+1}}, & i = (N/2 + 2), \dots, N. \end{cases} \quad (3.22)$$

3. **Inverse Fourier Transform:** The time series surrogate data is obtained by taking the inverse Fourier transform of the randomized signal.

$$x_{surr} = IFFT(X_{surr}) \quad (3.23)$$

Figure 3.11 shows an example of surrogate data generated with the random phases method. Figure 3.11a shows the real test data and its surrogate in the time domain.

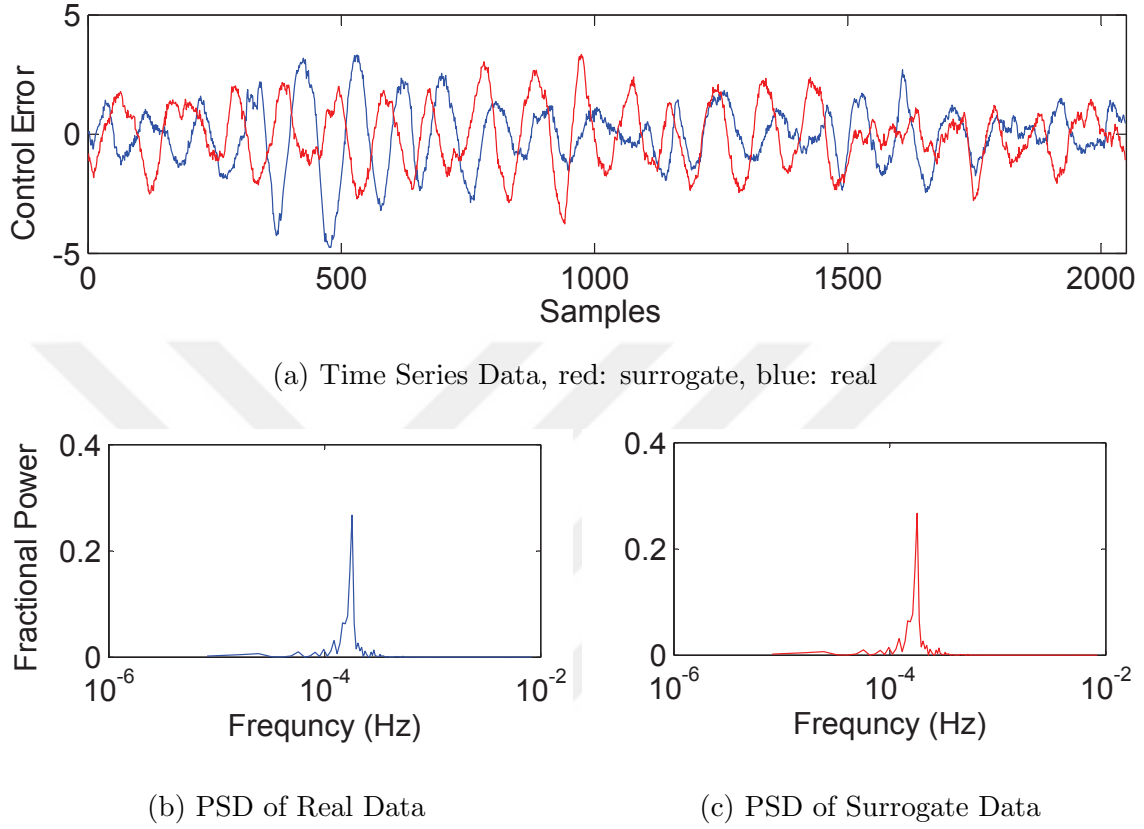


Figure 3.11: An Example for Surrogate Data

Figures 3.11b and 3.11c represent the PSDs of the signals. As can be seen, the PSD of the real test data and the PSD of the generated surrogates are identically same but the data are different in the time domain (Figure 3.11a).

Then, as Thornhill [2005] described, the embedded matrix ($\mathbf{Y}$) is constructed with certain number of columns (E) such that:

$$\mathbf{Y} = \begin{bmatrix} y(1) & y(2) & y(3) & \dots & y(E) \\ y(2) & y(3) & y(4) & \dots & y(E+1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y(N-E+1) & y(N-E+2) & y(N-E+3) & \dots & y(N) \end{bmatrix} \quad (3.24)$$

Then, for each row of $\mathbf{y}_i$ of $\mathbf{Y}$, indices j_p where $p = 1, 2, \dots, nn$ of nn nearest neighbour rows $\mathbf{y}_{j_p}$ having the nn smallest values of $\|\mathbf{y}_{j_p} - \mathbf{y}_i\|$ are found. Here, the near-in-time neighbour exclusion constraint is applied with $|j_p - i| > E/2$.

Afterwards, the sum of squared prediction errors is calculated such that:

$$\Gamma_{test} = \sum_{i=1}^{N-H} \left(y(i+H) - \frac{1}{nn} \sum_{p=1}^{nn} y(j_p+H) \right)^2 \quad (3.25)$$

Next, the surrogate data sets are generated with any of the methods presented previously. Equation 3.24 is applied to obtain the embedded matrix for the surrogate data sets. After obtaining the matrix, the sums of the prediction errors for the each surrogate data sets $\Gamma_{surr_1}, \Gamma_{surr_2}, \dots, \Gamma_{surr_M}$ are calculated by applying Equation 3.25. Finally, NPI can be calculated as:

$$NPI = \frac{\frac{1}{M} \sum_{i=1}^M \Gamma_{surr_i} - \Gamma_{test}}{3\sigma_{\Gamma_{surr}}} \quad (3.26)$$

Here the method requires some critical parameters. Definitions and recommended values are given in Table 3.3. Selection of parameters play an important role in the

Table 3.3: Default Values for Surrogate Analysis

Description	Default Value
samples per cycle, S	$7 \leq S \leq 25$
number of columns in embedded matrix $\mathbf{Y}$, E	$E = \text{floor}(S)$
prediction horizon, H	$H = E$
number of cycles of oscillation	$C \geq 12$
number of near neighbours, nn	$nn = 8$
number of surrogate data sets, M	$M = 50$

method. The effects of these parameters are discussed below [Thornhill, 2005]:

- ***Samples per cycle, S :***

It is not a strict limit alone; rather, it is better to consider S with number of cycles of oscillation C . Practically the data length for analysis is $S \times C$. In theory, increasing S might increase computation time, since the method requires measuring the distances of binary selections of the rows of the embedded matrix, $\mathbf{Y}$. On the other hand, decreasing S too much might cause neglect of the harmonics. For $S = 7$, third harmonics, which is the most significant harmonic in square or triangular type of waves, might be lost. Subsampling or upsampling may be required.

- ***Number of columns in embedded matrix, E :***

It is suggested to be equal to S . Since, decreasing values might lead to method to fall into the false neighbours. Floor function presented in Table 3.3 represents the lower near integer value of S .

- ***Prediction horizon, H :***

The prediction horizon represents the data to be estimated ahead. It is suggested to be equal to E . The performance of method has been discussed for varying values of E and H by Thornhill [2005].

- ***Number of cycles of oscillation, C :***

Value of 12 is suggested for that parameter. It has been again discussed in conjunction with number of near neighbours nn by Thornhill [2005].

- ***Number of near neighbours, nn :***

Similar to S , increasing values increases the computational requirements. However, due to end-matching requirement (discussed later), a conservative value of 8 is suggested. The graphical representation of the concept is given in Figure 3.12, adopted from Thornhill [2005].

The bold lines given in Figure 3.12b are the five nearest neighbours of the original signal given in Figure 3.12a. In addition, the points represented with $\circ$ in Figure 3.12b are the local predictions and the average of those points giving the prediction for the point $\times$ in Figure 3.12a.

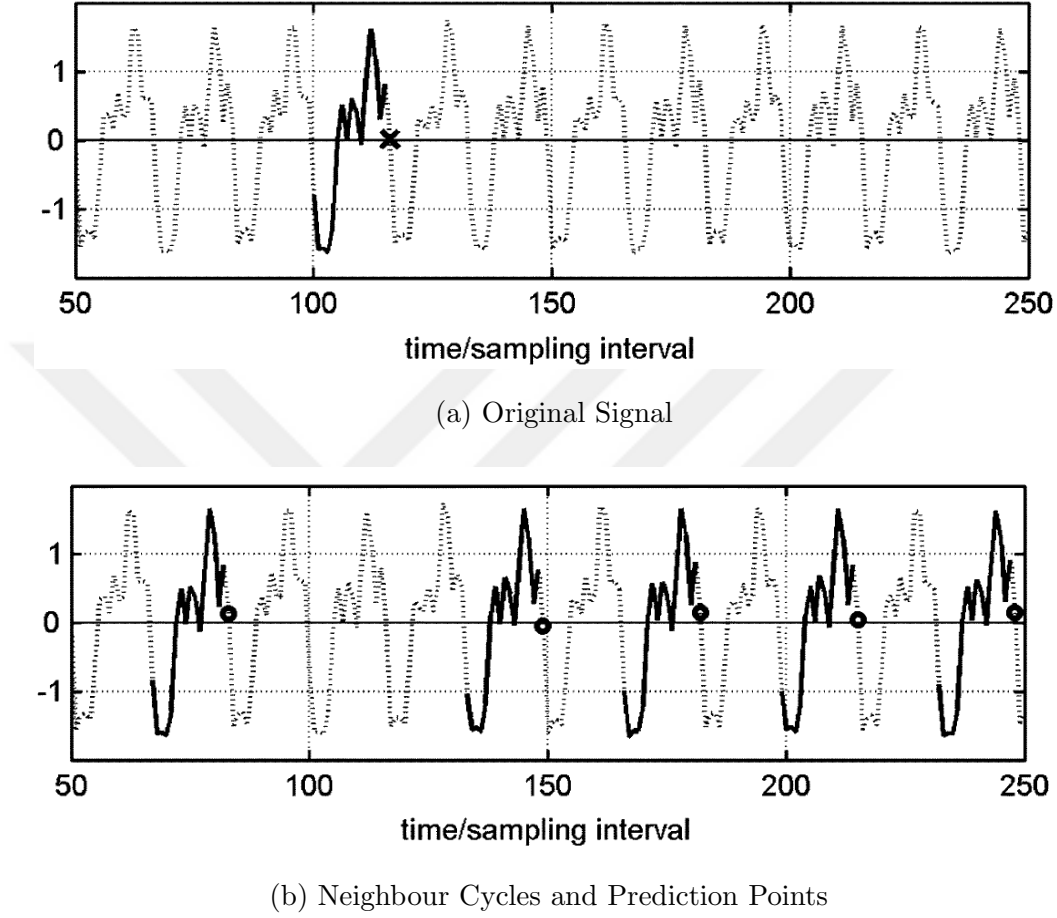


Figure 3.12: Nearest Neighbour Concept

Moreover, another critical aspect is the requirement of end-matching. The analysis of the surrogate data requires having complete cycles Thornhill [2005]. Otherwise, the spectral leakage problem may occur. To overcome that problem, end-matching has been suggested. A method proposed by Hegger et al. [2004] includes minimization of discontinuities in data. Another approach propose obtaining a data length of an integer multiple of oscillation period of signal has been suggested by Stam et al. [1998]. The method tries to find the data length which results in complete cycles by defining the frequency mismatch error as:

$$E_{fmm} = \sum_{i=1}^p (x_i - x_{kN+i})^2 \quad (3.27)$$

where x_i standing for the non-matched data. Stam et al. [1998] have proposed starting

from $kN = N - p$ and search for the first minimum of E_{fmm} by decreasing kN by one. Suggested search value of p is 10.

3.3.3 Summary of Non-linearity Analysis Methods

In 3.3, two different methods are given as bispectral analysis and surrogate analysis. Each method has both advantages and disadvantages over the other one. For example, the bispectral analysis is a powerful analysis for characterization of non-linearity [Choudhury et al., 2004]. One can analyze the interacting frequencies over 3D squared bicoherence plot. In addition, the method produces useful indices (NGI and NLI) which describe the system further. However, the method is based on DFT of signals. In addition, it requires several parameters (segment length, DFT point, window function and overlapping ratio). Although some defaults have been proposed by Choudhury et al. [2006a,b], the selection of parameters might change with respect to the system analyzed. That fact makes the method hard to automate. However, obtained frequencies from the bicoherence can be used to detect the stiction in control valves [Choudhury et al., 2008]. On the other hand, for better analysis, a long length of data (4096) is required. Conversely, the surrogate analysis method can give reliable results with smaller data lengths (500) [Thornhill, 2005]. In addition, with proper end-matching application, the possibility of spectral leakage is minimized, even if the method requires several parameters such as samples per cycle, prediction horizon and the others. However, it lacks of the characterization of the non-linearities. A proper method might be required to characterize the non-linear signal.

3.4 Stiction Detection

In control loops, processes are regulated with final control elements. Control valves are the most frequently used ones. They are used to control flows, pressures, temperatures and liquid levels in processes. Movements of the valve positions can be controlled either by electrical or pneumatic or hydraulic actuators. Control signal is calculated by the controller and sent to the actuator. A control valve has three essential components

as actuator, body and accessories. The schematic representation is given in Figure 3.13.

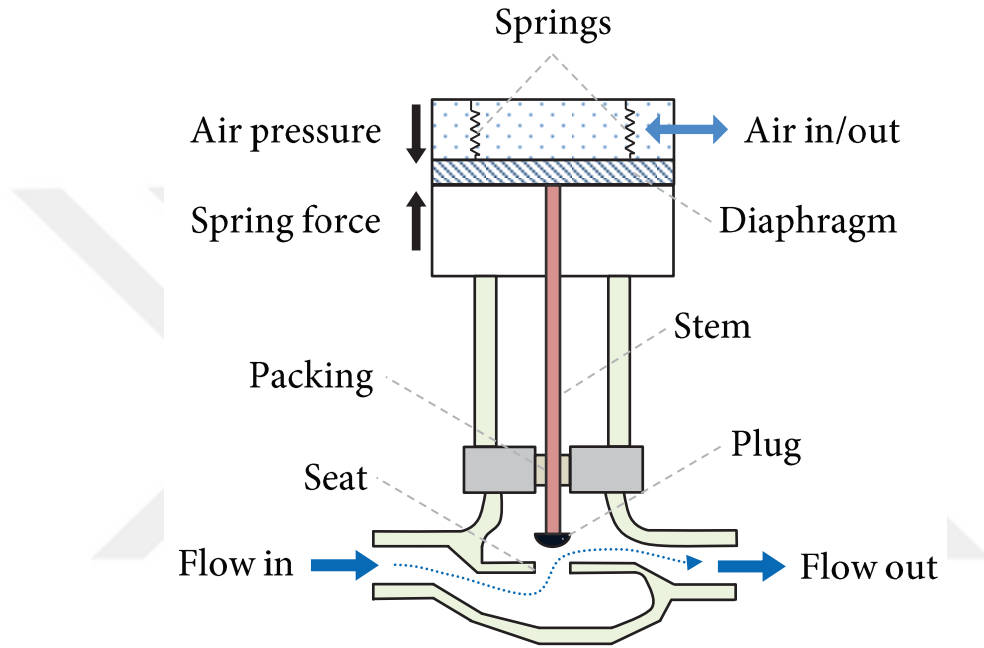


Figure 3.13: Schematic Representation of a Pneumatic valve

Figure 3.13 shows several mechanical parts in valves. Almost continuously movement of those mechanical parts results in mechanical wear and finally result in different problems. Most frequent ones are increase in deadband, stiction, saturation, corrosion, hysteresis and backlash. As control valves are the final elements to control processes, in case of any of those problems, performance degradation is inevitable. Surveys conducted by Paulonis and Cox [2003], Torres et al. [2006] and Desborough and Miller [2001] show that significant amount of industrial control loops perform poorly as a result of the control valve problems. Therefore, the detection of valve problems with non-invasive methods is a crucial requirement in CPM applications. The behaviors of some problems discussed are given in Figure 3.14 [Choudhury et al., 2008].

Among those, stiction is the most frequent problem. Being a constructed word from terms *static* and *friction*, stiction defines the resistance of the actuator to start

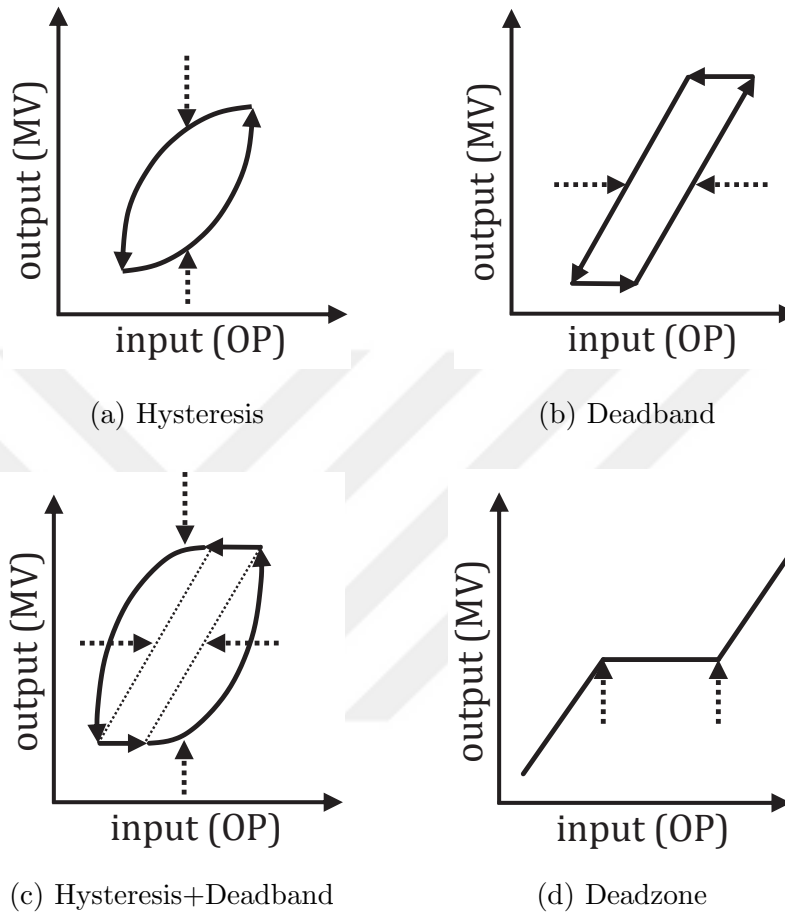


Figure 3.14: Input Output Behaviors of Some Valve Problems

the motion. The resistance occurs between the valve stem and the packing, represented in Figure 3.13. It starts with sticking of valve at a certain position. Then, controller starts to increase control signal. At a certain point, the static friction is surpassed and the valve takes the first move with jumping to a high level, usually greater than the calculated controller signal [Ordys et al., 2006]. At that point, the control error becomes larger and the controller tries to decrease the error by sending opposite signal to the valve. This procedure is repeated several times in both forward and backward direction, which results in limit cycles as discussed in 3.3. Typical behavior of a valve suffering from stiction is given in Figure 3.15. Rossi and Scali [2005] state the stiction components represented in Figure 3.15 by sticking (S), jump

(J) and motion (moving phase).

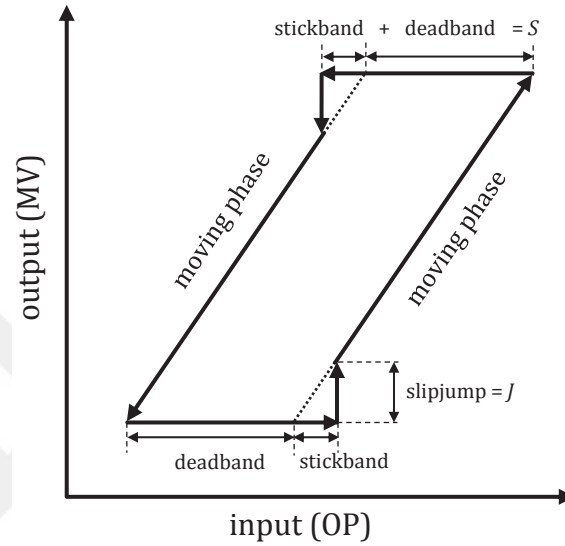


Figure 3.15: Schematic Representation of a Valve Suffering from Stiction

There are numerous studies to model stiction in control valves both in terms of physical and data-driven bases. Physical modelling approaches include studies from Kayihan and Doyle [2000], Fitzgerald [1995], Olsson [1996] and Karnopp [1985]. In data-driven part of modeling studies include [Stenman et al., 2003], [Kano et al., 2004] [Choudhury et al., 2005] and [He et al., 2007]. Those studies created a basis for detection and quantification of stiction. In the following sections, two different stiction detection methods are discussed.

3.4.1 Curve-Fitting Analysis

Stiction in control valves has several main fingerprints. If MV and OP data are available, visual inspection of MV-OP plots for the loops might help to detect valve problems, as given in Figures 3.14 and 3.15. However, usually in plants MV data is not measured except for smart valves Jelali and Huang [2010]. Therefore, detection of stiction with available data is a very critical task. One of those methods is proposed by He et al. [2007]. They state that in case of stiction in a control valve, true valve

position (MV) moves back and forth, producing a rectangular wave. However, it is converted to triangular wave because of the integrator actions in the loop [He et al., 2007]. An example from an industrial control loop is given in Figure 3.16.

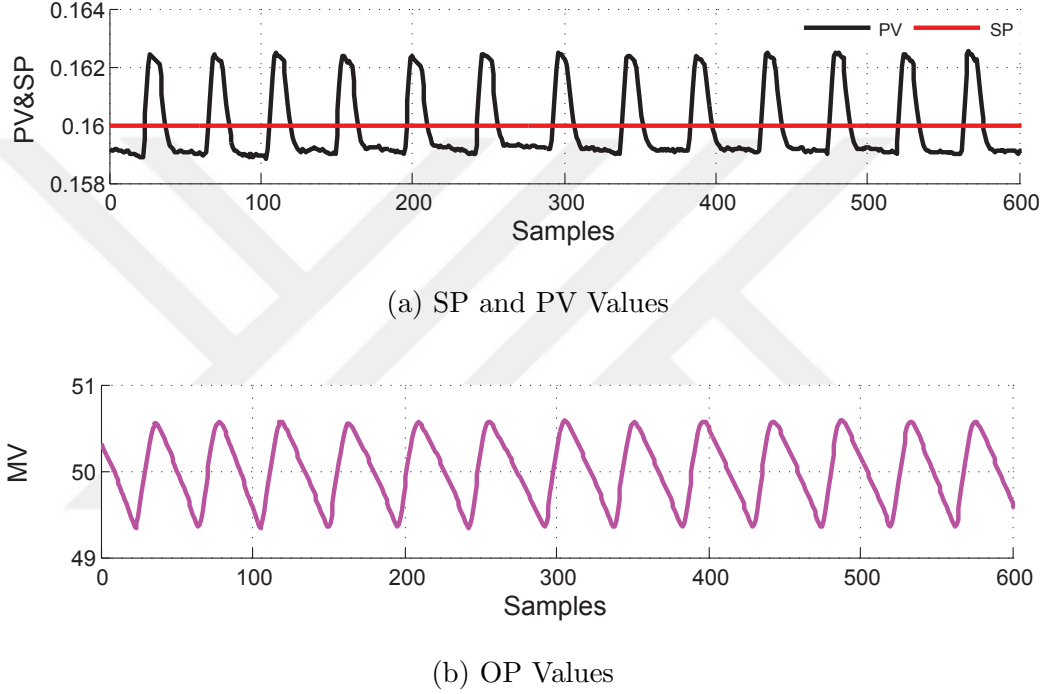


Figure 3.16: An Example of Loop Values for Strong Stiction Case

On the other hand, in case of sinusoidal external disturbance, OP and PV signals creates sinusoidal shapes with frequencies almost the same with the disturbance. By exploiting those features, they suggested analyzing the shape of signals. The algorithm is basically to fit both sinusoidal and triangular curves for half cycles. Then comparing MSE values for each, He et al. [2007] proposed stiction index as follows:

$$SI_{cf} = \frac{\overline{MSE}_{sin}}{\overline{MSE}_{sin} + \overline{MSE}_{tri}} \quad (3.28)$$

In order to detect stiction, first, the loop is analyzed for oscillation. After detection of oscillation, zero-crossing points are detected as shown in Figure 3.17. He et al. [2007] suggest using OP signal for self-regulating processes (e.g. flows) and PV signal

for integrating processes (e.g. levels). Then, the signal is fitted to sinusoidal curve and triangular wave for each half period as shown in Figure 3.17. The reason of using half periods is to capture different oscillation dynamics. He et al. [2007] state that oscillation amplitude and period may change which may result in asymmetrical oscillations.

Sinusoidal signal equation is given as:

$$S_{j,sin} = A_{sin} \times \sin(\omega(t_i : t_{i+1} - t_i)) \quad (3.29)$$

where, the schematic representation is given in Figure 3.17a. It should be noted that there is no phase parameter in Equation 3.29; since, for piece-wise fitting, the phase can be said to be equal to zero. Then, $\overline{MSE}_{sin}$ in Equation 3.28 can be calculated as:

$$\overline{MSE}_{sin} = \frac{1}{ncy_{csin}} \sum_{j=1}^{ncy_{csin}} MSE(y_j(t), S_{j,sin}) \quad (3.30)$$

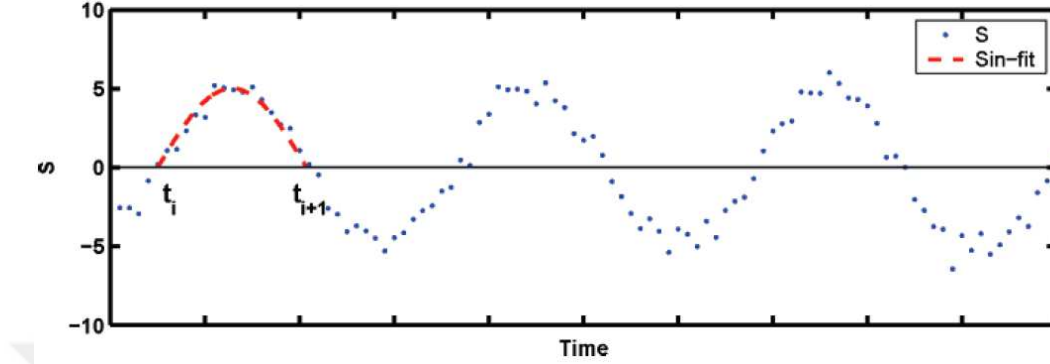
Similarly for triangular fitting as represented in Figure 3.17b;

$$S_{j,tri} = a_{tri} \times (t_p - t_i) + b_{tri} \quad (3.31)$$

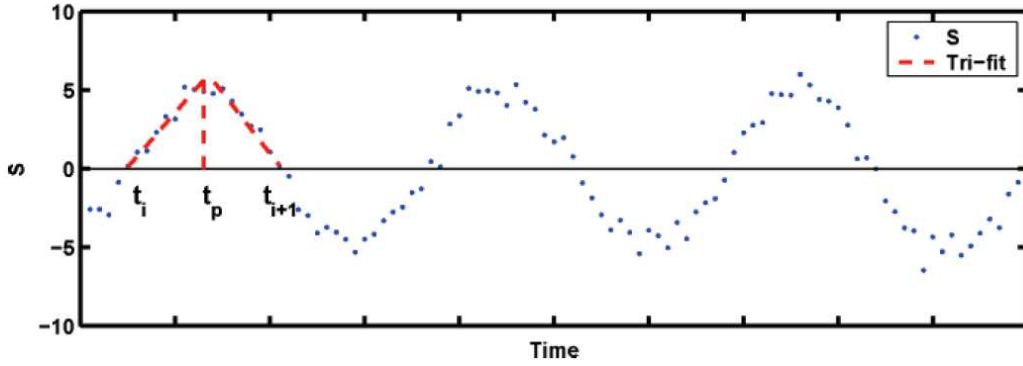
Then, $\overline{MSE}_{tri}$ in Equation 3.28 can be similarly calculated using Equation 3.30 for triangular sections. He et al. [2007] state that if $SI_{cf} \geq 0.6$ one can conclude to stiction. On the other hand, for signals having $SI_{cf} \leq 0.4$, there is no stiction. Finally, for SI_{cf} between 0.4 – 0.6, a certain decision cannot be made. In other words, if the signal fits better to triangular shape, $\overline{MSE}_{sin}$ calculated by Equation 3.30 approaches to higher values compared to $\overline{MSE}_{tri}$, making $SI_{cf} \rightarrow 1$

3.4.2 PV-OP Mapping Analysis

Quantification of stiction is an important requirement as well as detecting it. A method jointly used with non-linearity analysis method discussed in 3.3.1 was proposed by Choudhury et al. [2006b]. The fingerprint of process data in the presence of stiction (e.g. MV-OP plot in Figure 3.15) is discussed previously. However, as discussed in 3.4.1, usually the valve position signal is not available. In such cases, instead



(a) Sinusoidal Fitting



(b) Triangular Fitting

Figure 3.17: A Schematic Representation of Curve-Fitting Method

of MV data, PV can be used to characterize the shape of the plot. Choudhury et al. [2006b] state that since cyclic behavior exists both in PV and OP, the resulting plot of PV-OP shows similar cyclic patterns. An example of such a loop is given in Figure 3.18. As Figure 3.18b implies, the cyclic behavior is similar to ellipse shape. Having that feature, Choudhury et al. [2006b] proposed fitting an ellipse to PV-OP plot to characterize the amount of stiction. However, the raw plot of PV-OP shows somehow noisy behavior because of real measurement noise and disturbances. To overcome that problem, it is better to use a filter before the analysis. Choudhury et al. [2008] suggest using Wiener filter. Manolakis and Ingle [2011] describe that Wiener filter is an optimum filter which approximates the desired signal. However, true Wiener filter

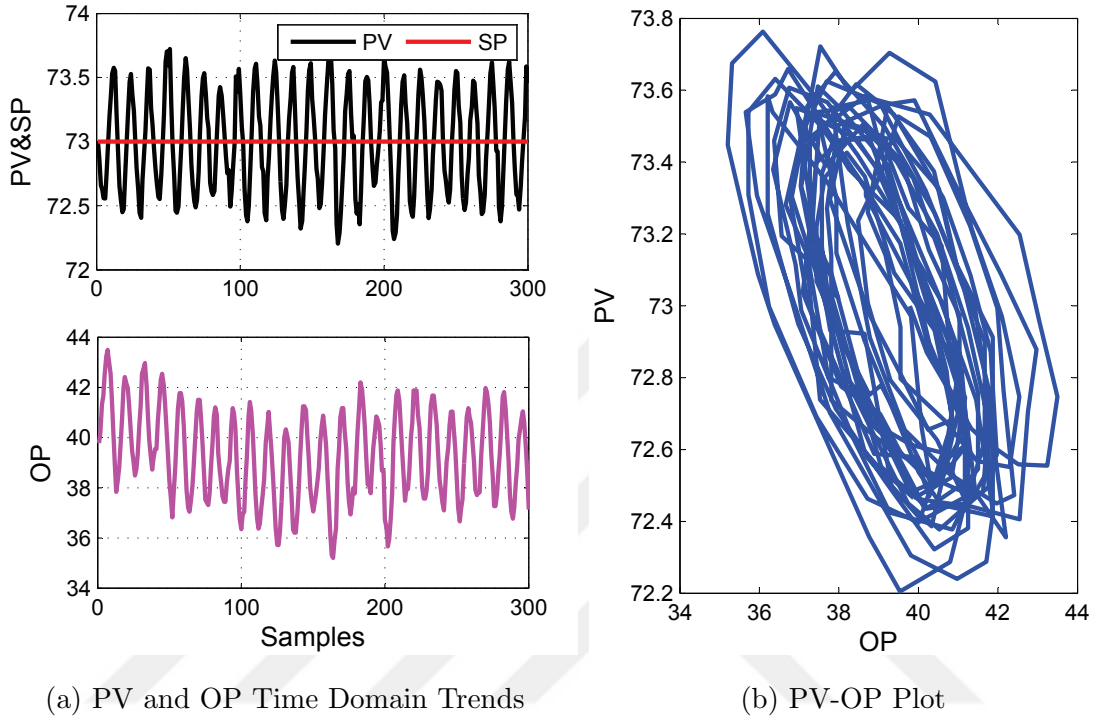


Figure 3.18: An Example of Loop Values for a Stiction Case with PV-OP Plot

requires the gain of noise at each frequency [Smith, 2003], which may not be trivial to determine if the desired signal is not known exactly. Manum [2006] states that an approximate Wiener filter can be used by zeroing out the unwanted frequencies. The frequencies are determined from the bispectral analysis described in 3.3.1. After filtering, a certain segment of data having the highest *regularity* (given in 3.2.4) is selected. Finally, the filtered and cropped PV and OP data are plotted and analyzed to fit an ellipse. The overall algorithm proposed by Choudhury et al. [2008] is given in Figure 3.19. There are several steps in the proposed algorithm. Key concepts are discussed below:

- *Filtering:* Choudhury et al. [2006b] suggest using Wiener filter to isolate frequencies shown up in bispectral analysis. However, true Wiener filter requires the gain of noise at each frequency. An alternative is to use approximate Wiener filter, which zeros-out unwanted frequencies. However, if the time domain data

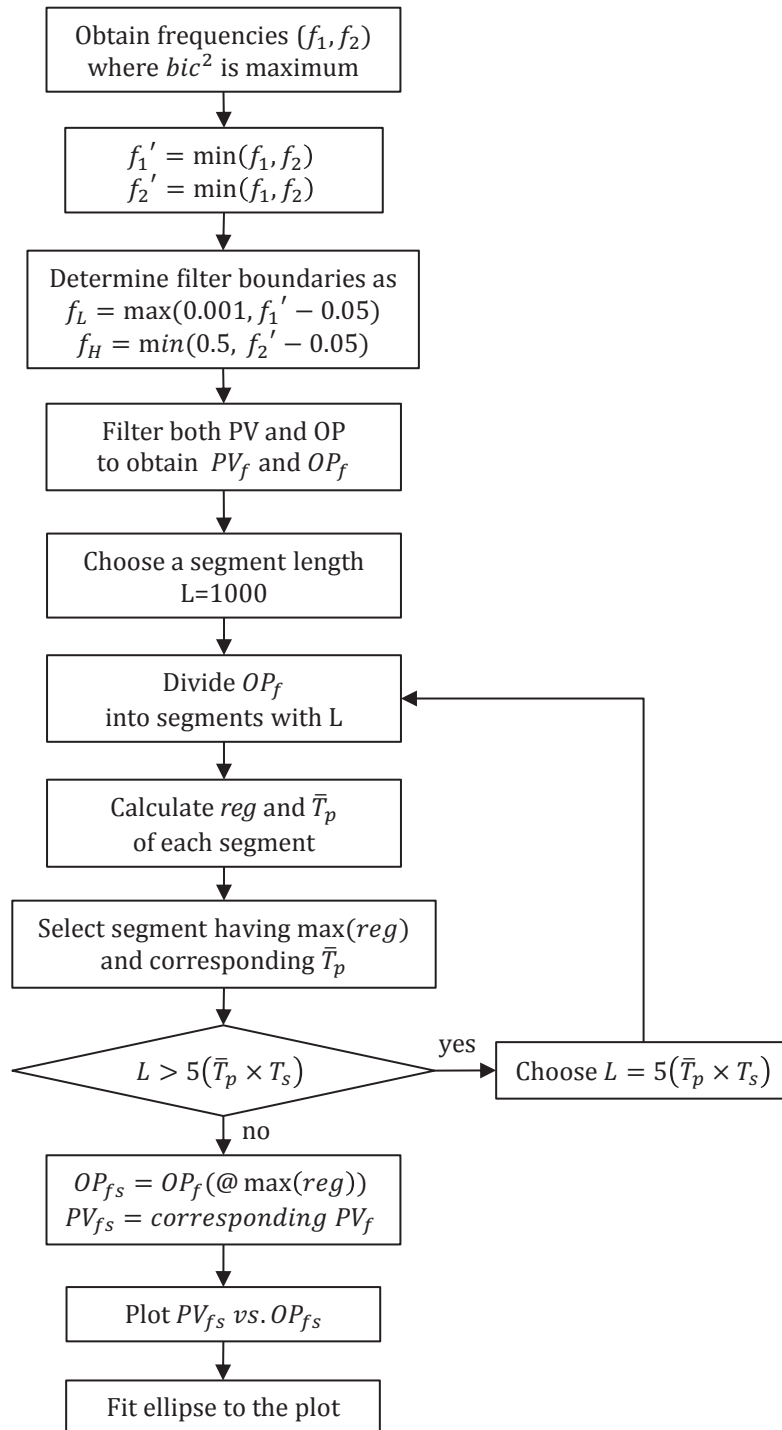


Figure 3.19: Algorithm Proposed for Stiction Detection with PV-OP Mapping

is not periodic with an integer multiple, the data is said to have discontinuities which result in a well-known "Gibbs phenomenon" [Nahin, 2006]. In such cases, an appropriate band pass filter can be used. For that specific purpose, a popular filter design method, *Parks-McClellan algorithm* can be used. It tries to minimize the errors both in the pass-bands and stop-bands [Oppenheim and Schaffer, 2011]. In addition to filter type selection, filter boundaries are also important. In their method, Choudhury et al. [2006b] propose a min-max selection with certain fixed frequencies. However, those are given for $Ts = 1s$; thus, maximum frequency becomes 0.5. If the squared bicoherence plot is obtained with true sampling frequency, one should be careful with the frequency selection.

- *Segmentation*: It is an important step in the proposed method; since, if most cyclic segment of OP data is used, it is easier and reliable to fit ellipse to data. Therefore, $\bar{T}_p$ is multiplied by T_s to obtain the true period. For the estimation of the period, the method proposed in 3.2.4 was suggested [Choudhury et al., 2006b].
- *Ellipse fitting*: Fitting an ellipse to plot of PV_{fs} vs. OP_{fs} makes enable to quantify the amount of stiction and hysteresis at the same time. One can use the method proposed by Gander et al. [1994]. First, following matrices are built as:

$$\mathbf{op} = x_1 = [OP_{fs}(1), OP_{fs}(2), \dots, OP_{fs}(N)]^T \quad (3.32)$$

$$\mathbf{pv} = x_2 = [PV_{fs}(1), PV_{fs}(2), \dots, PV_{fs}(N)]^T \quad (3.33)$$

The mathematical representation of a conic is given as [Gander et al., 1994]:

$$a_1x_1^2 + a_{12}x_1x_2 + a_2x_2^2 + b_1x_1 + b_2x_2 + c = 0 \quad (3.34)$$

In order to generalize the problem for the rotated and shifted ellipses, following transformation is introduced:

$$\mathbf{x} = \mathbf{Q}\bar{\mathbf{x}} + \mathbf{t} \quad (3.35)$$

In addition, Equation 3.34 can be written in compact form as:

$$\mathbf{x}^T \mathbf{A} \mathbf{x} + \mathbf{b}^T \mathbf{x} + c = 0 \quad (3.36)$$

where, $\mathbf{x} = [x_1, x_2]^T$ and $\mathbf{A} = [a_1 \ a_{12}/2; \ a_{12}/2 \ a_2]$ and $\mathbf{b} = [b_1 \ b_2]^T$. Substitution of Equation 3.35 into Equation 3.36:

$$\bar{\mathbf{x}}^T \mathbf{Q}^T \mathbf{A} \mathbf{Q} \bar{\mathbf{x}} + (2\mathbf{t}^T \mathbf{A} + \mathbf{b}^T) \mathbf{Q} \bar{\mathbf{x}} + \mathbf{t}^T \mathbf{A} \mathbf{t} + \mathbf{b}^T + c = 0 \quad (3.37)$$

Equation 3.37 can further be written in compact form such that:

$$\bar{\mathbf{x}}^T \bar{\mathbf{A}} \bar{\mathbf{x}} + \bar{\mathbf{b}}^T \bar{\mathbf{x}} + \bar{c} = 0 \quad (3.38)$$

where, $\bar{\mathbf{A}} = \mathbf{Q}^T \mathbf{A} \mathbf{Q}$, and $\bar{\mathbf{b}}^T = (2\mathbf{t}^T \mathbf{A} + \mathbf{b}^T) \mathbf{Q}$ and $\bar{c} = \mathbf{t}^T \mathbf{A} \mathbf{t} + \mathbf{b}^T + c$. Equation 3.38 can be solved by choosing $\mathbf{Q}$ so that $\bar{\mathbf{A}} = \text{diag}(\lambda_1, \lambda_2)$ and choose $\mathbf{t}$ so that $\bar{\mathbf{b}} = 0$, where λ_1 and λ_2 are stating the eigenvalues of $\mathbf{A}$. Then, Equation 3.38 can be reduced to:

$$\lambda_1 \bar{x}_1^2 + \lambda_2 \bar{x}_2^2 + \bar{c} = 0 \quad (3.39)$$

Equation 3.39 defines an ellipse if $\lambda_1 > 0$, $\lambda_2 > 0$ and $\bar{c} < 0$. In that point, Bookstein [1979] proposes to solve the following least squares problem:

$$\bar{\mathbf{x}}^T \bar{\mathbf{A}} \bar{\mathbf{x}} + \bar{\mathbf{b}}^T \bar{\mathbf{x}} + \bar{c} \approx 0 \quad (3.40)$$

$$\lambda_1 \bar{x}_1^2 + \lambda_2 \bar{x}_2^2 = a_1^2 + 2a_{12}^2 + a_2^2 = 1 \quad (3.41)$$

where, $x_1 = \mathbf{op}$ and $x_2 = \mathbf{pv}$.

Gander et al. [1994] propose using singular value decomposition (SVD) to solve the least squares problem by constructing the following matrices:

$$\mathbf{u} = (a_1, 2a_{12}, a_2, b_1, b_2, c)^T \quad (3.42)$$

$$\mathbf{v} = (b_1, b_2, c)^T \quad (3.43)$$

$$\mathbf{w} = (a_1, \sqrt{2}a_{12}, a_2)^T \quad (3.44)$$

$$S = \begin{bmatrix} x_1(1) & x_2(1) & 1 & x_1(1)^2 & \sqrt{2}x_1(1)x_2(1) & x_2(1)^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1(N) & x_2(N) & 1 & x_1(N)^2 & \sqrt{2}x_1(N)x_2(N) & x_2(N)^2 \end{bmatrix} \quad (3.45)$$

QR decomposition of S yields:

$$\begin{bmatrix} R_{11} & R_{12} \\ 0 & R_{22} \end{bmatrix} \approx 0 \quad (3.46)$$

where, $R_{22} \times w = 0$. SVD of R_{22} yields $U\Sigma V^*$ where $\mathbf{w} = V_3^*$. Then $\mathbf{v}$ can be found as:

$$\mathbf{v} = -R_{11}^{-1} R_{12} \mathbf{w} \quad (3.47)$$

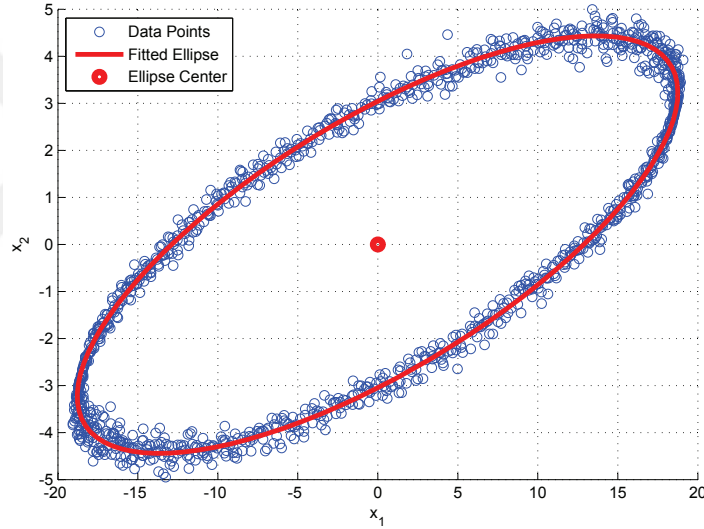


Figure 3.20: Evaluation of the Proposed Ellipse Fitting Algorithm

Then, the amount of stiction and hysteresis are found as [Choudhury et al., 2006a]:

$$stiction = \frac{2L_{maj} \times L_{min}}{\sqrt{L_{maj}^2 \sin^2 \theta + L_{min}^2 \cos^2 \theta}} \quad (3.48)$$

$$hysteresis = \frac{2L_{maj} \times L_{min}}{\sqrt{L_{maj}^2 \cos^2 \theta + L_{min}^2 \sin^2 \theta}} \quad (3.49)$$

where, L_{maj} and L_{min} are the major and minor axes of the fitted ellipse, and θ is the rotation angle, respectively. Then, the coordinates of the center of the ellipse are found:

$$\mathbf{t} = -0.5 \times \mathbf{A}^{-1} \mathbf{b} \quad (3.50)$$

Substituting $\mathbf{t}$ and $\mathbf{b}$ into Equation 3.38, one can obtain $\bar{c}$. Then, L_{maj} and L_{min} can be calculated such that:

$$L_{maj} = \sqrt{\frac{-\bar{c}}{\max(\lambda_1, \lambda_2)}}, L_{min} = \sqrt{\frac{-\bar{c}}{\min(\lambda_1, \lambda_2)}} \quad (3.51)$$

Finally, rotation angle θ is calculated as:

$$\theta = \arctan 2(V_{\lambda_2}, V_{\lambda_1}) \quad (3.52)$$

where $\arctan 2$ stands for *Four-quadrant arctangent* function, and V_{λ_1} and V_{λ_2} are the eigenvectors of corresponding eigenvalues.

Jelali and Huang [2010] propose checking the quality of fitted ellipse by introducing the confidence-limit ellipses. To quantify the quality, the fraction of data points within the enclosed region of inner and outer ellipses can be calculated. Estimation starts with computing the variance of residuals as [O’Leary and Zsombor-Murray, 2004]:

$$\sigma_{resid} = \left(\sum_{i=1}^N resid_i^2 \right)^{1/2} \quad (3.53)$$

The equation of confidence ellipses is obtained as:

$$a_1 x_1^2 + a_{12} x_1 x_2 + a_2 x_2^2 + b_1 x_1 + b_2 x_2 + c \pm f \sigma_{resid} / \sqrt{N} = 0 \quad (3.54)$$

where f stands for the degree of confidence interval. For $cL \approx 95\%$, $f = 2$. Figure 3.21 represents confidence ellipses and the stiction and hysteresis amounts.

3.4.3 Summary of Stiction Detection Methods

In 3.4.1 and 3.4.2, two different methods to detect stiction are given. Method proposed by He et al. [2007] makes use of fingerprints in OP data in case of stiction, whereas method proposed by Choudhury et al. [2006b] makes use of both PV and OP data. In terms of complexity, curve-fitting method seems to be the easiest one to implement; since, it only requires fitting of sinusoids and triangles. In addition, filtering to eliminate noise in the signal is not required usually. Moreover, piece-wise

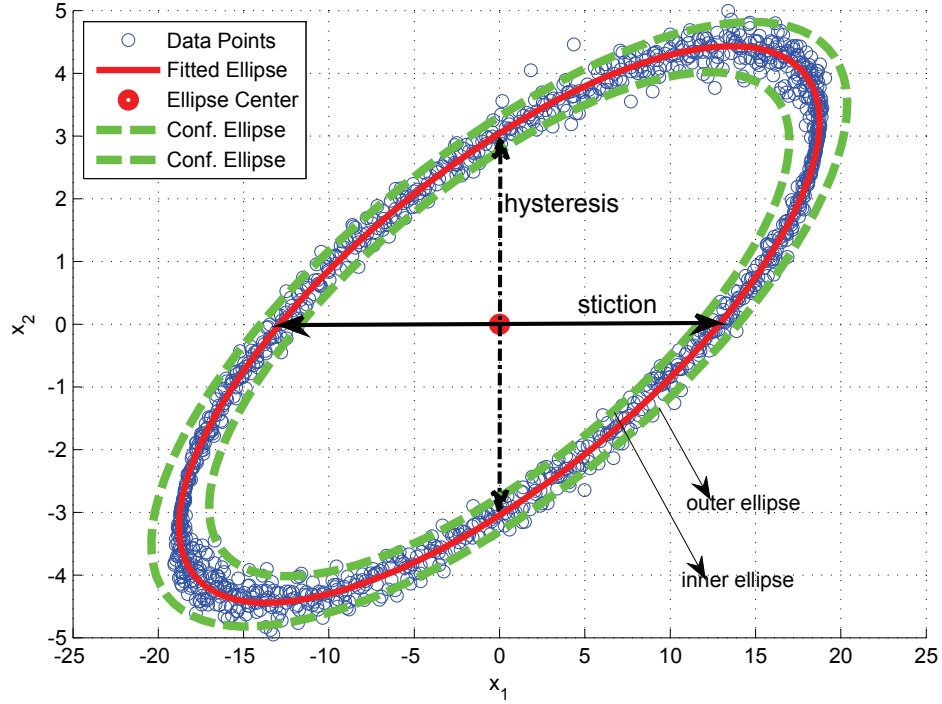


Figure 3.21: Confidence Ellipses and Stiction & Hysteresis Amounts

fitting of both triangles and sinusoids makes enable to catch asymmetrical signals. However, as discussed in [He et al., 2007], in some cases, the method falls into no decision region, which may cause to neglect possible problems. On the other hand, the method does not require advanced signal processing tools in contrast to PV-OP mapping analysis suggested by Choudhury et al. [2006b]. However, it lacks quantification of stiction. Here, PV-OP mapping analysis provides valuable information. It enables to detect the amount of stiction and hysteresis in control valves. In addition, in the presence of some assumptions, the method can be said to be robust to non-linear valves (e.g. equally percentage and quick opening) [Choudhury et al., 2008]. However, when considered jointly with bispectral analysis method given in 3.3.1, there are several pre-parameters to be selected. Although, some defaults have been suggested in [Choudhury et al., 2008], some tuning may require to get more robust results, especially in the selection of filter boundaries [Manum, 2006]. In addition, it is reported

that ellipse shape might be lost in case of highly integrating processes [Kvam, 2009]. Furthermore, with varying loads, one can obtain several ellipses in parallel, which may be hard to detect with the method proposed in [Choudhury et al., 2006b]. Finally, as suggested in [Jelali and Huang, 2010], a confidence limit may be required to get reliable results.

Other than methods discussed in this thesis, there are several other studies in the literature to detect stiction. Those include, [Kano et al., 2004] which makes use of MV-OP shapes, [Yamashita, 2006] which makes use of local trends in MV-OP shapes, [Horch, 2000] which makes use of cross-correlation of PV and OP signal and analysis of the histogram of second derivate of PV signal. Here, only methods in [He et al., 2007] and [Choudhury et al., 2006b] are discussed; since, they are either popular in commercial software or industrially used.

Finally, Jelali and Huang [2010] summarize the expectations from stiction detection methods as:

- Use of available data (i.e. PV, SP and OP signals)
- Be robust to noise and non-stationary data
- Work as much automatic as possible with the least user input requirements
- Have no uncertainty region
- Quantify the problems (preferably stiction; hysteresis adds more)

Chapter 4

ROOT CAUSE ANALYSIS OF MULTIPLE LOOPS

Detection of poor performing control loops is presented and discussed extensively in Chapter 2. Further, in Chapter 3, the methods to analyze and diagnose those poor performing loops in detail are given. Tuning problems, oscillating external disturbances, valve problems cause performance degradation in control loops. However, plants cannot be considered as single units. Mostly, there are lots of unit operations, equipment and streams connected to each other even in a simple plant. Thornhill et al. [2003b] states that recycle streams and heat integrations cause disturbances to propagate. Having that complexity, a problem arising in a specific location propagates and affects other processes. These problems are called *plant-wide disturbances*. These disturbances mostly show up as oscillations in control loops. Fixing these oscillations improve process performance, increase profit and safety [Shunta, 1995]. Therefore, automatic detection of source of disturbance with routine operating data is a very crucial requirement. Approaches cover finding clusters of control loops which have similar oscillation periods and non-linearity analysis [Ordys et al., 2006]. Figure 4.1 adopted from Thornhill and Horch [2007] represents the categories of plant-wide disturbance detection methods.

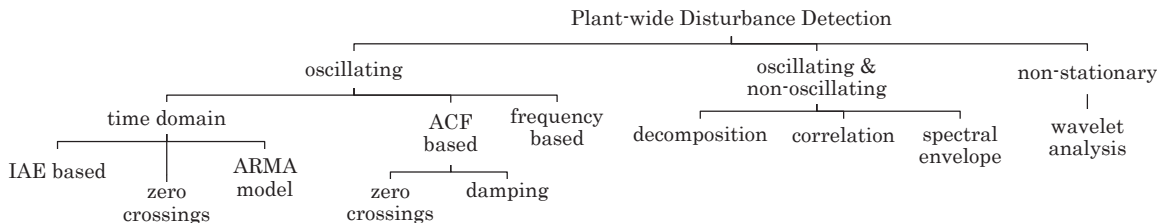


Figure 4.1: Methods for Plant-wide Disturbance Detection

For that purpose, one can use one of the oscillation detection methods such as PSD (frequency based) or regularity of ACF (ACF based) by Thornhill et al. [2003a]. However, PSD mostly requires visual inspection and detection of oscillation frequency from PSD is not suggested [Jelali and Huang, 2010]. The reason is that either inappropriate selection of DFT length can cause spectral leakage or low SNR can suppress the exact frequency location. On the other hand, regularity of ACF is destroyed in case of multiple oscillations. In that aspect, finding similarities in categorical time series with a robust method have been first studied by Stoffer et al. [1993]. In this approach, using Fourier transform, common frequencies of a bulk data have been extracted. Later, McDougall et al. [1997] extended the proposed approach to real-valued time series. Spectral envelope derives optimal coefficients to extract common frequencies in a bulk dataset. Having that feature, one can easily analyze different signals having different order of magnitudes. Jiang et al. [2007] used that approach and developed a method to find oscillating variables and the root cause of oscillation. Before doing the analysis, the variables of control loops (PV, MV, OP and SP) or indicators (only PV) must be selected. Spectral envelope is defined as:

$$\lambda(\omega) = \sup \left\{ \frac{\beta^* \mathbf{P}_{\mathbf{x}}(\omega) \beta}{\beta^* \mathbf{V}_{\mathbf{x}} \beta} \right\} \quad (4.1)$$

Equation 4.1 represents the largest portion of signal in PSD. Stoffer [1999] states that the term "envelope" represents the enclosure placed onto a specific frequency at spectrum. Due to that, first PSD must be estimated with input vector defined as:

$$\mathbf{x}(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_z(t) \end{bmatrix}, \quad \mathbf{X} = \begin{bmatrix} \mathbf{x}(0) & \mathbf{x}(1) & \dots & \mathbf{x}(N-1) \end{bmatrix}$$

$$= \begin{bmatrix} x_1(0) & x_1(1) & x_1(2) & \dots & x_1(N-1) \\ x_2(0) & x_2(1) & x_2(2) & \dots & x_2(N-1) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_z(0) & x_z(1) & x_z(2) & \dots & x_z(N-1) \end{bmatrix} \quad (4.2)$$

where each row in Equation 4.2 represent a set of normalized time domain data belonging to each variables ($1 \rightarrow z$). Normalization is done by subtracting mean of each variable and dividing the standard deviation. It is an important step because normalization makes comparison between variables and estimation of envelope easier. After having normalized input data, the periodogram is estimated as:

$$\hat{\mathbf{I}}_N(\omega_f) = \frac{1}{N} \left[\sum_{t=0}^{N-1} \mathbf{x}(t) \exp(-2\pi i t \omega_f) \right] \left[\sum_{t=0}^{N-1} \mathbf{x}(t) \exp(-2\pi i t \omega_f) \right]^* \quad (4.3)$$

In Equation 4.3, $*$ represents conjugate and transpose operation. In order to smooth the periodogram estimated, moving average filter is applied such that:

$$\hat{\mathbf{P}}_{\mathbf{X}}(\omega_f) = \sum_{j=-r}^r h_j \hat{\mathbf{I}}_N(\omega_{f+j}) \quad (4.4)$$

PSD of continuous signal is estimated by DFT. However, maximum frequency that DFT can resolve is the half of Nyquist frequency [Salkind, 2006]. Due to that, the maximum frequency is limited to total time period constructed from half of the all data points. For example, for $N = 500$ data points sampled at $Ts = 5$ second, maximum frequency is $500/2 \times 5 = 1250 \text{second}$. Then, DFT can resolve frequencies $[0, Ts/2, Ts, 3Ts/2, \dots, N \times Ts/2]$. ω_f in Equation 4.4 represents those discrete frequencies. After that, to smooth PSD, the coefficients h_j are selected such that:

$$\sum_{j=-r}^r h_j = 1 \quad (4.5)$$

Satisfying Equation 4.5, coefficients can be selected as $h_j = (r - |j| + 1)/(r + 1)^2$, for $|j| = 1, 2, \dots, r$. Number of smoothing coefficients r is chosen depending on the desired smoothness. Selecting $r = 2$ results in $h_0 = 3/9, h_1 = 2/9, h_2 = 1/9$, which is enough in most of the cases. One can also increase the degree to higher numbers but should be careful about smoothing the actual frequency peaks [Stoffer et al., 2000]. Then one can estimate $\lambda(\omega)$ using $\hat{\mathbf{P}}_{\mathbf{X}}(\omega_f)$ and $\hat{\mathbf{V}} = \text{diag}(\hat{\mathbf{V}}_{\mathbf{X}})$ by rewriting Equation 4.1 as:

$$\hat{\lambda}(\omega_f) = \sup \left\{ \frac{\boldsymbol{\beta}^* \hat{\mathbf{P}}_{\mathbf{X}}(\omega_f) \boldsymbol{\beta}}{\boldsymbol{\beta}^* \hat{\mathbf{V}} \boldsymbol{\beta}} \right\} \quad (4.6)$$

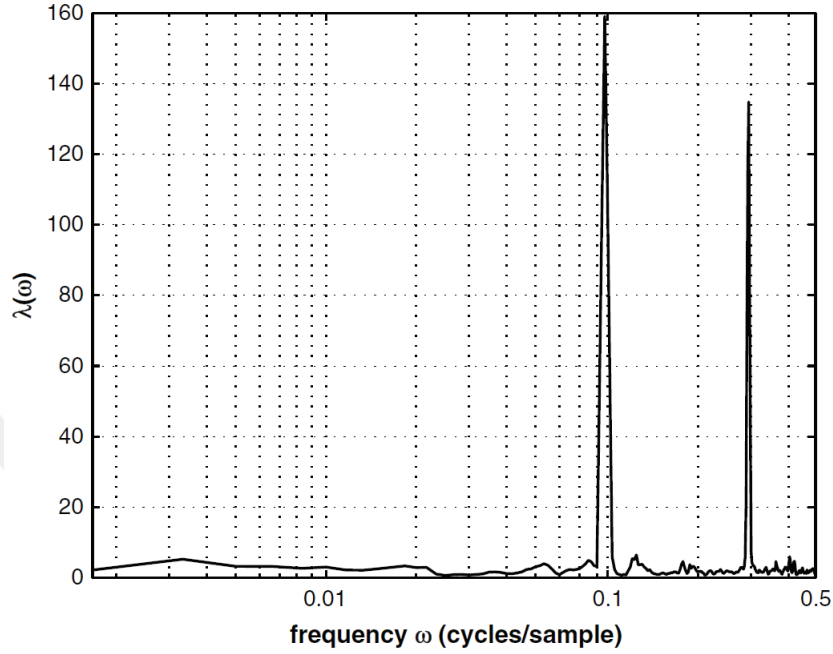


Figure 4.2: An Example of Spectral Envelope

From Equation 4.6, it is clear that $\hat{\lambda}(\omega_f)$ is the largest portion of signal at specific frequency ω_f . Then, the eigenvalue is estimated by determinant equation of:

$$|\mathbf{P}_{\mathbf{X}}(\omega) - \lambda(\omega)\mathbf{V}_{\mathbf{X}}| = 0 \quad (4.7)$$

Then, optimal scaling vector $\beta(\omega)$ can be estimated as:

$$\lambda(\omega)\mathbf{V}_{\mathbf{X}}\beta(\omega) = \mathbf{P}_{\mathbf{X}}\beta(\omega) \quad (4.8)$$

Since all the variables are normalized before, $\hat{\mathbf{V}} = \text{diag}\{1, 1, \dots, 1\}$. Thus, Equation 4.8 reduces to $\beta^*\hat{\mathbf{V}}\beta = 1$. At the end, one can easily state that $\hat{\lambda}(\omega_f)$ is the largest eigenvalue of $\hat{\mathbf{P}}_{\mathbf{X}}(\omega_f)$, and $\hat{\beta}^*(\omega_f)$ is the corresponding eigenvector. Finally, one can estimate the spectral envelope for each frequency. Figure 4.2 shows a bank of simulated signals having 12 variables oscillating at frequencies 0.1 Hz and 0.3 Hz, adopted from Jiang et al. [2007].

After detection of common frequencies, one can determine which variables are oscillating at those frequencies. To that end, Stoffer [1999] proposed applying statistical

hypothesis testing on $\hat{\beta}(\omega_f)$. He states that if $\hat{\lambda}(\omega_f)$ has a distinct root, for large number of observations $v_N[\hat{\beta}(\omega) - \beta(\omega)]$ converges to multivariate normal distribution and $v_N[\hat{\lambda}(\omega) - \lambda(\omega)]/\lambda(\omega)$ converges to standard normal distribution. If proposed moving average smoothing in Equation 4.5 is used, v_N becomes:

$$v_N = \left(\sum_{j=-r}^r h_j^2 \right)^{1/2} \quad (4.9)$$

Then, one can write the asymptotic covariance matrix of the optimum scaling vector $\hat{\beta}(\omega)$ as:

$$\mathbf{V}_\beta = v_N^{-2} \lambda_1(\omega) \sum_{i=2}^z \lambda_i(\omega) [\lambda_1(\omega) - \lambda_i(\omega)]^{-2} \beta_i(\omega) \beta_i^*(\omega) \quad (4.10)$$

In Equation 4.10, $\lambda_1(\omega) = [\lambda(\omega), \lambda_2(\omega), \dots, \lambda_z(\omega)]$ are the eigenvalues of $\mathbf{P}_\mathbf{x}(\omega)$ in decreasing order and $\beta_1(\omega) = [\beta(\omega), \beta_2(\omega), \dots, \beta_z(\omega)]$ are the corresponding eigenvectors.

Then, the statistical test on $\hat{\beta}(\omega)$ can be written as:

$$TestStat_i(\omega) = \frac{2 |\hat{\beta}_{1,i}(\omega) - \beta_{1,i}(\omega)|^2}{\sigma_i(\omega)} \quad (4.11)$$

where $i = 1, 2, \dots, z$ and $\sigma_i(\omega) = \text{diag}(\hat{\mathbf{V}}_\beta)_i$.

Stoffer [1999] states that defined $TestStat_i(\omega)$ in Equation 4.11 converges to a Chi-squared (χ^2) distribution with 2 degrees of freedom. Then, for a certain confidence level (cL), if $TestStat_i(\omega) > \chi_{cL,2}^2$, the variable i is said to be oscillating at frequency ω . One can select $\chi_{0.001,2}^2 = 13.816$ for $cL = 99.9\%$ or $\chi_{0.01,2}^2 = 9.210$ for $cL = 99\%$.

Detection of common frequencies and determining the oscillating signals at those frequencies give valuable information about the analyzed multivariate data. By using spectral envelope, one can detect plant-wide oscillations. However, locating the source of plant-wide disturbance is crucial since, the units in the plants are connected each other by recycling streams, heat integrations and even simple upstream and downstream connections, problems arising in a specific location propagates and affects other loops. With that goal, based on spectral envelope, Jiang et al. [2007] proposed *OCI* index which gives an indication about the root cause of those oscillations. *OCI*

represents the relative contribution of a variable to that specific frequency and can be calculated as:

$$OCI_i(\omega) = \frac{\hat{\beta}_{1,i}(\omega)}{2\sigma_{\hat{\beta}}(\omega)} \quad (4.12)$$

The term $\sigma_{\hat{\beta}}(\omega)$ in Equation 4.12 represents the standard deviation of all optimal scaling coefficients at a certain frequency ω for all variables. Jiang et al. [2007] state that variables having $OCI_i(\omega) > 1$ are the most probable causes of plant-wide oscillations at frequency ω . They also state that in case of no root cause, OCI values will be less than one. However, in such cases, OCI can be beneficial to sort variables according with respect to their contributions at frequencies identified in the spectral envelope.

Chapter 5

CASE STUDIES

5.1 Simulation

In this part of the thesis, to clarify the root cause detection algorithm discussed above, a simulation was used. The model was designed with Aspen HYSYS® software and simulated dynamically. Figure 5.1 shows the control structure of the simulated column. The controllers at the top are the column (C-1) top temperature controller

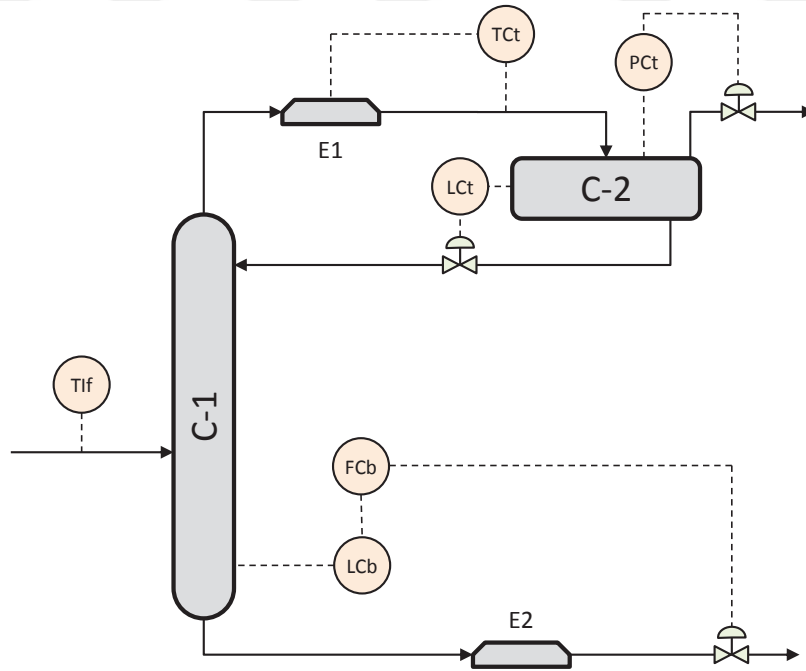


Figure 5.1: Simulated Column

TCt, overhead drum (C-2) pressure controller PCt, and overhead drum level controller LCt. At the bottom, the level is controlled by LCb in cascade with flow controller FCb. Finally, the temperature of the feed is measured with Tif.

First, at steady state conditions, the spectral envelope of the controller data was obtained and given in Figure 5.2. The figure indicates that at normal conditions, there

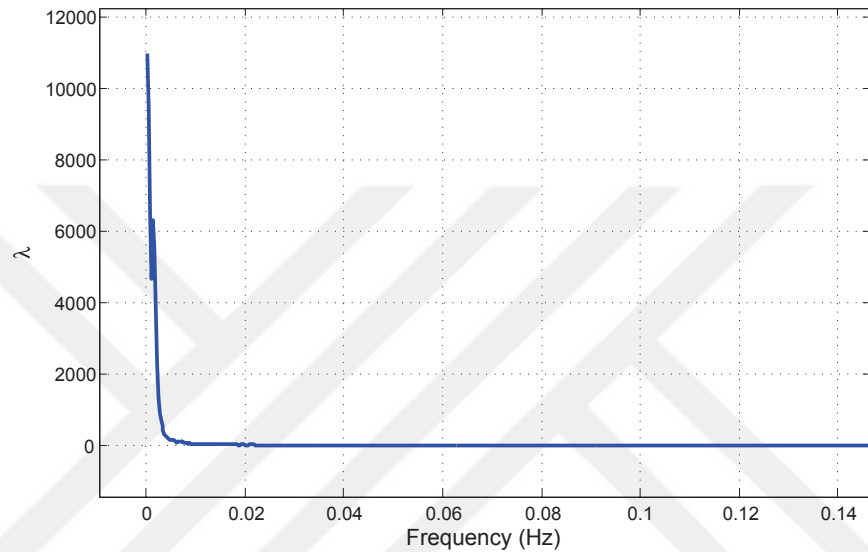


Figure 5.2: Spectral Envelope of Simulation Case Study (Normal Conditions)

does not exist any peak in the envelope. This means that the loops are not oscillating. After that, a sinusoidal temperature disturbance was given to column feed stream with a period of 300s. As stated before, the column feed temperature is measured with TIf. The simulation was let to run for a while and data was collected. Figure 5.3 shows the spectral envelope covering the sinusoidal disturbance. The peak at frequency 0.0333 Hz (period of 300s) shows that some of the loops are oscillating in that frequency. Table 5.1 summarizes the *TestStat* and *OCI* values for each controller. Table 5.1 shows that the indicator TIf has the highest *OCI* value. Then, PCt, TCt and LCt follow. The result is physically meaningful since the variations in the column inlet temperature changes the vapor fraction of the feed stream. Then, the stream enters the column and the amount of vapor going up changes. The first effect is observed in the column top pressure which is controlled by PCt in this case. Similarly, the top temperature of the column changes accordingly. The method correctly identified the root cause.

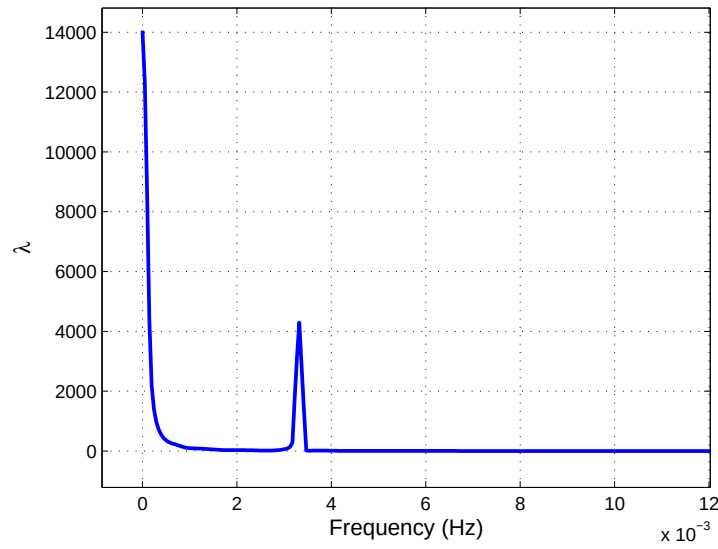


Figure 5.3: Spectral Envelope of Simulation Case Study (Sinusoidal Disturbance)

Table 5.1: Spectral Envelope Analysis for Simulation

Loop Name	<i>TestStat</i>	<i>OCI</i>
TIf	PV: 154319	PV: 1.13
PCt	PV: 1054720	PV: 1.12
	OP: 1004438	OP: 1.12
TCt	PV: 779257	PV: 1.12
	OP: 322880	OP: 1.12
LCt	PV: 86462	PV: 1.07
	OP: 13613	OP: 0.98
FCb	PV: 7018	PV: 0.59
	OP: 1638	OP: 0.18
LCb	PV: 80823	PV: 0.07
	OP: 2.753	OP: 0.01

5.2 Industrial Loops

In this part of the thesis, a refinery unit of Turkish Petroleum Refineries Corporation located at Izmit Refinery is examined. The unit processes an intermediate product to meet the specifications and is composed of mainly a reactor (C3) and a distillation column (C1). In Figure 5.4, E's represent the heat exchangers, C's represent the columns and drums and F represents the furnace. In the control system, FFC's represent flow ratio controller, FC's represent flow controller, PC's represent pressure controller, TC's represent temperature controller and finally LC's represent level controller.

To this end, total of 22 loops were monitored for 1-month interval with $T_s = 15s$. Each day contains 5760 samples. In order to analyze data in details, the days were divided into 5 segments having 1152 samples each. Finally 155 data segments were obtained covering 1-month interval. Data was not filtered before. For the analyses, CPM algorithm (Figure 1.6) given in Chapter 1 was used. First, the performances of control loops were assessed with the methods given in Chapter 2 and then poor performing loops were further analyzed with the techniques given in Chapter 3. Finally, all loops were analyzed in terms of plant-wide disturbance with the method given in Chapter 4.

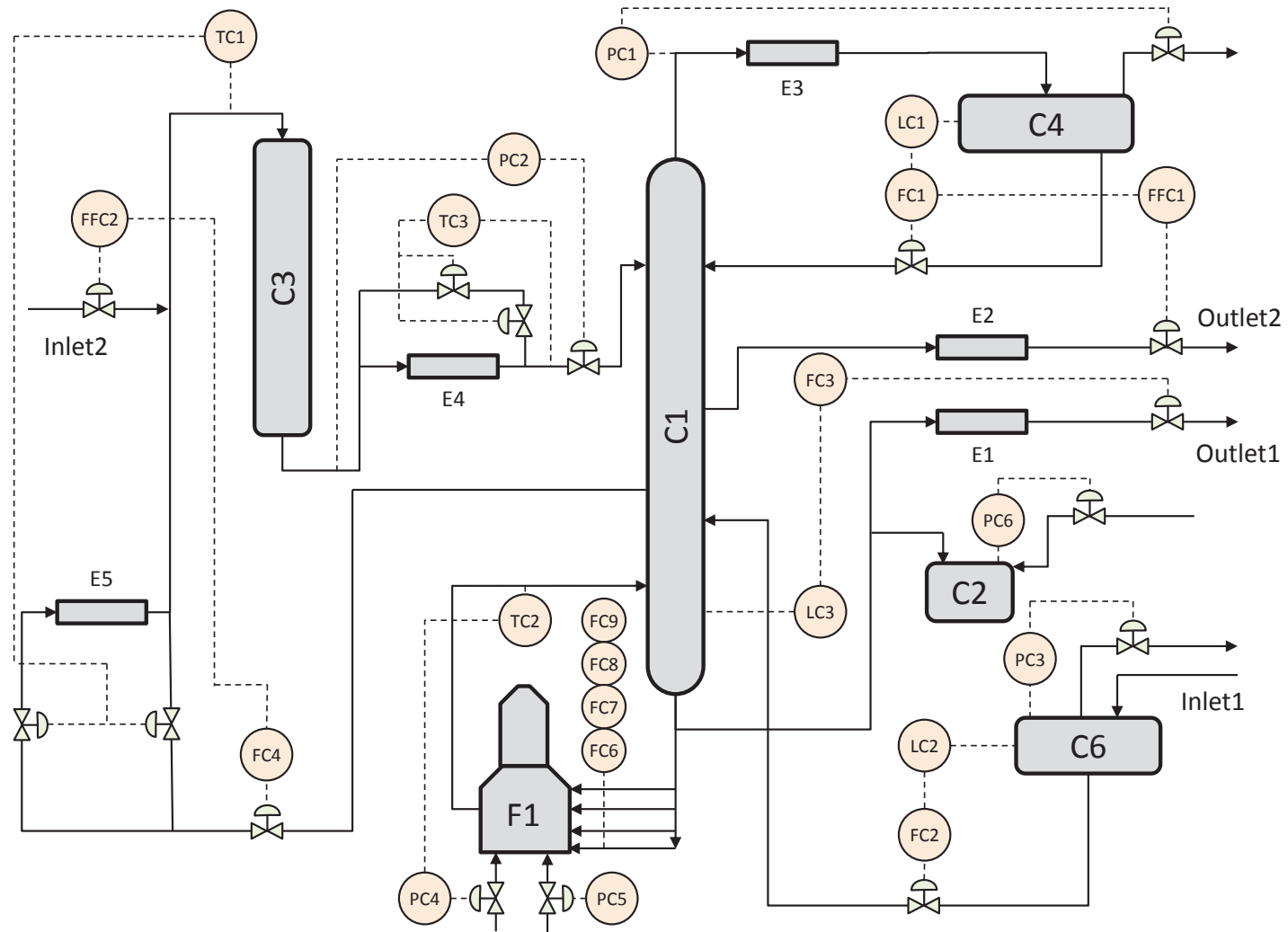


Figure 5.4: PFD and Control Structure of the Plant

5.2.1 Performance Assessment

For performance assessment two different algorithms were applied simultaneously with the same parameters. These were AR-LS (2.3.1) and FCOR (2.3.2). For model order (m), 30 was selected. Delays (k) were determined with either prior process knowledge or visual inspection of process trends. For each segment having 1152 samples, all data was used to assess the performance. Preliminary analysis showed that AR-LS and FCOR algorithms did not differ. Therefore, FCOR algorithm was selected as basis to assess performances. Figure 5.5 shows the assessment results for loop FFC1. After selecting the performance assessment algorithm, control modes were examined.

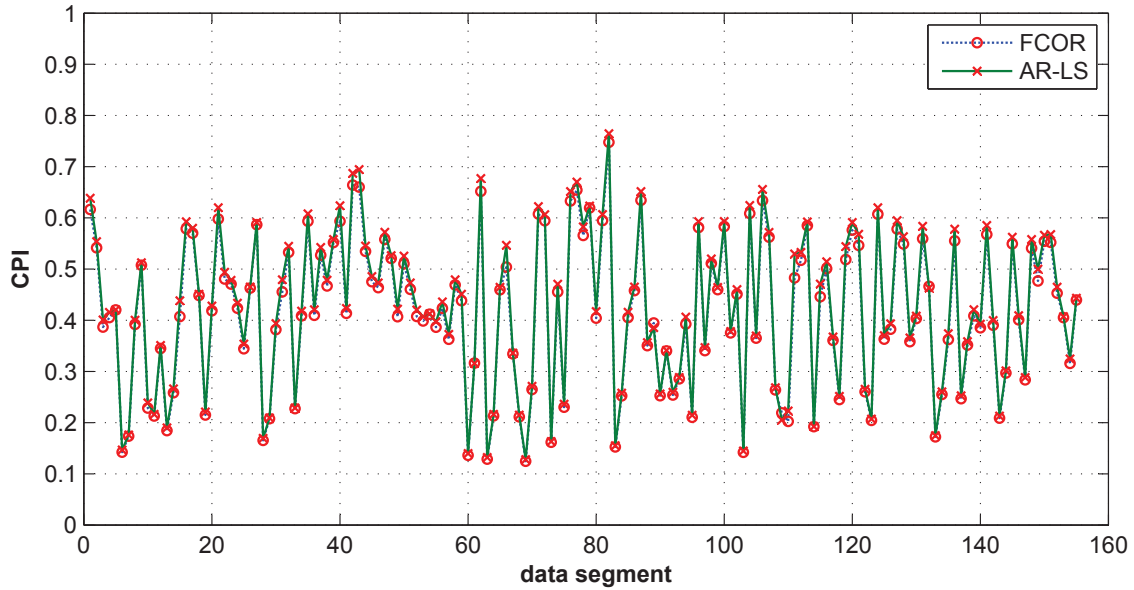


Figure 5.5: Comparison of AR-LS and FCOR Algorithms for FFC1

As discussed in 2.3.4, during the assessment period, controllers are expected to be in automatic mode. However, due to several reasons, their modes might be changed to manual. Taking the possibilities discussed in 2.3.4 into account, the method proposed in Longhi et al. [2012], "Grade" approach which penalizes the manual modes and saturation times, was used.

Following figures show the performances of the controllers for 1-month period.

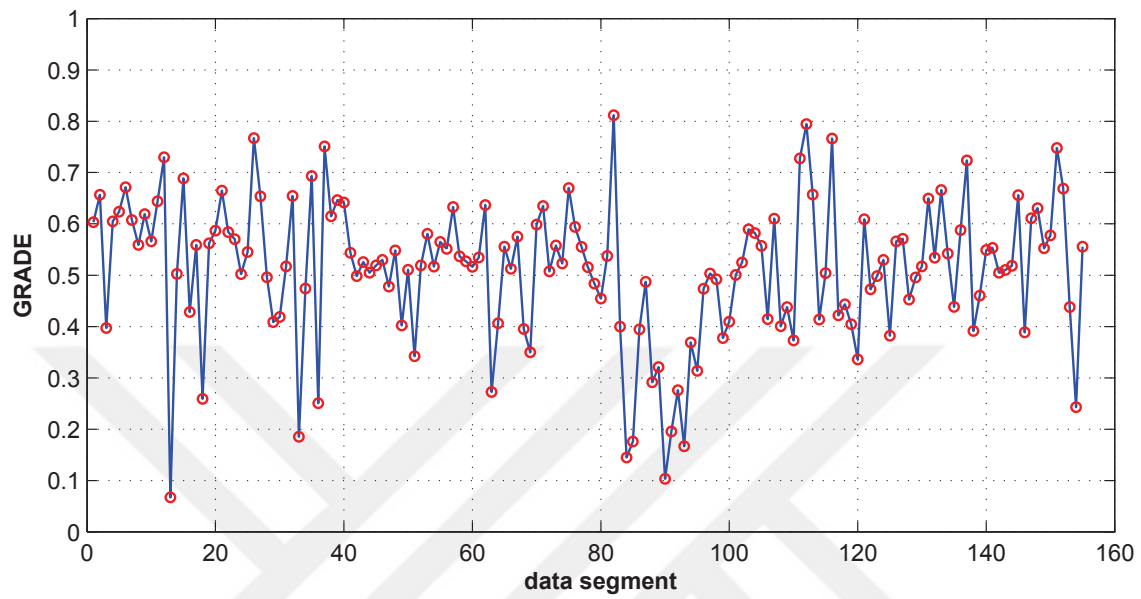


Figure 5.6: Grade for FFC1

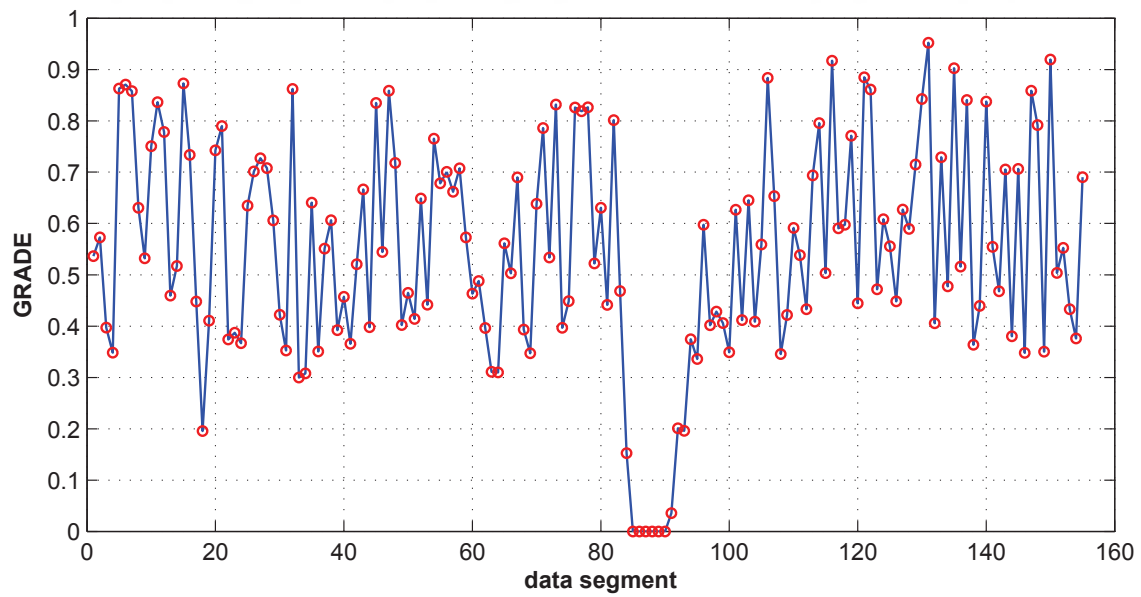


Figure 5.7: Grade for FFC2

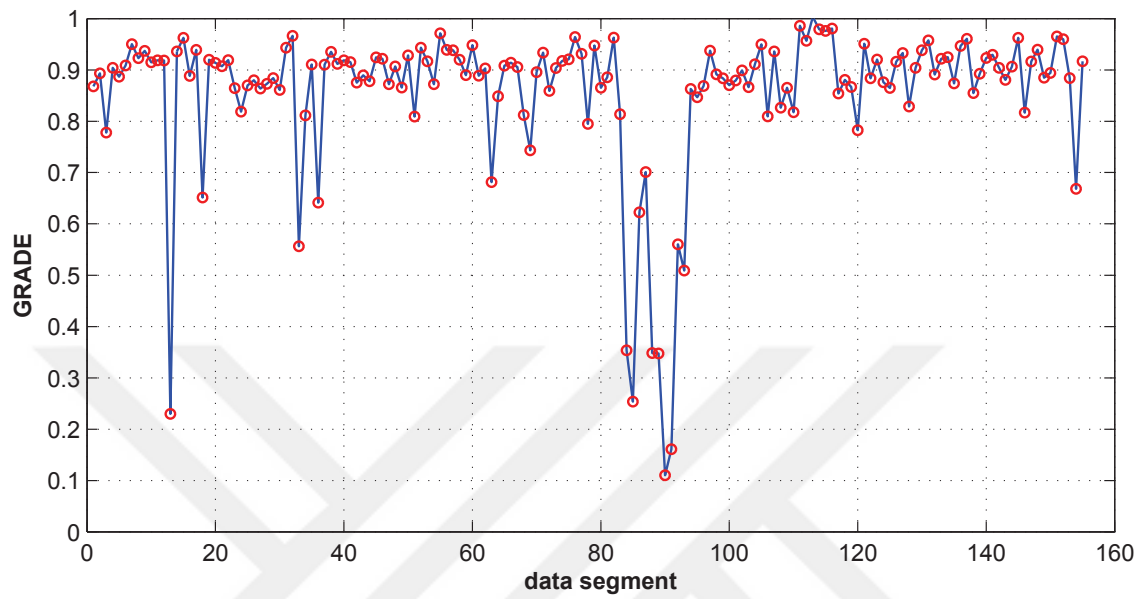


Figure 5.8: Grade for FC1

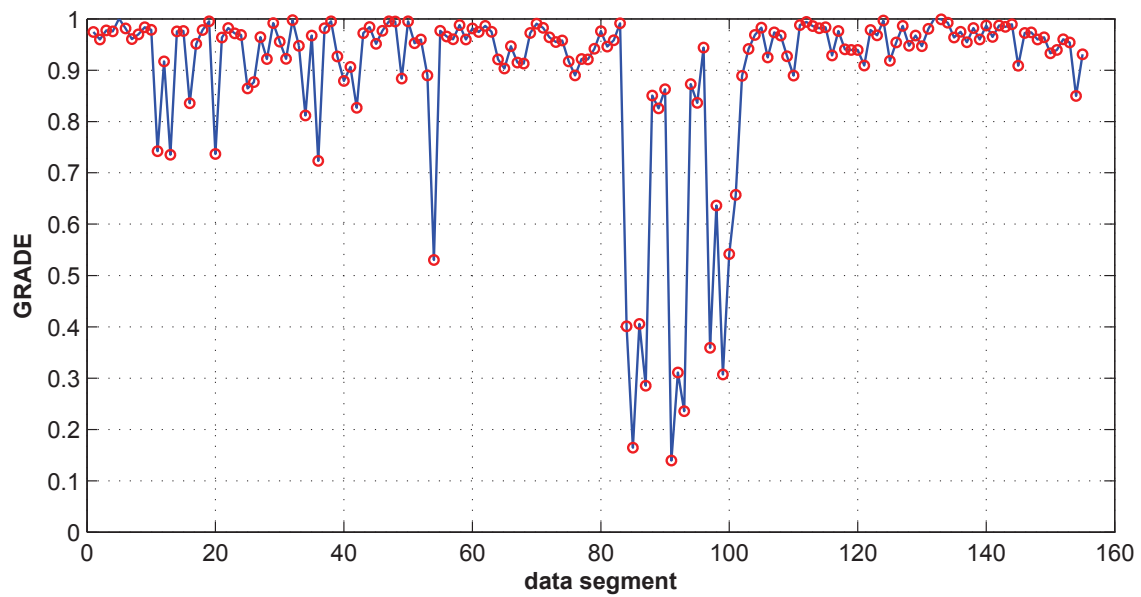


Figure 5.9: Grade for FC2

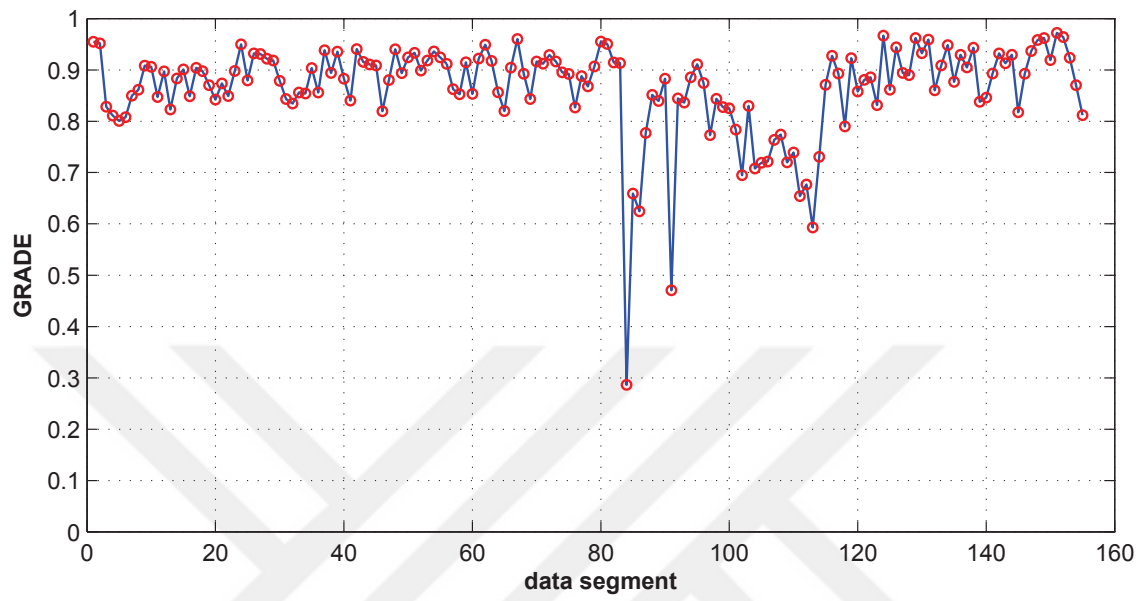


Figure 5.10: Grade for FC3

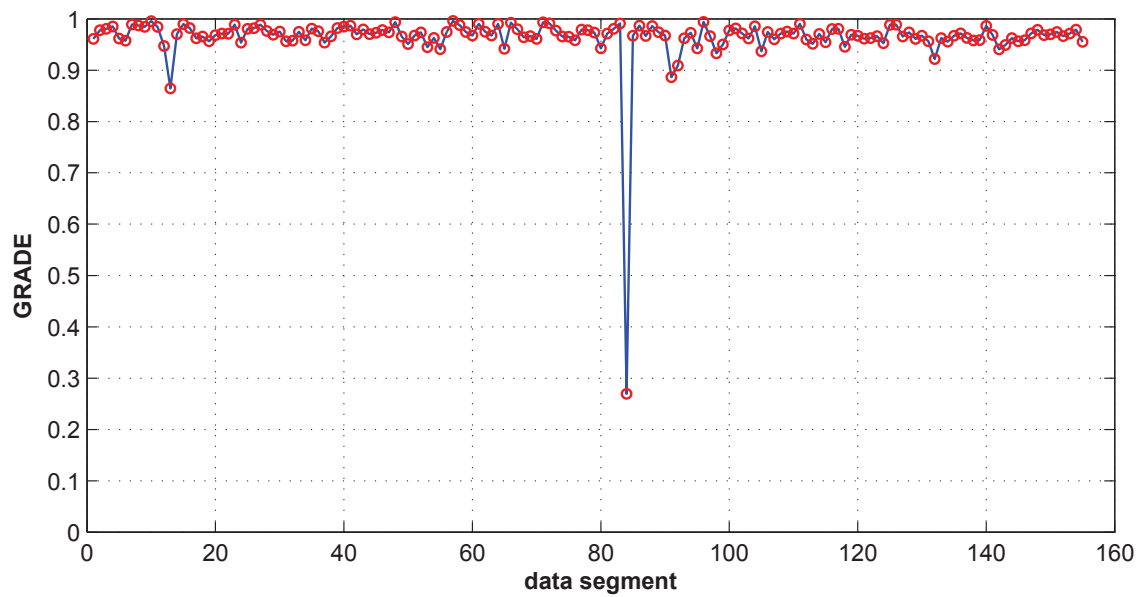


Figure 5.11: Grade for FC4

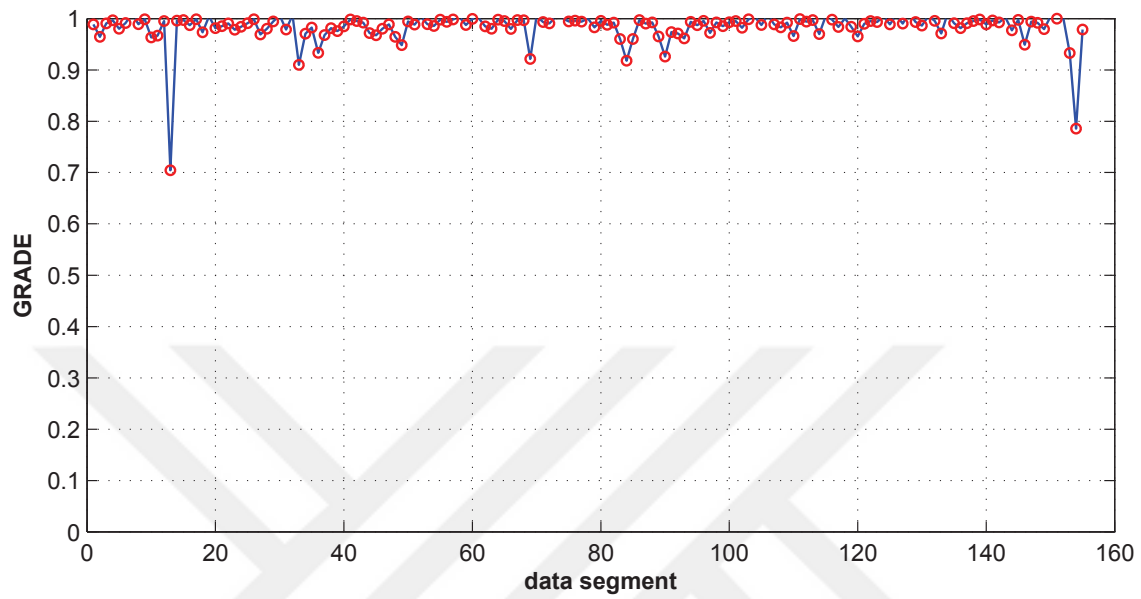


Figure 5.12: Grade for FC6

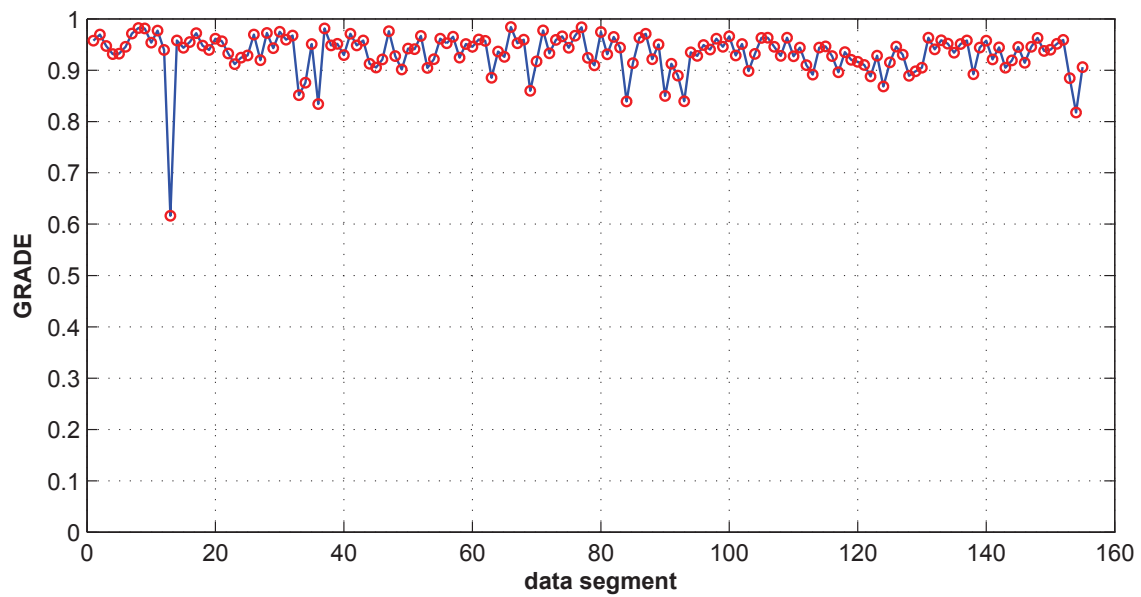


Figure 5.13: Grade for FC7

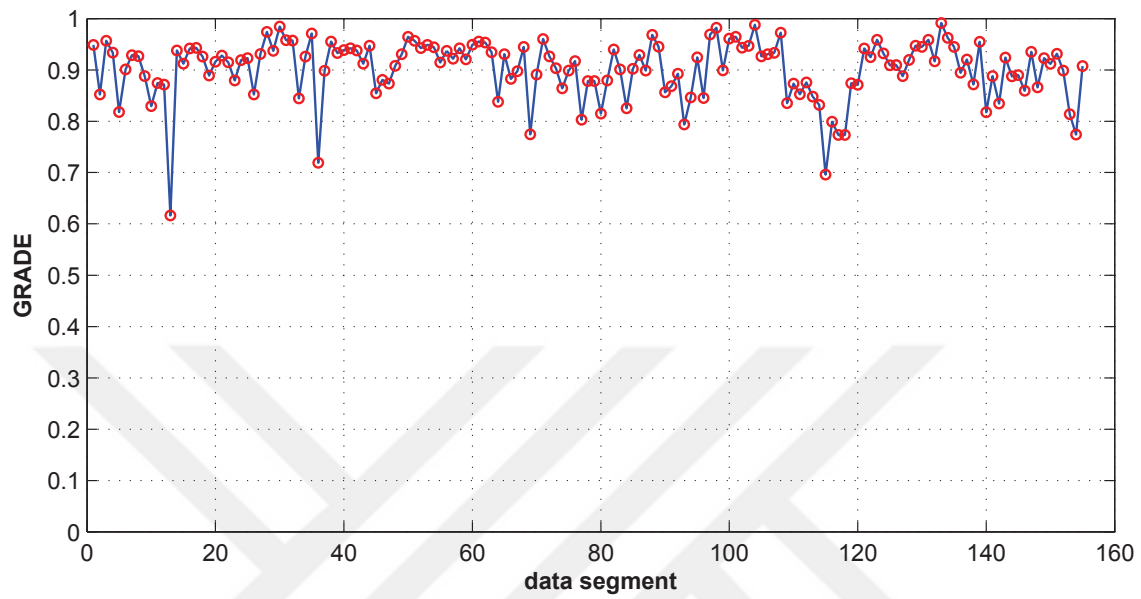


Figure 5.14: Grade for FC8

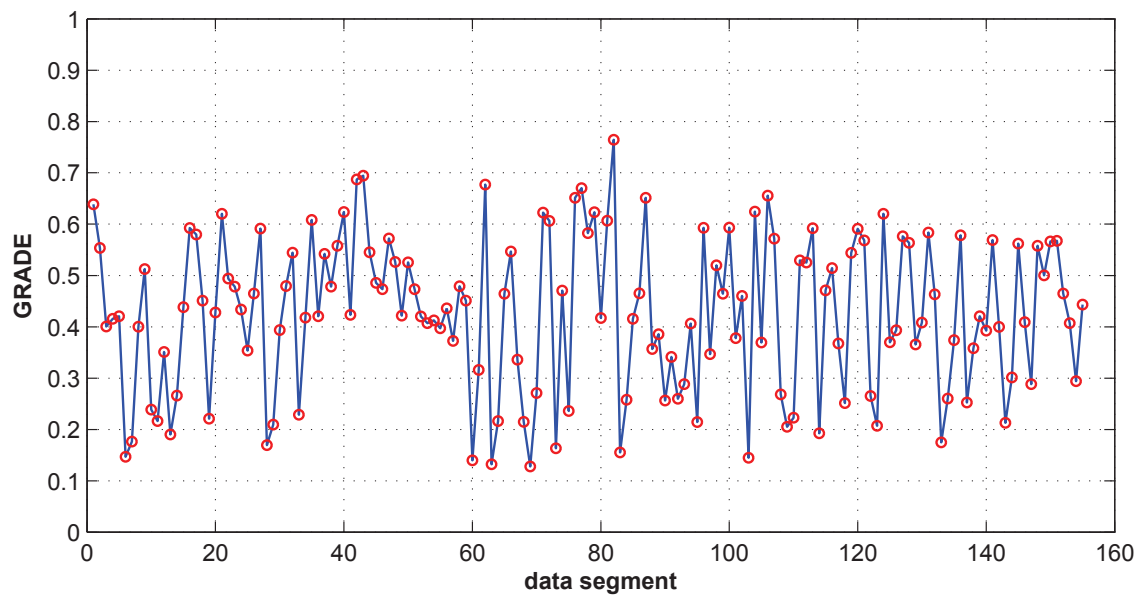


Figure 5.15: Grade for FC9

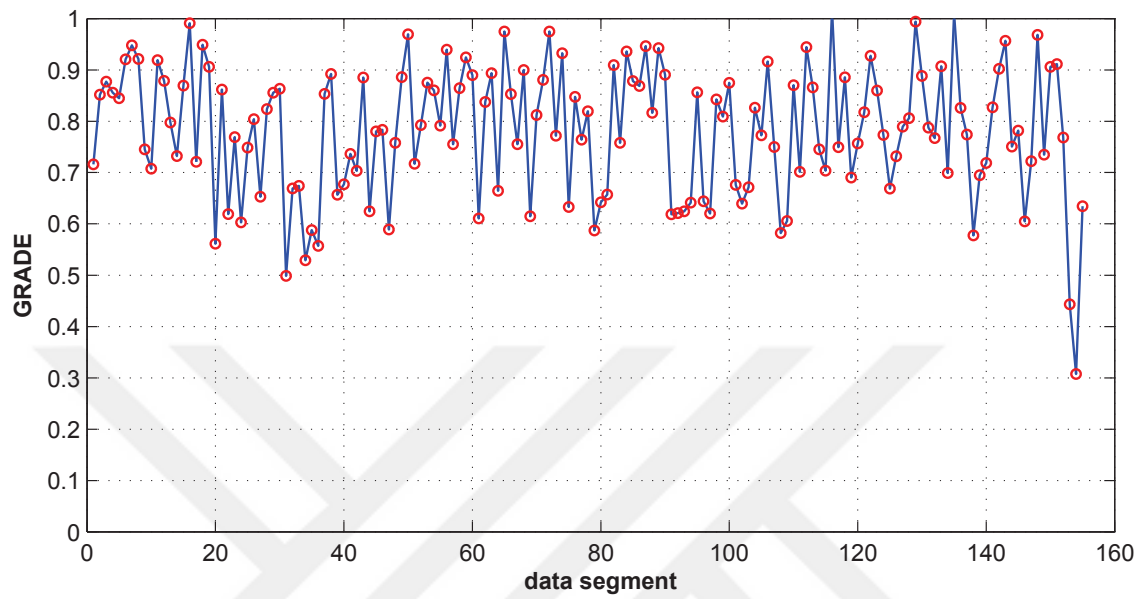


Figure 5.16: Grade for LC1

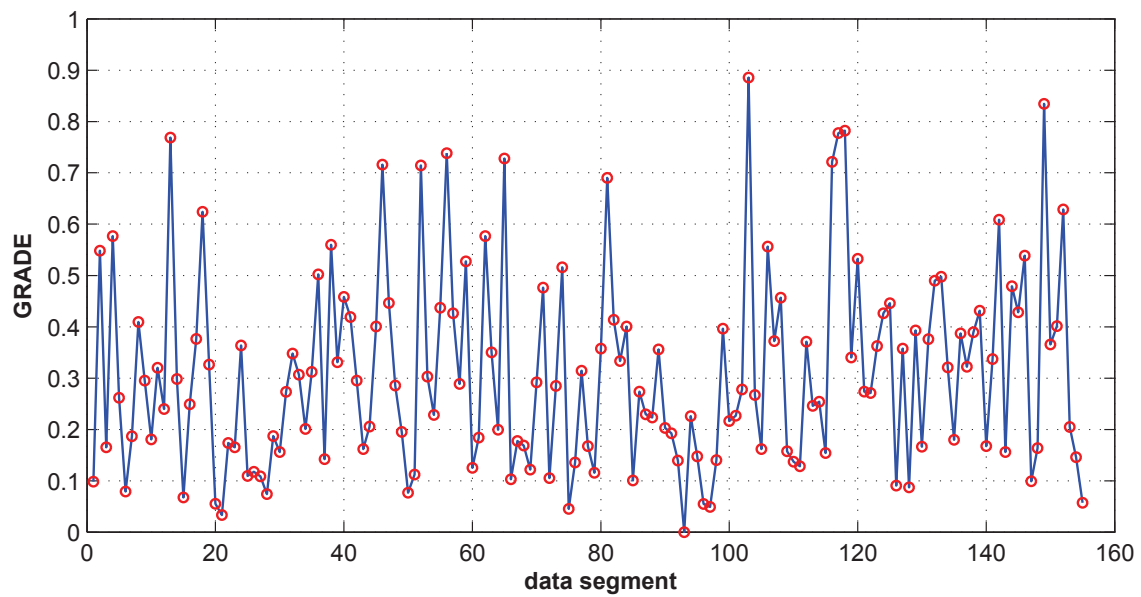


Figure 5.17: Grade for LC3

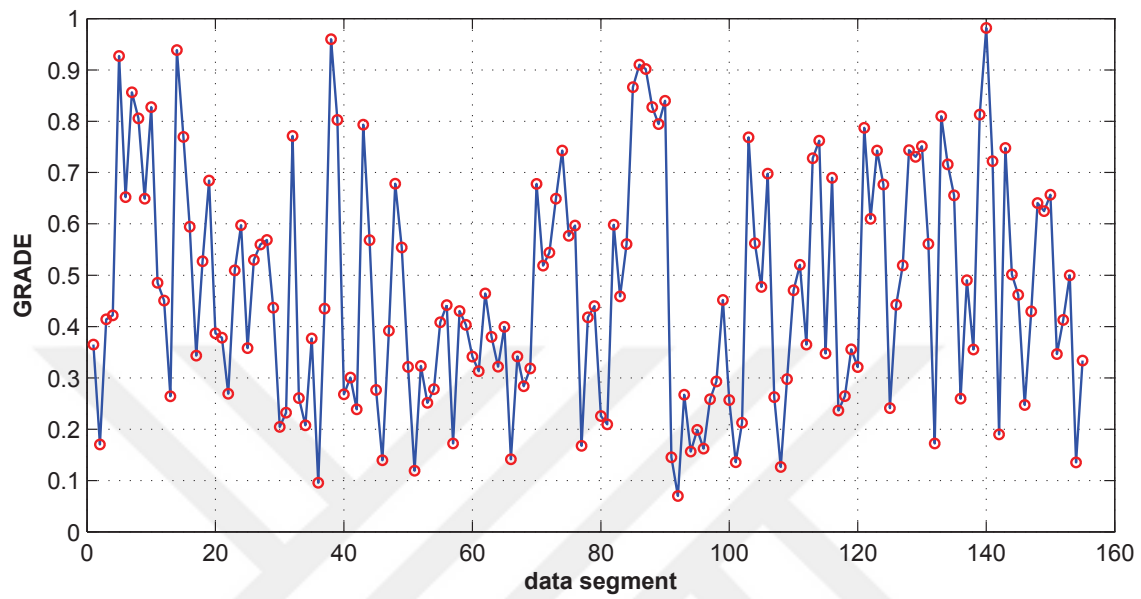


Figure 5.18: Grade for PC1

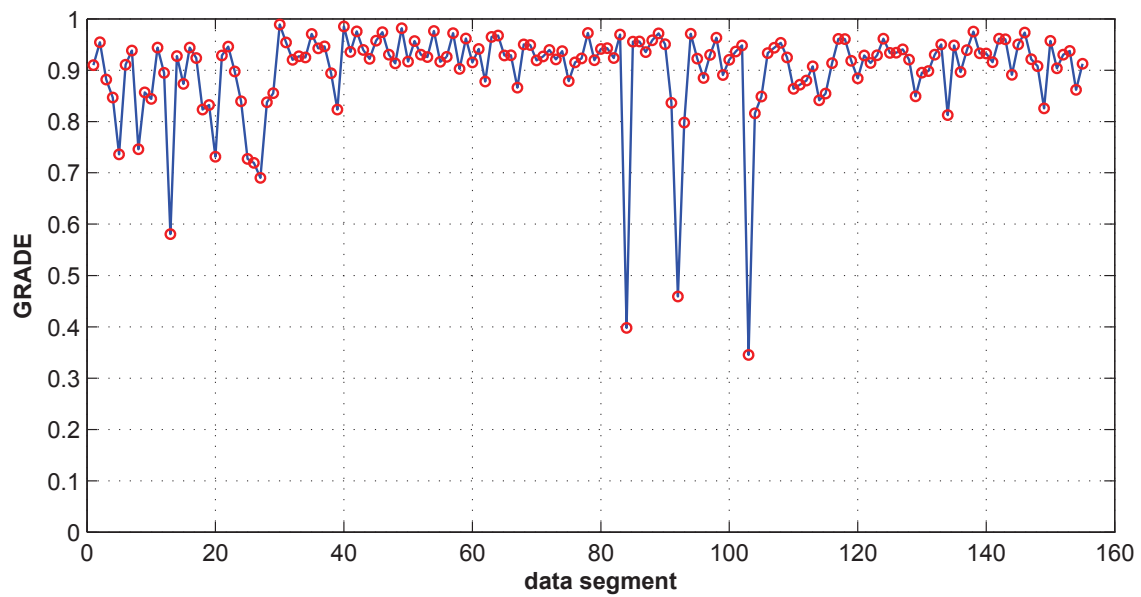


Figure 5.19: Grade for PC2

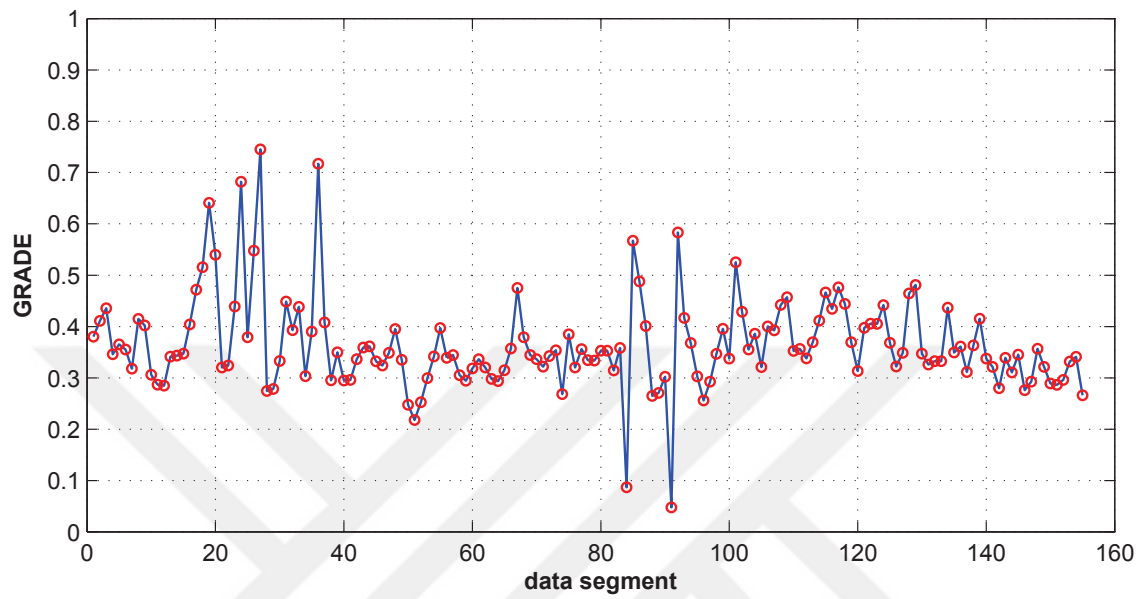


Figure 5.20: Grade for PC3

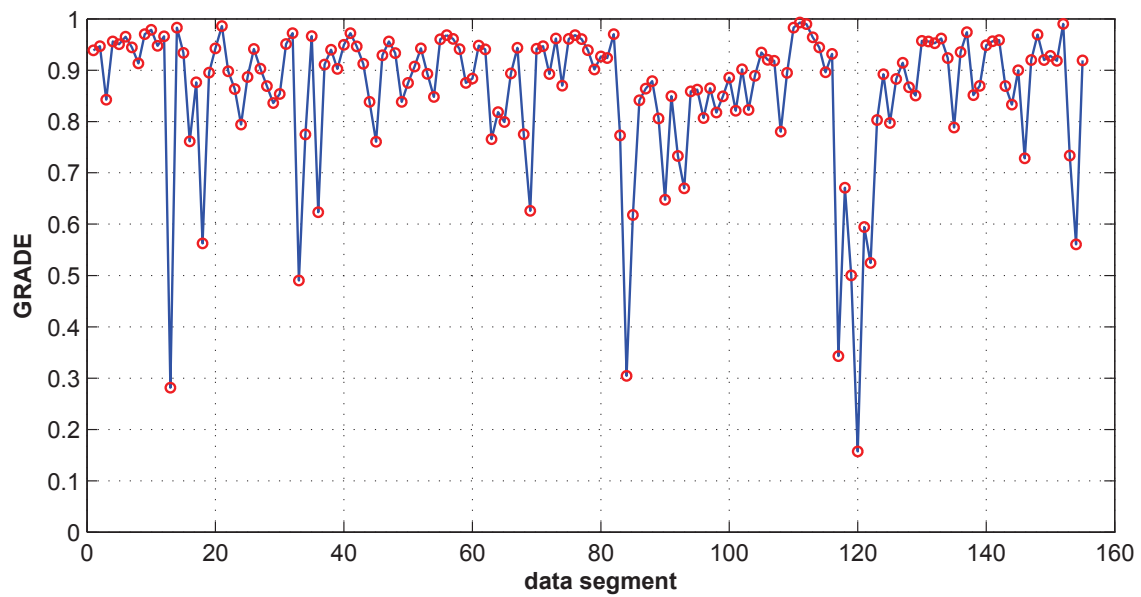


Figure 5.21: Grade for PC5

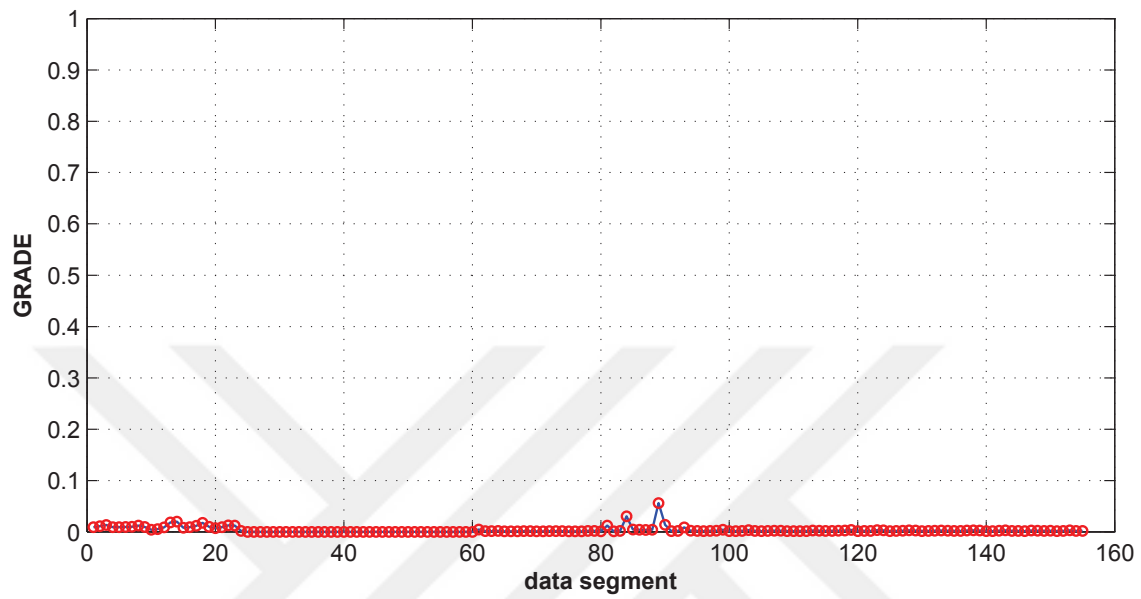


Figure 5.22: Grade for PC6

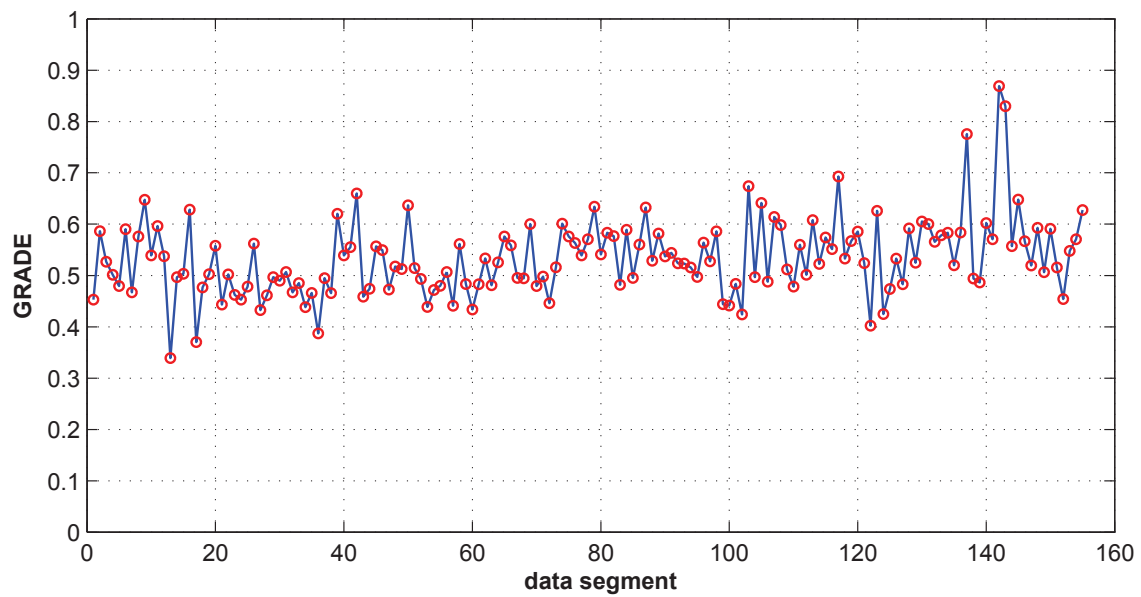


Figure 5.23: Grade for TC1

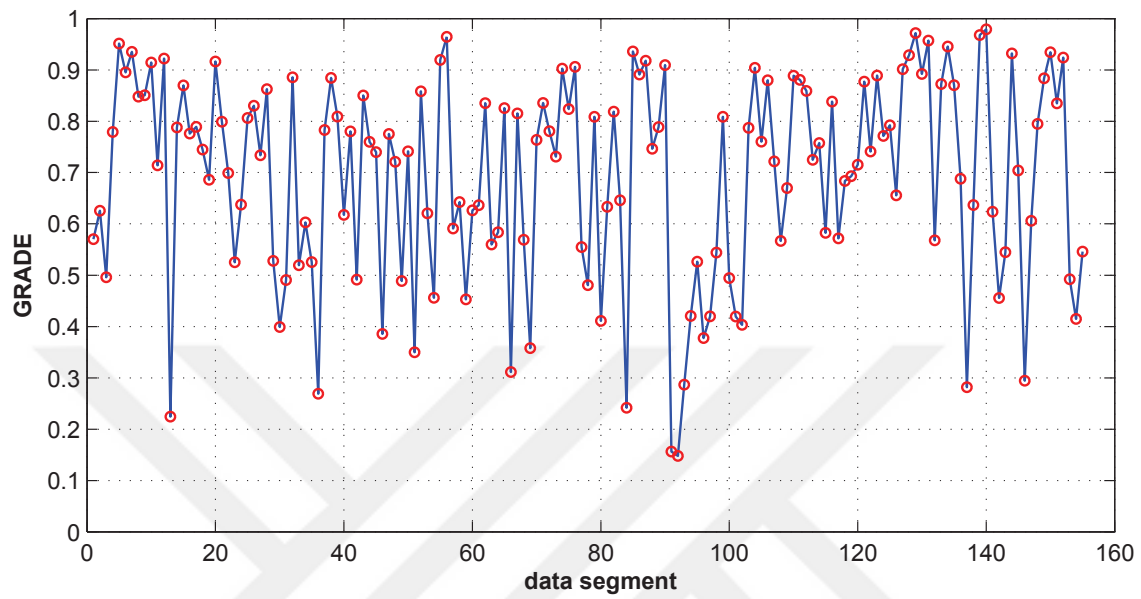


Figure 5.24: Grade for TC3

Table 5.2: Performance Assessment Summary

Loop Name	Average Grade	Low Performance Segments	Comments
FFC1	0.5106	Too much variation	Further analysis for all
FFC2	0.5464	Too much variation	Manual mode for segments 85-90
FC1	0.8552	13, 18, 33, 63, 84-93	Further analysis for low performance
FC2	0.8973	11, 13, 54, 84-105	Further analysis for low performance
FC3	0.8651	84-113	Further analysis for low performance
FC4	0.9637	13, 84	Further analysis for low performance
FC6	0.9831	13, 154	Further analysis for low performance
FC7	0.9333	13, 36, 84	Further analysis for low performance
FC8	0.9020	13, 36, 69, 115	Further analysis for low performance
FC9	0.4258	Too much variation	Further analysis for all
LC1	0.7817	Too much variation	Further analysis for all
LC2	0	-	Fully manual mode
LC3	0.3100	Too much variation	Further analysis for all
PC1	0.4719	Too much variation	Further analysis for all
PC2	0.8999	13, 84, 92, 103	Further analysis for low performance
PC3	0.3647	84, 91	Overall low performance
PC4	0	-	Fully manual mode
PC5	0.8594	13-18, 33, 69, 84, 117-123	Further analysis for low performance
PC6	0.0035	All	Overall low performance
TC1	0.5338	-	Stable but overall low performance
TC2	0	-	Fully manual mode
TC3	0.6929	Too much variation	Further analysis for all

Table 5.2 summarizes the performances of all control loops given. Table also gives the numbers of low performing segments. As the table indicates, controllers FFC1 and FFC2 have moderate performance. They also have too much variation in terms of performance. These ratio controllers have a remote set-point which is calculated separately and manipulated by the plant operators. Variations are believed to be the result of those changes. For the controllers from FC1 to FC8, the performances are satisfactory, except FC9. Although it is known that FC6, FC7, FC8 and FC9 give same service and have exactly same type of indicator and the control valve, FC9 has a significant performance problem. Level controllers are below moderate. LC2 is intentionally in manual mode in order to keep the dynamics of C1 stable. The pressure controllers have different performance grades. PC2 and PC5 have satisfactory performance whereas PC1 and PC3 are below moderate. Similarly, PC6 is poor. PC4 is kept in manual mode; since, during the analysis period the control structure of F1 has been revised by the control engineers. Similarly master controller TC2 for PC4 is also at manual mode due to same reasons. Finally, the other temperature controllers TC1 and TC3 are above moderate.

Table 5.2 also shows that there are common segments in which performances of most of the controllers decrease. Segments 11, 13, 84 are some of them. In these segments, the charge of the unit (Inlet1 in Figure 5.4) is known to be decreasing (Figures 5.25, 5.26, 5.27, 5.28). Since, FC2 controls the flow to C1; the performances of controllers around (PC1, LC1, and LC3) start to decrease. In addition, from Figure 5.25, FC2 seems to be slightly poor for load disturbance rejection. Further details of performance degradations are discussed in the following sections.

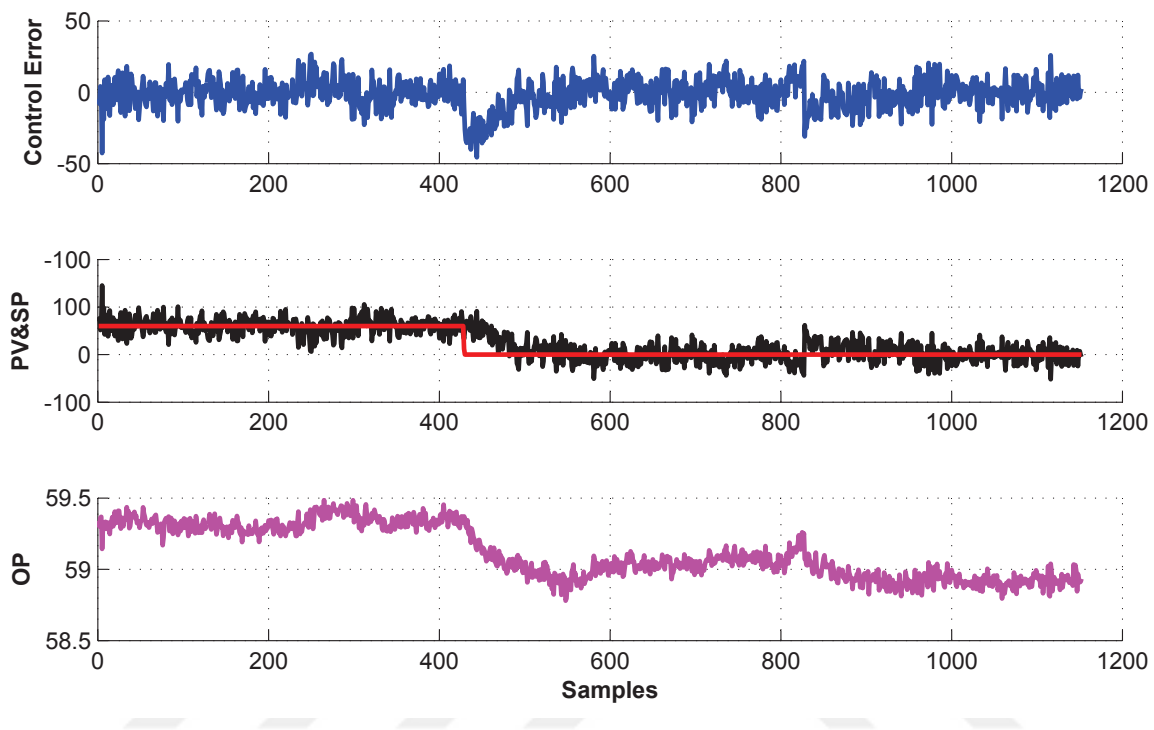


Figure 5.25: Process Data for FC2 in Segment 11

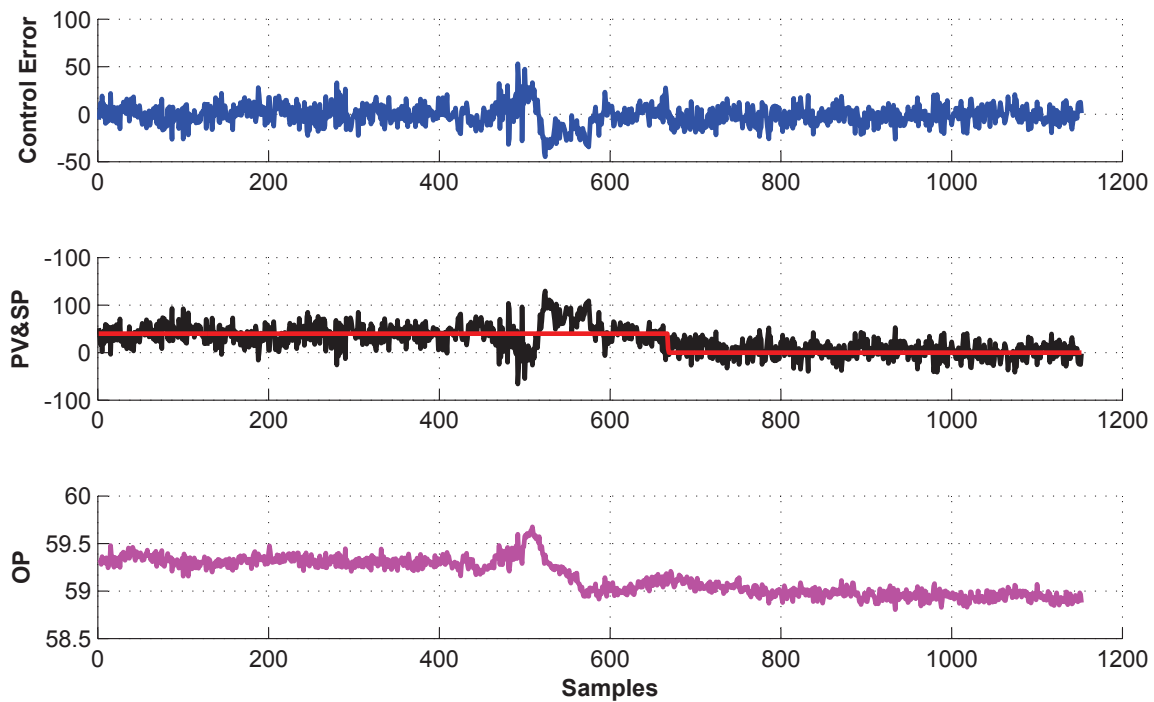


Figure 5.26: Process Data for FC2 in Segment 13

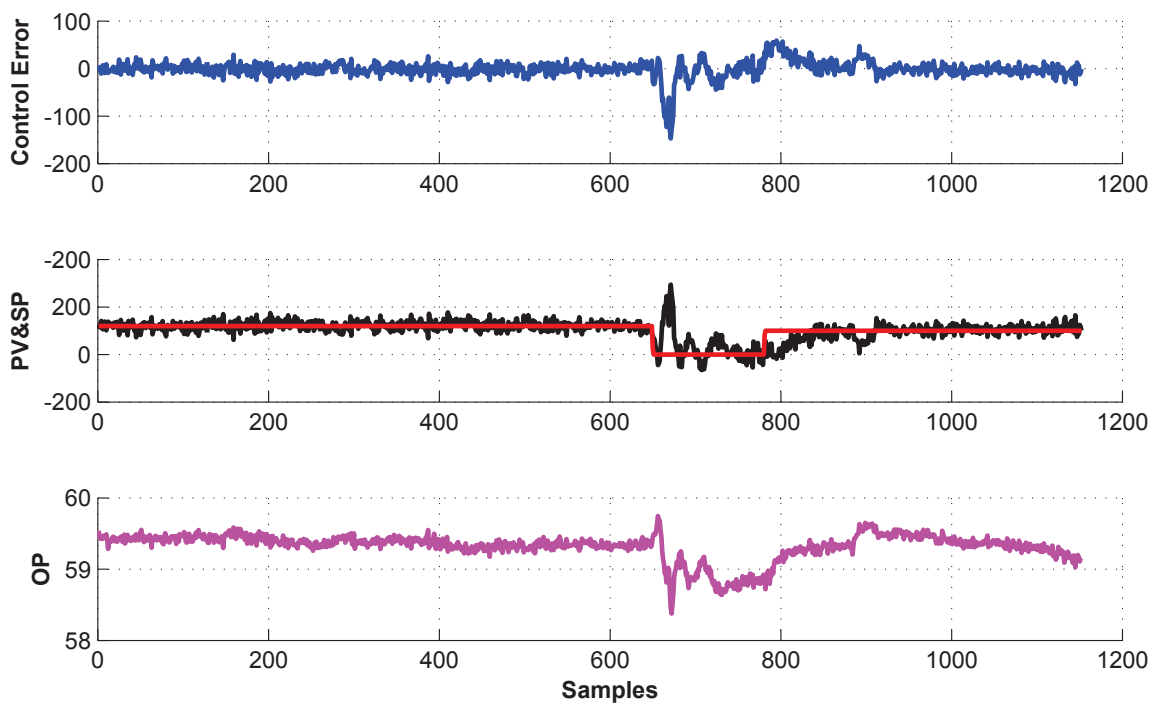


Figure 5.27: Process Data for FC2 in Segment 84

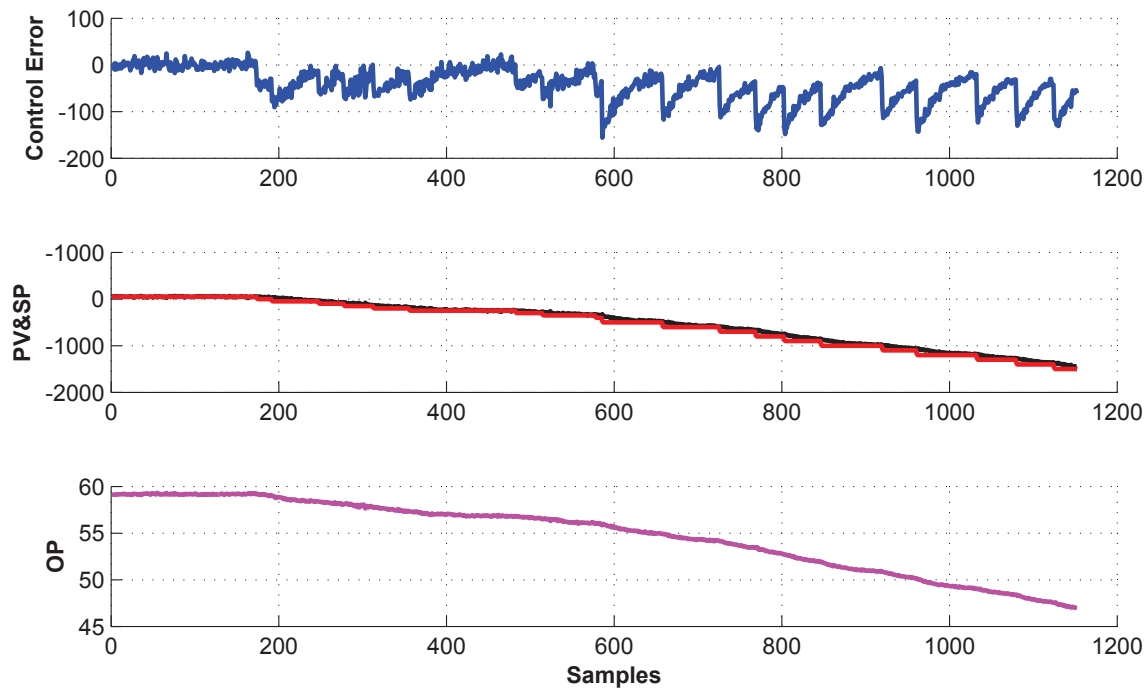


Figure 5.28: Process Data for FC2 in Segment 85

5.2.2 Oscillation Detection

Similar to performance assessment, in oscillation detection, four different algorithms were applied simultaneously. These were power spectrum analysis (3.2.1), regularity of time domain data (3.2.2), decay of auto-covariance function (3.2.3) and regularity of auto-covariance function (3.2.4). For power spectrum analysis, periodogram method which is based on DFT of time domain signal was used. Frequency axes were presented in log-scale. For y-axis, fractions were used to obtain the relative power in the signal for the associated frequency. Below, some representative analyses are shown with respect to results given in Table 5.2.

LC1, FC1 and FFC1: It is a connected control structure and was analyzed together. FFC1 is a flow ratio controller which gets its set-point according to FC1. The set-point of FC1 is controlled by LC1 in cascaded structure. LC1 and FFC1 have varying performances. Figure 5.29 show PSD and ACF of LC1 for segment 4. Figure 5.29a indicates that the peak at 877.71s covers 13.5% of the signal. Similarly,

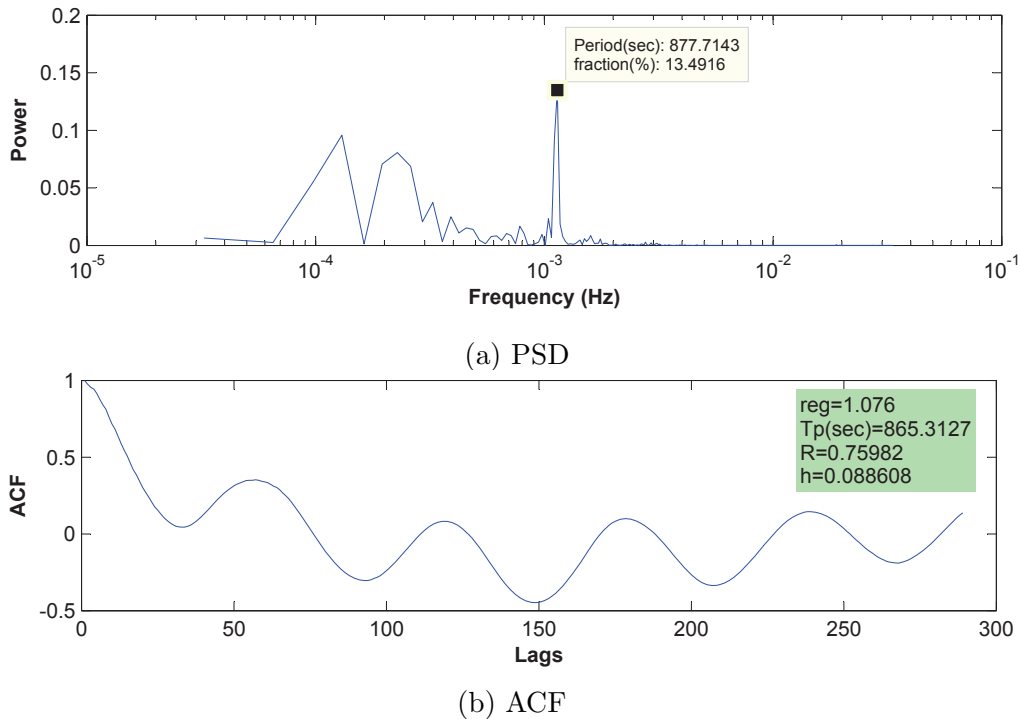


Figure 5.29: Oscillation Analysis of LC1 for Segment 4

Figure 5.29b shows the results of other detection methods. $reg = 1.076 > 1$ indicates that ACF of the signal has a regularity with a period of 865.21s. At the same time, decay ratio, R , represents that the oscillation is significant ($R > 0.5$). On the other hand, $h = 0.0887 < 0.4$ shows that oscillations are not regular in time domain. Peaks with larger widths on the left of Figure 5.29a can be misleading for visual inspection. They exist because of low frequency components (set-point changes). In addition, Figure 5.30 shows the PSD and ACF of FC1 for the same segment. As Figure 5.30a indicates, the frequencies are exactly the same with LC1. However, the power of the signal is less (3.63%) for FC1. The ACF of the signal (Figure 5.30b) seem to be regular visually. However, the methods based on ACF fail because of local dynamics (spurious zero-crossings and direction changes in ACF). Therefore, in this case, only PSD could capture the oscillation. Finally, oscillation detection analysis for FFC1

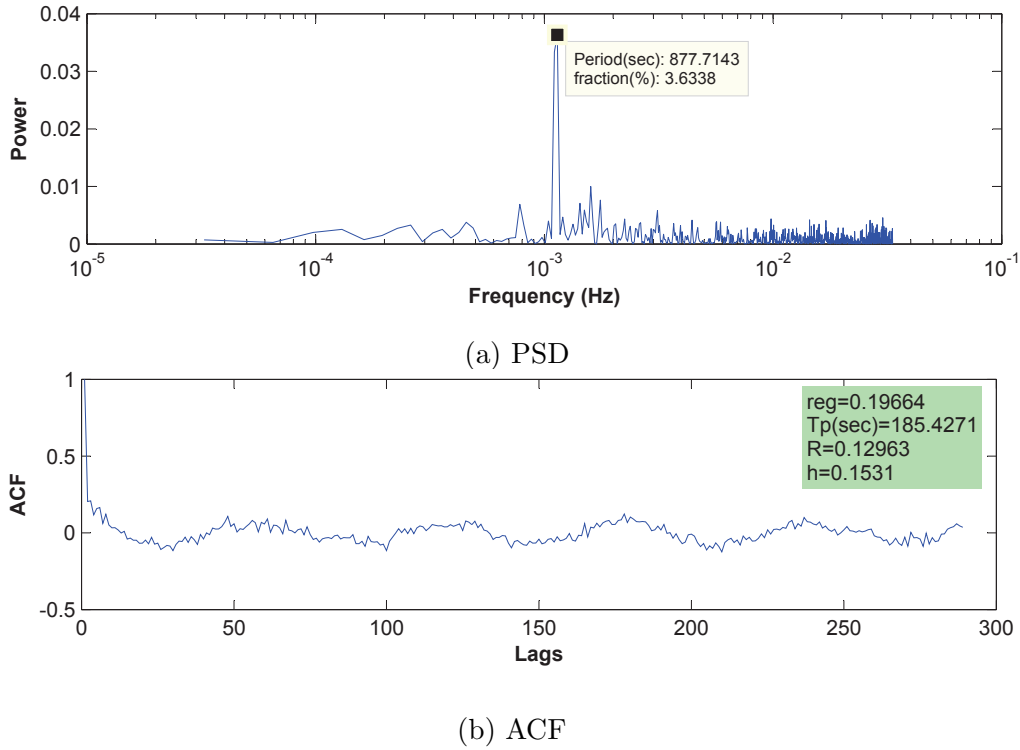


Figure 5.30: Oscillation Analysis of FC1 for Segment 4

is given in Figure 5.31. Similarly, the same period 877.71s with power of 8.77% is

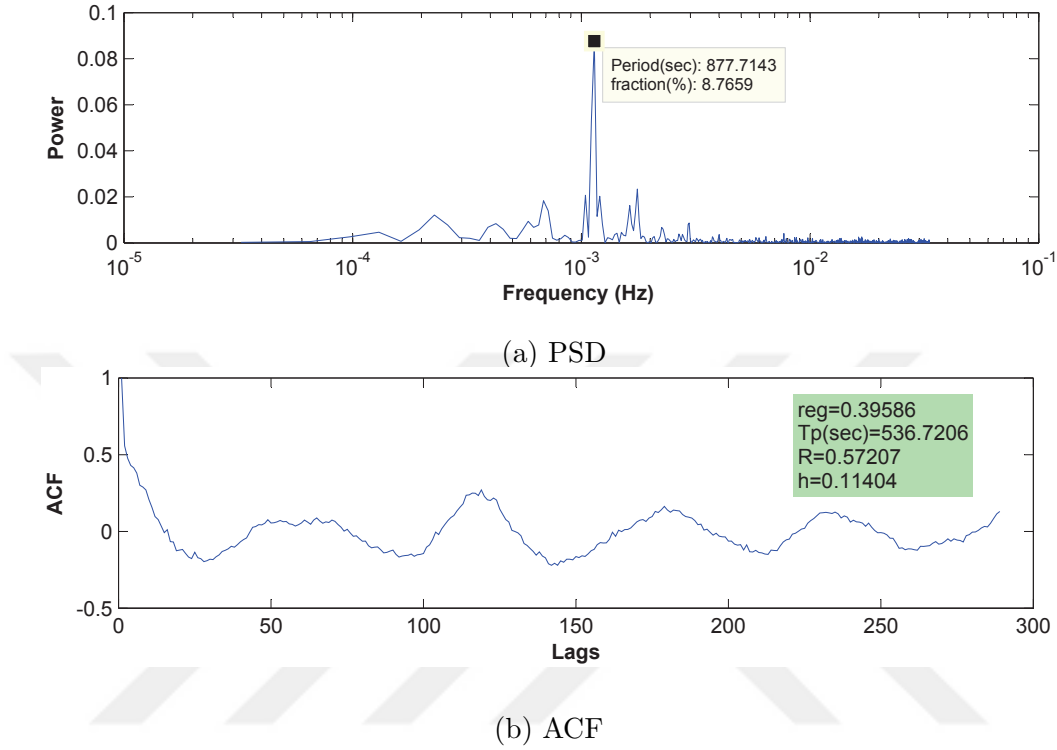


Figure 5.31: Oscillation Analysis of FFC1 for Segment 4

revealed in PSD in Figure 5.31a. However, other than that, there are faster dynamics in the loop. Little peaks on the right of the main peak have powers around 2% and destroy the regularity pattern of ACF in Figure 5.31b. Therefore, the method of regularity of ACF fails to detect the oscillation. Likewise, $h = 0.11404 < 0.4$ indicates that the oscillations are not regular in time domain. Conversely, $R > 0.5$ implies that oscillations are significant in ACF. Oscillations exist also for the segments given in Table 5.2 for FC1.

FC4 and FFC2: Similar to FC1-FFC1 structure, FFC2 is a ratio controller which gets its set-point in relation with FC4. In this structure, any significant oscillation was not observed. However, there are intermittent oscillations for FFC2. Figure 5.32 shows the PSD and ACF of FC4 for segment 1. Figure 5.32a is similar to the spectrum of white noise, and 5.32b is similar to ACF of white noise as well.

Figure 5.33 shows the oscillation analyses for FFC2 for the same segment. Al-

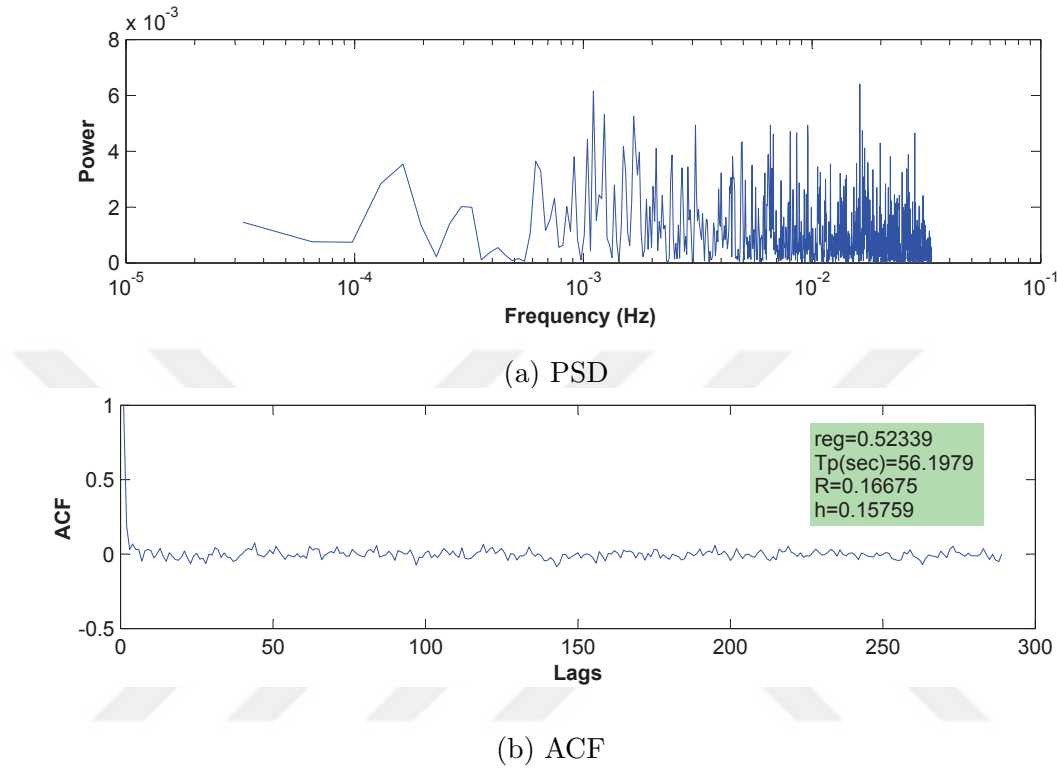
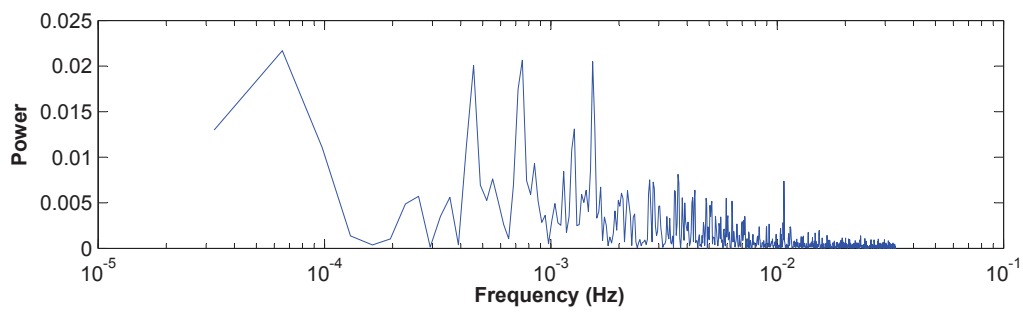


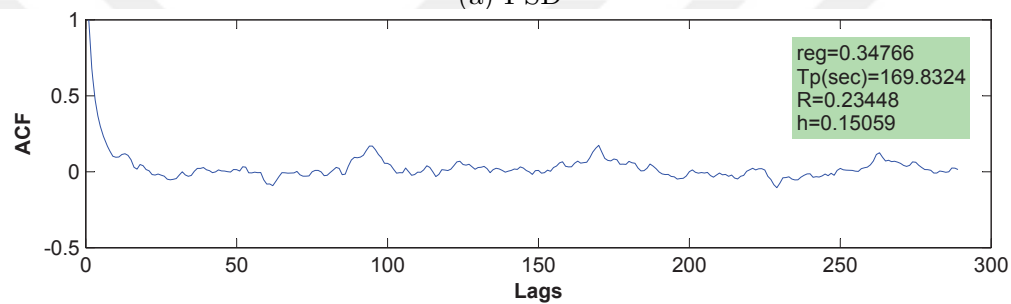
Figure 5.32: Oscillation Analysis of FC4 for Segment 1

though PSD of FFC2 is not similar to that of FC4, again it does not show a significant frequency. There are peaks around 10^{-3} Hz , however they are known to be the result of set-point changes as shown in Figure 5.34. On the other hand, there are some segments in which oscillations are significant. Figure 5.35 represents one of them. As Figure 5.35a indicates, there are low frequency components. Figure 5.35b also verifies that result. However, any of the methods could not capture the oscillation. Finally, in Table 5.2, for FC4, low performing segments were given as 13 and 84. In these segments, any significant oscillation was not observed.

LC2 and FC2: In this structure, FC2 is cascaded to LC2. However, it is not being used by the plant operators, since any variation of LC2 disturbs the dynamics of C1. Therefore, LC2 is kept at manual mode. As a result, only FC2 was analyzed. Figure 5.36 shows the PSD and ACF of FC2 for segment 1.



(a) PSD



(b) ACF

Figure 5.33: Oscillation Analysis of FFC2 for Segment 1

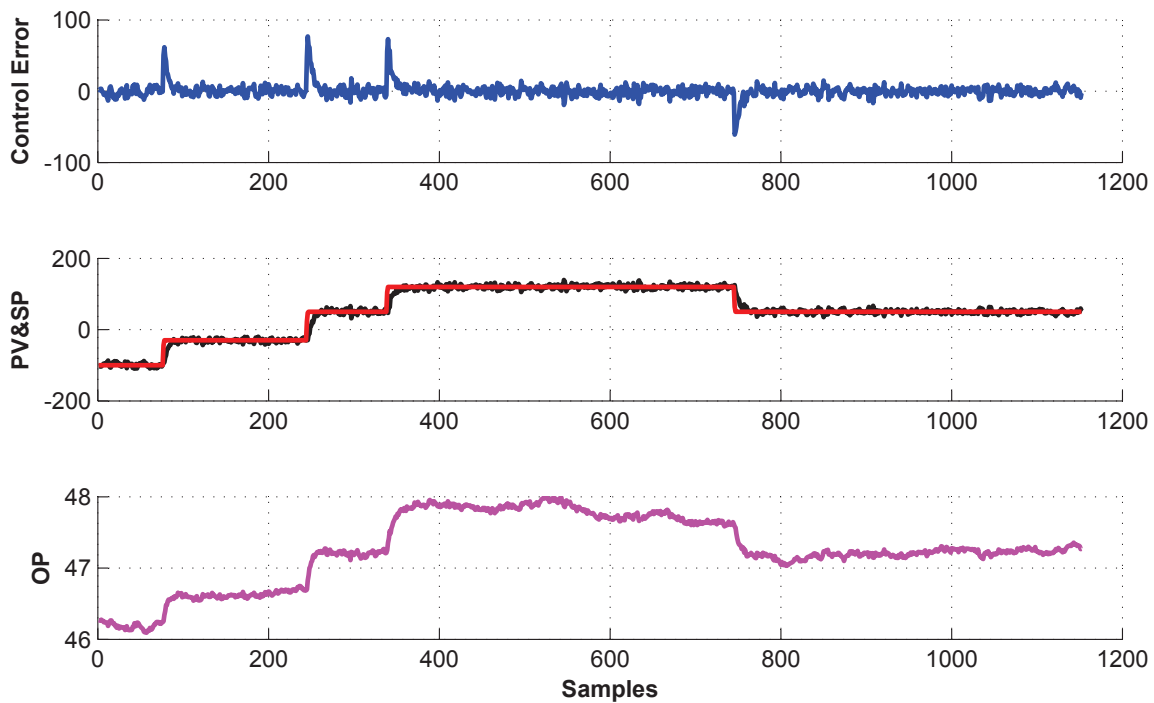
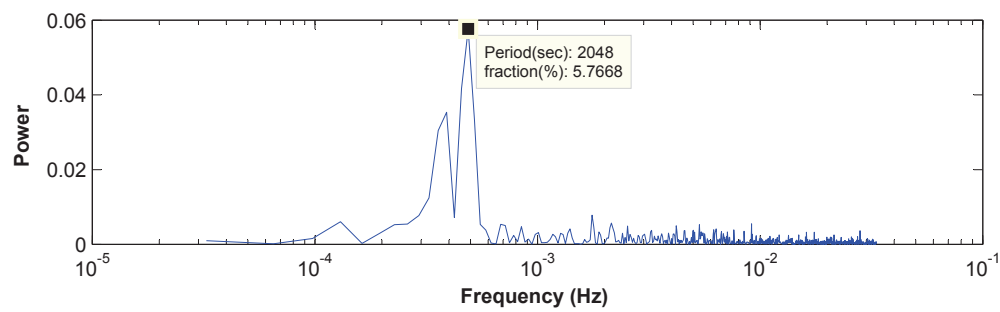
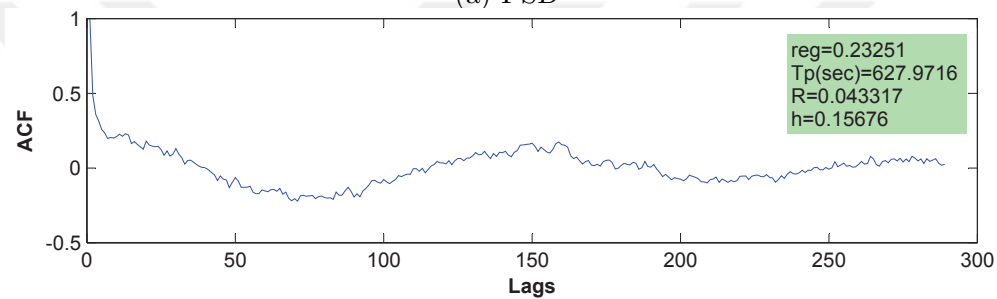


Figure 5.34: Process Data for FFC2 in Segment 1

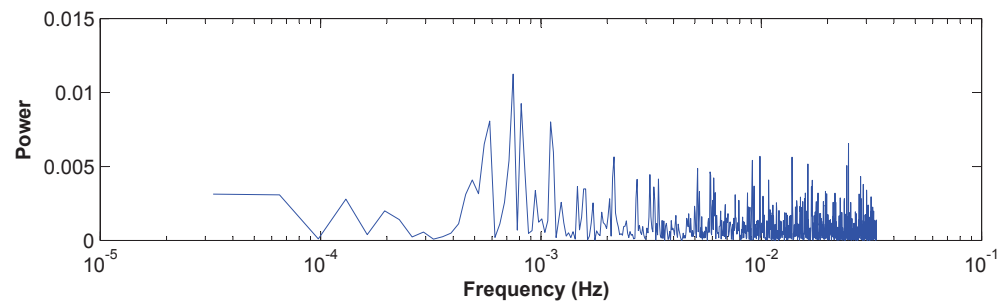


(a) PSD

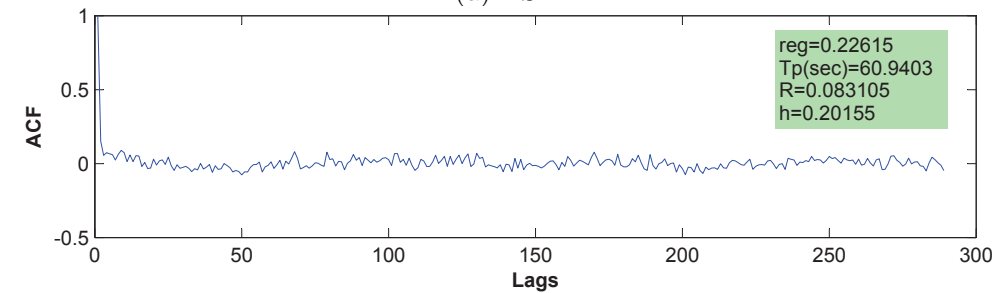


(b) ACF

Figure 5.35: Oscillation Analysis of FFC2 for Segment 48



(a) PSD



(b) ACF

Figure 5.36: Oscillation Analysis of FC2 for Segment 1

LC3 and FC3: FC3 cascaded to LC3 controls the bottom level of C1. Oscillation analysis of LC3 shows that there is not any oscillation in the loop. However, the loop fails to reject disturbances. Figure 5.37b reveals that fact, since ACF cannot decay in the given window. At that point, the loop can be said to be sluggish. Detailed analysis is given in the following sections.

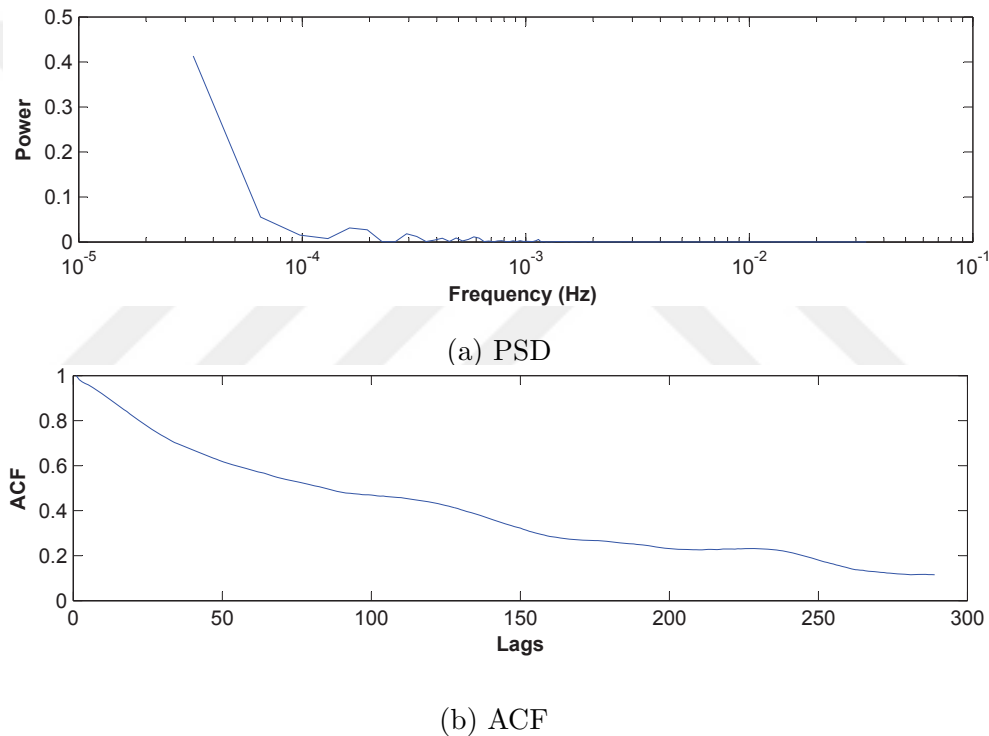


Figure 5.37: Oscillation Analysis of LC3 for Segment 4

Similarly, the analysis of FC3 does not indicate any oscillation. However, there are some segments in which oscillations are intermittent. Segments 3 and 4 are such examples. Especially for segment 3, the regularity of ACF can easily be seen. In addition, for segment 3, $reg = 2.3902 > 1$ with the period of 188.91s. Corresponding frequency covers approximately 2.7% of the signal. Figure 5.38 shows these results. On the other hand, for segment 4, oscillations decay over time. Figure 5.39 shows the oscillation analysis of FC3 for segment 4. As Figure 5.39a implies, there is not a significant oscillation, frequencies are dispersed. Therefore, the regularity of ACF

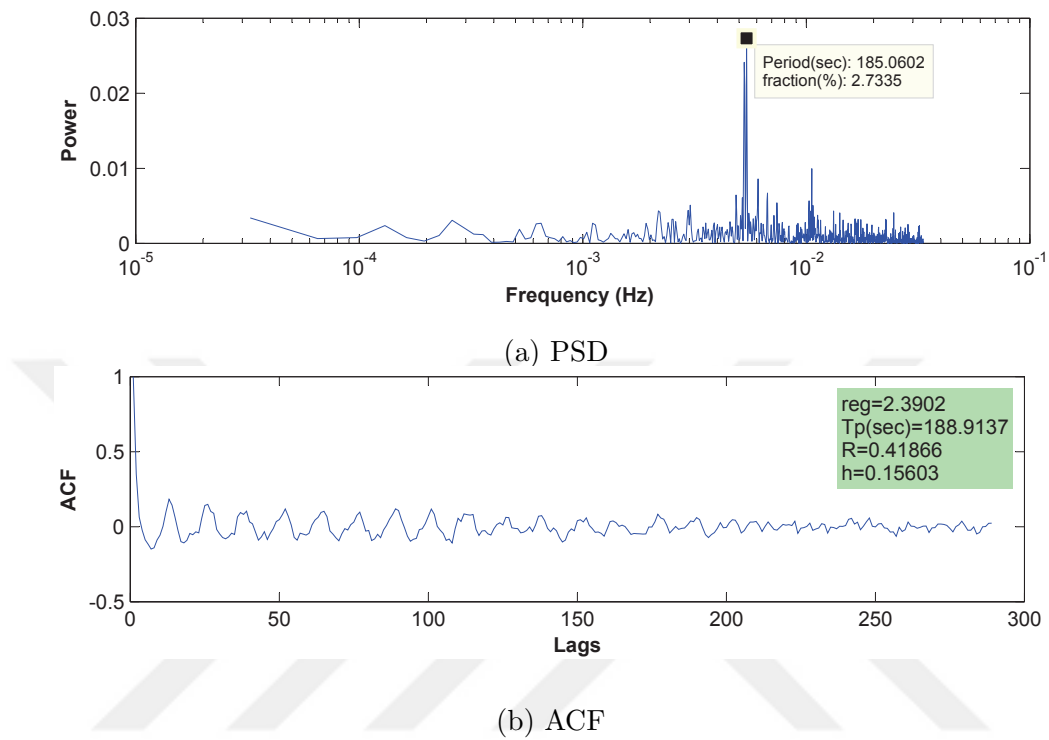


Figure 5.38: Oscillation Analysis of FC3 for Segment 3

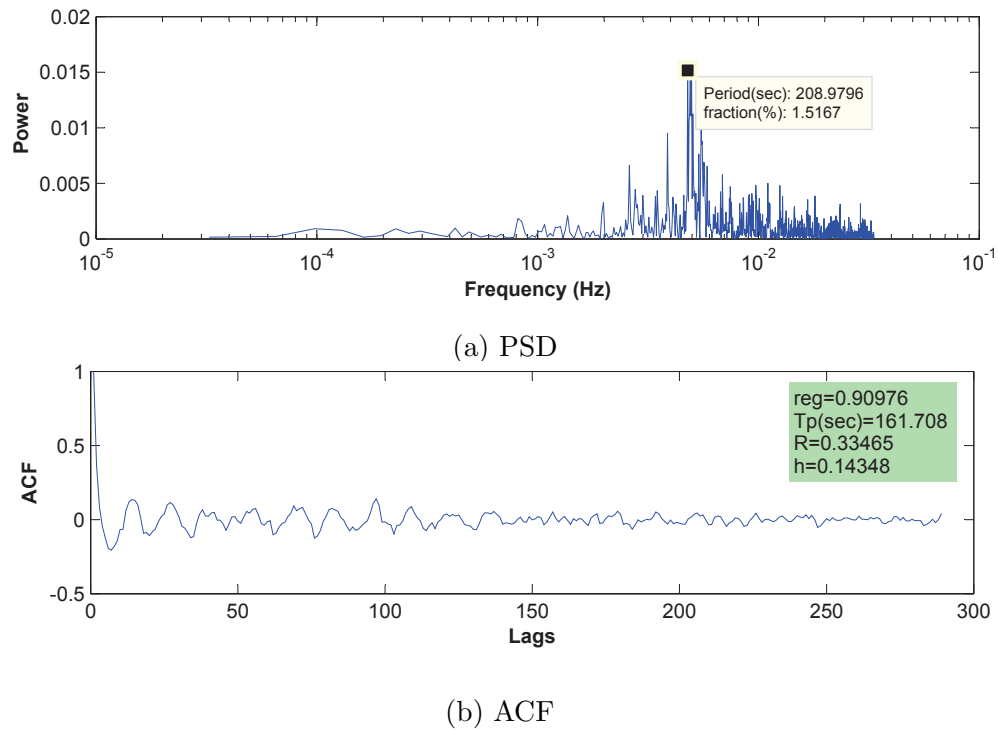


Figure 5.39: Oscillation Analysis of FC3 for Segment 4

(Figure 5.39b) is destroyed. Although the ACF of the signal seems to be regular, decaying coefficients through lags 150 destroy the regularity and result in $reg = 0.9096 < 1$.

FC6, FC7, FC8 and FC9: These controllers adjust the flow through furnace F1. They serve for the same fluid, thus they have identical indicators and control valves. However, as Table 5.2 implies, FC9 is the lowest performing one with $Grade = 0.4258$. Figure 5.40 shows the oscillation analysis of FC6 for segment 12. As Figure 5.40a in-

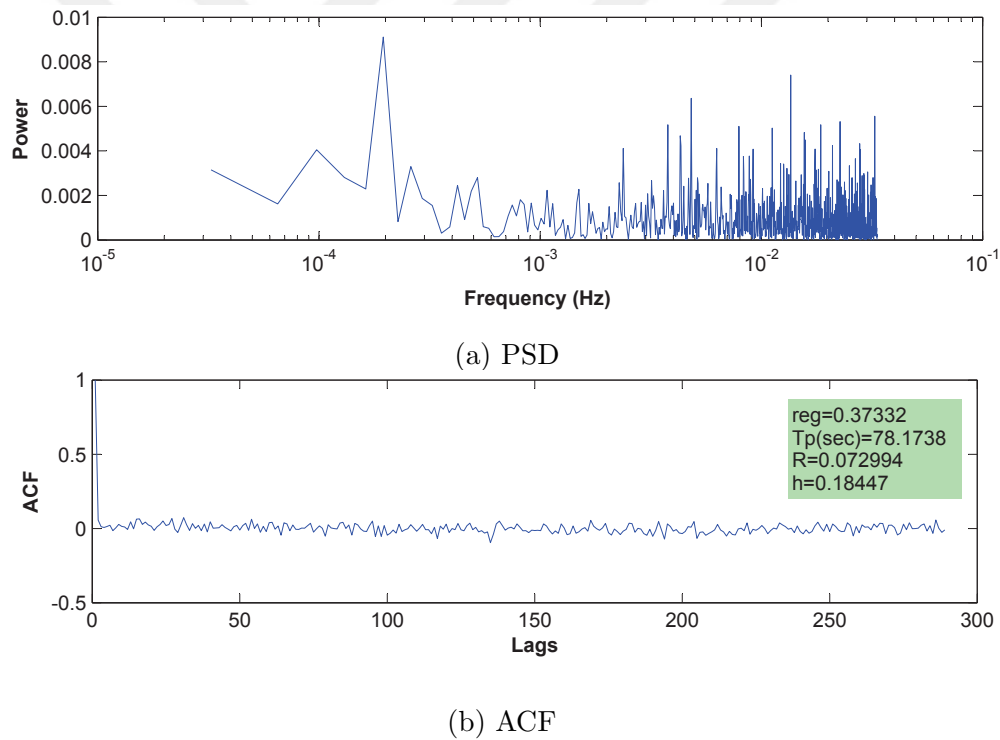
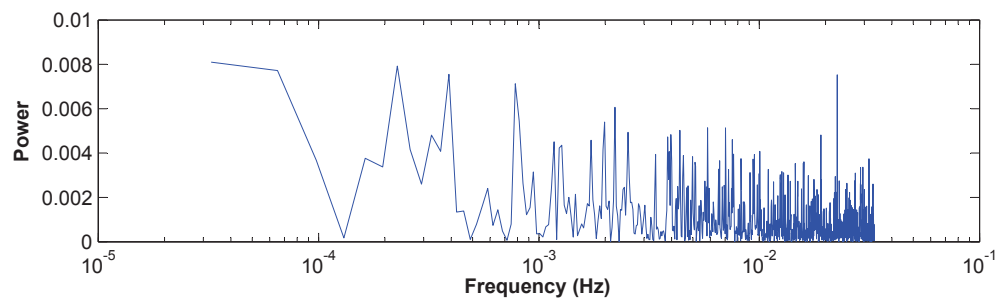
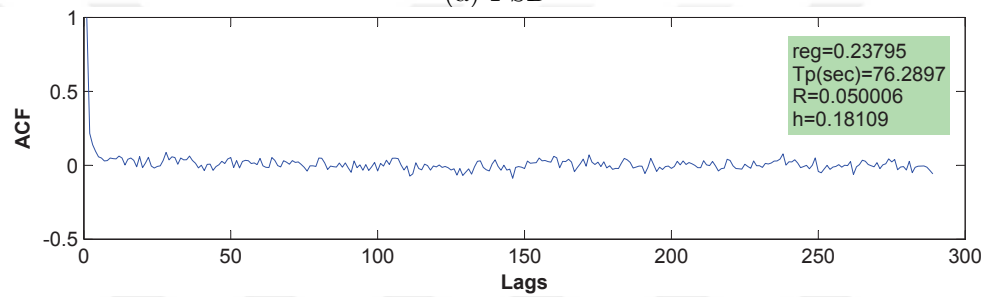


Figure 5.40: Oscillation Analysis of FC6 for Segment 12

dicates, the PSD of the signal is similar to that of white noise. ACF of the signal (Figure 5.40b) verifies that interpretation. Parallel results can be concluded with the oscillation analysis for FC7. Figure 5.41 shows the results of this analysis. As Figure 5.41b demonstrates, ACF decays quickly and correlations become almost zero for further lags. Analysis given in Figure 5.42 also does not indicate any oscillation. Finally, oscillation analysis for FC9 is shown in Figure 5.43. Similar to analyses of FC6,

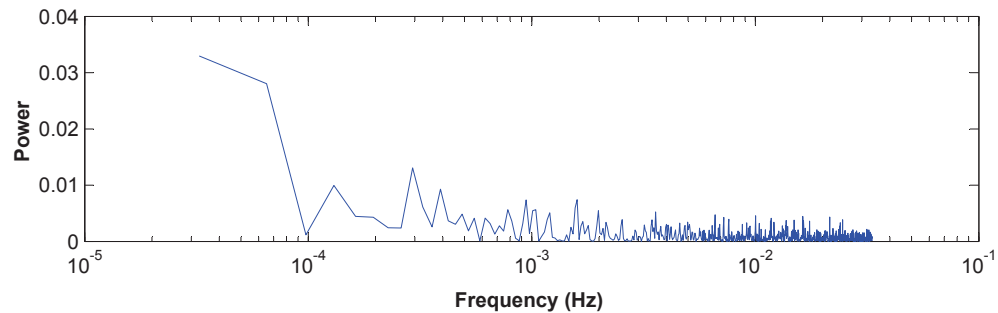


(a) PSD

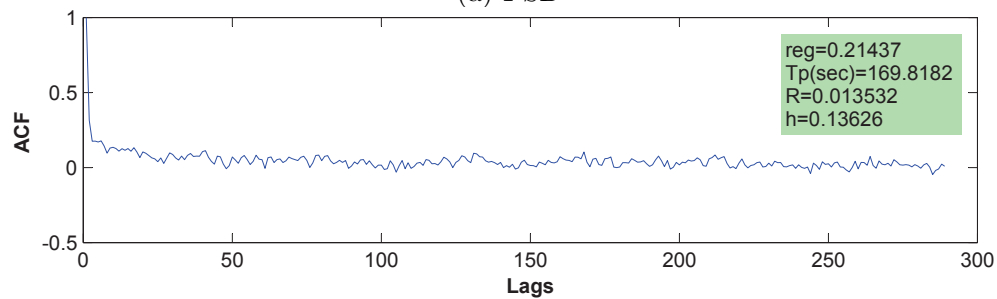


(b) ACF

Figure 5.41: Oscillation Analysis of FC7 for Segment 12



(a) PSD



(b) ACF

Figure 5.42: Oscillation Analysis of FC8 for Segment 12

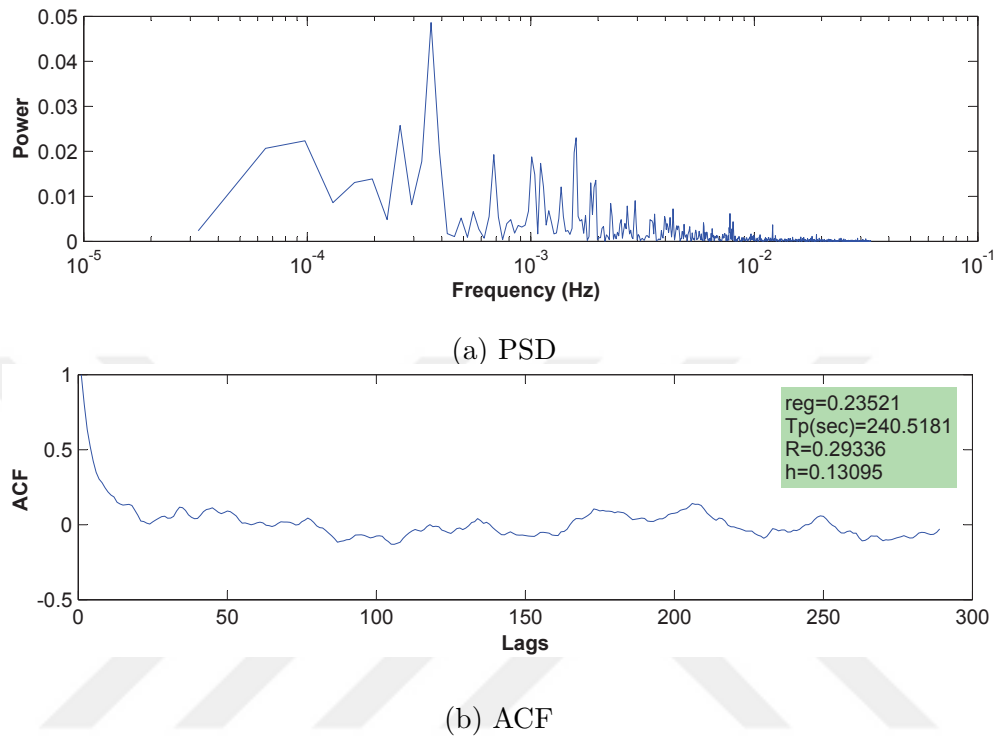
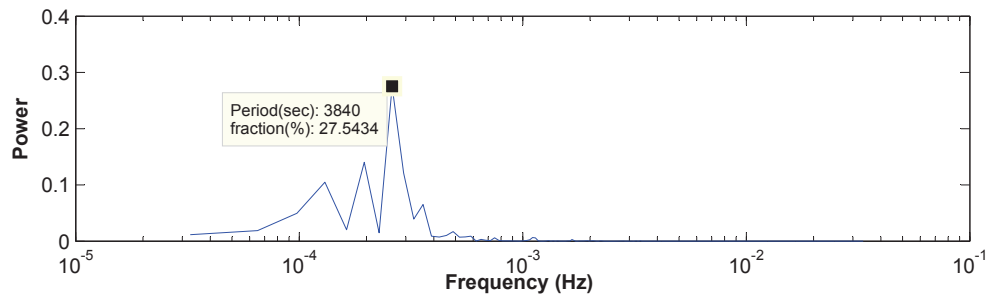


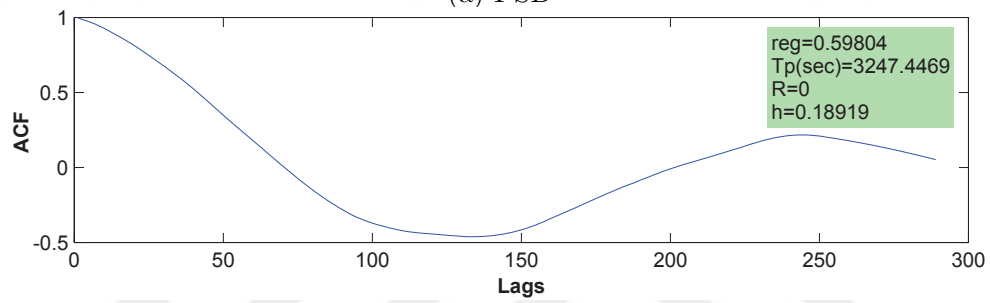
Figure 5.43: Oscillation Analysis of FC9 for Segment 12

FC7 and FC8, oscillation detection indices do not indicate any oscillation. However as Figure 5.42a shows, there are some frequencies around 10^{-3} which dominates the spectrum slightly. In addition, the peak around 3×10^{-3} also affects the spectrum. These peaks make ACF slightly regular. However, the regularity is not significant; therefore, ACF based methods could not detect any oscillation. On the other hand, it is known that FC9 has the lowest grade among the controllers regulating flow through furnace F1. Similar results are also obtained with other segments. Further analysis is discussed later.

PC1: It is the controller which controls the pressure of C4 and indirectly the top pressure of C1. From the process knowledge, it is known that any perturbation of the column dynamics causes variations in the top pressure, which makes this controller sensitive to other dynamics. Therefore, the PSD and ACF of the segments change greatly. However, there are some common characteristics of PSDs. Figure 5.44

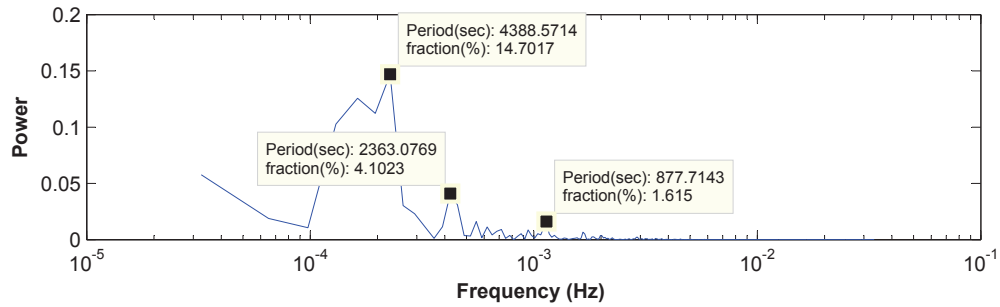


(a) PSD

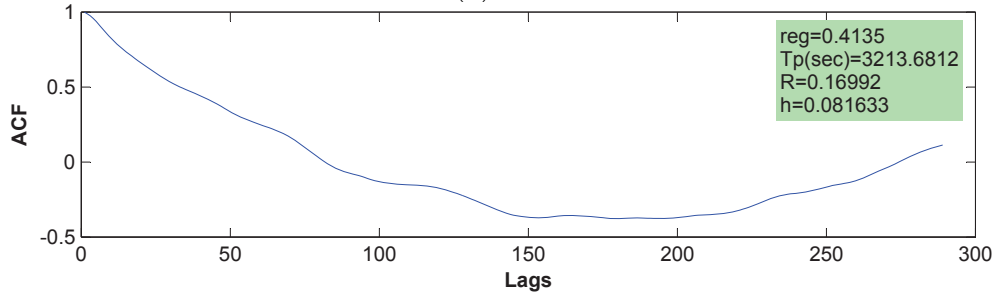


(b) ACF

Figure 5.44: Oscillation Analysis of PC1 for Segment 2



(a) PSD



(b) ACF

Figure 5.45: Oscillation Analysis of PC1 for Segment 3

shows an oscillation with a period of 3840s for segment 2. Similarly Figure 5.44b implies that ACF of the signal is also periodic. However, the lag range of the ACF is not enough to interpret. Therefore, ACF based methods fail to detect oscillation. When it comes to segment 3, different frequencies are seen from Figure 5.45a. Same discussions are also valid for ACF of the signal in Figure 5.45b. For segment 3, it is better to draw attention to the little peak at 877.71s; since, approximately the same period is also observed for segment 7 at 903.53s with a power of 10% (Figure 5.46a). However, the regularity of ACF is destroyed because of the low frequency components less than $10^{-3}Hz$. Same observations are valid for the other segments of the loop. The significant period of oscillation for the loop stays around 800-900s which is also observed for LC1, FC1 and FFC1 loops.

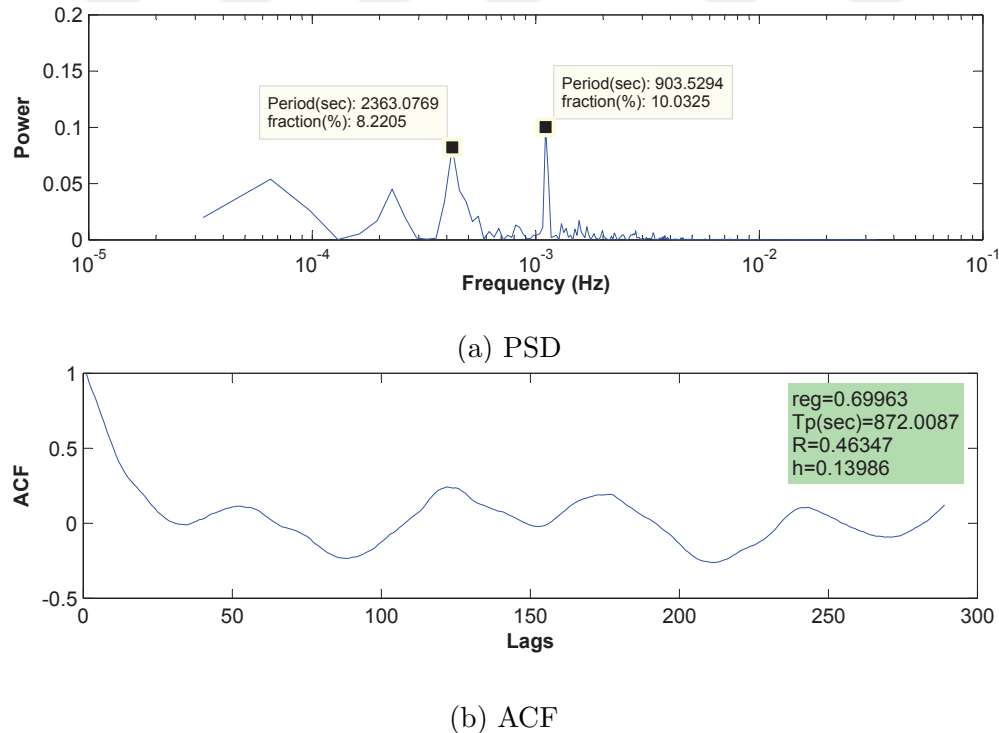


Figure 5.46: Oscillation Analysis of PC1 for Segment 7

PC2: It is the controller which regulates the pressure of reactor C3 and indirectly inlet pressure of column C1. Fortunately, the average performance of the loop is sat-

isfactory with a grade of 0.8999. However, there are some poor performing segments. Figure 5.47 shows the oscillation analysis for segment 13. Although the PSD of the

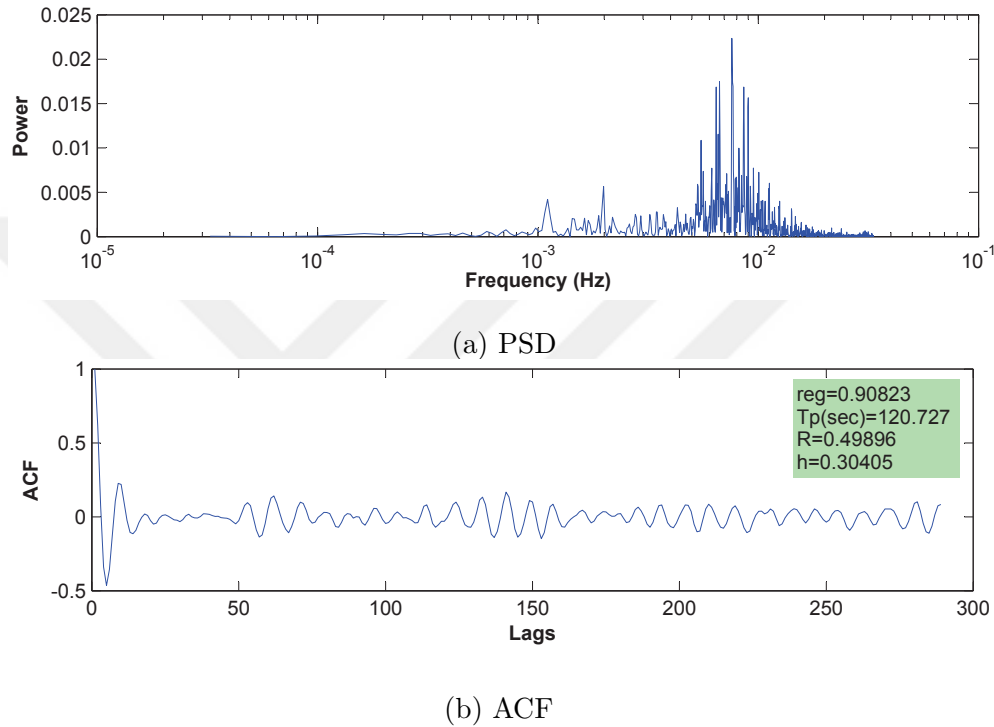


Figure 5.47: Oscillation Analysis of PC2 for Segment 13

signal (Figure 5.47a) does not indicate a significant oscillation, the ACF of the signal (Figure 5.47b) implies intermittent oscillations. ACF based methods are close to detect the oscillation ($reg \approx 1$ and $R \approx 0.5$) but fail. Performance degradation at these segments is the result of these intermittent oscillations. Similar results are also obtained for the other low performing segments.

PC3: This controller regulates the pressure of C5 by manipulating the gas flow out. As Table 5.2 indicates, the average performance is poor. However, there is not variation other than some segments such as 84 and 91. When PC3 is analyzed in terms of oscillation, there exists a consistent oscillation. Figure 5.48 shows the analysis for segment 2. As the figure indicates, the oscillation is regular with $reg = 7.2039 > 1$ with the period of 109.82s. Same results are also obtained by analyzing the PSD in Figure 5.48a. It is shown that this period of the signal covers approximately 5%

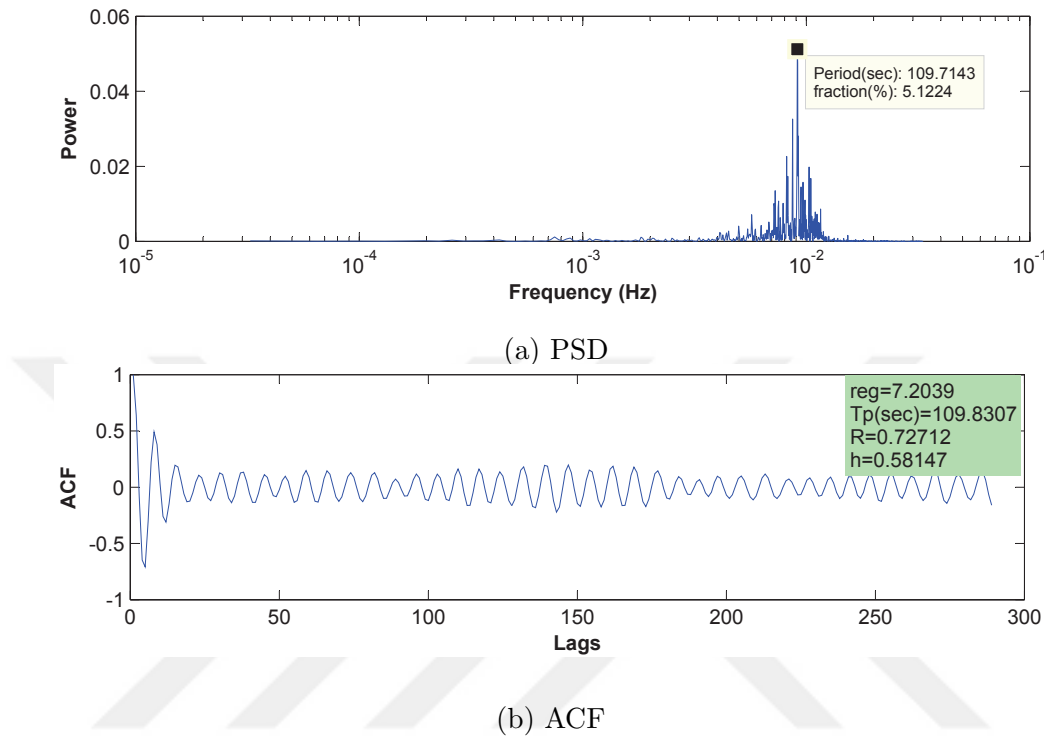


Figure 5.48: Oscillation Analysis of PC3 for Segment 2

of total. In addition, time domain based regularity (h) and ACF based decay ratio (R) are successful to capture the oscillation. Similar results are also observed for the other segments with changing periods in between 90 to 120s. On the other hand, for low performing segments of 84 and 91, rather than the oscillations, the performance degradation is because of load disturbance rejection problem. Figure 5.49 shows the time domain data for segment 84. It is seen that the disturbance was rejected between samples 634-756 (which is equal to 30.5 min).

PC4, TC2 and PC5: PC4 and PC5 both control the firing of furnace F1. PC4 regulates the fuel inlet pressure in cascade to TC2, whereas PC5 controls the air inlet pressure. Due to the modification studies for the control structure during the analysis period, PC4 and TC2 were at manual mode. Therefore, here only PC5 was analyzed. As Table 5.2 indicates, PC5 has a satisfactory performance with an average grade of 0.8594. For low performing segments, any significant oscillation was not observed.

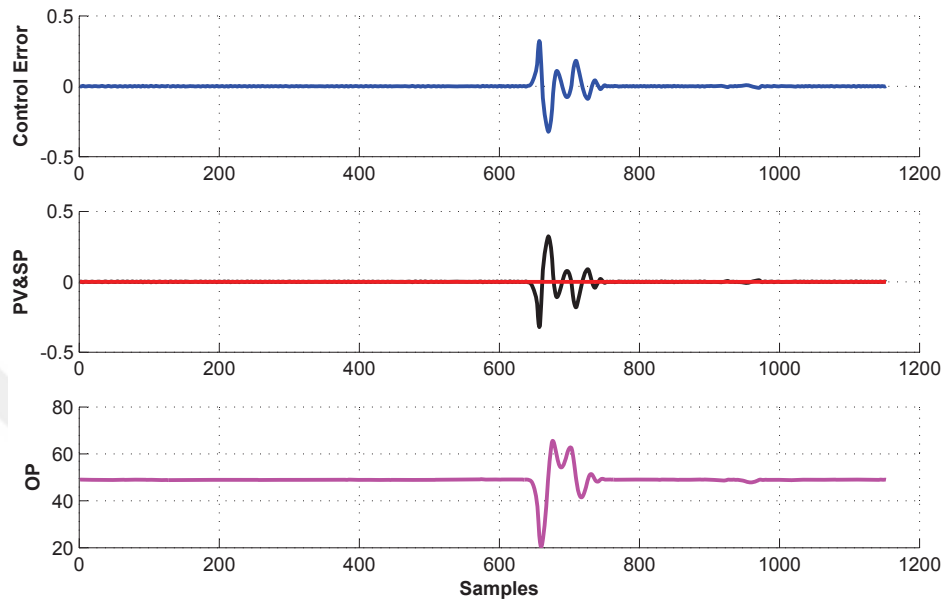


Figure 5.49: Process Data for PC3 in Segment 84

Performances degrade because of load disturbance rejection problems. Figure 5.50 gives the oscillation analysis for segment 18. As the PSD indicates, there is not a significant frequency. However, it is seen that the loop fails to reject disturbances, since ACF of the signal (Figure 5.50b) decays in considerable amount of samples.

PC6: It is the controller regulating the pressure of drum C2. Table 5.2 implies that it is the worst controller among all 22 controllers. The analysis of the loop indicates that it suffers from oscillations intensively. Figure 5.51 shows an example for segment 1. Figure 5.51a states that there are 2 dominant frequencies which have periods of 667.83s and 341.33s, and signal strengths 17.85% and 5.14% respectively. Similarly, the ACF of the signal in Figure 5.51b shows the oscillation. The estimated average period of the oscillation (683.68s) is different from the PSD since, the method calculates the average of two peaks. In addition, $reg = 2.5251 > 1$ indicates the oscillations are regular. Furthermore, $h > 0.4$ implies that the oscillations are regular also in time domain. However, the decay ratio method fails to capture the oscillation since $R \ll 0.5$. Figure 5.51 shows the features of stiction problem and is questioned in the following sections. Typical results are also obtained for the other segments.

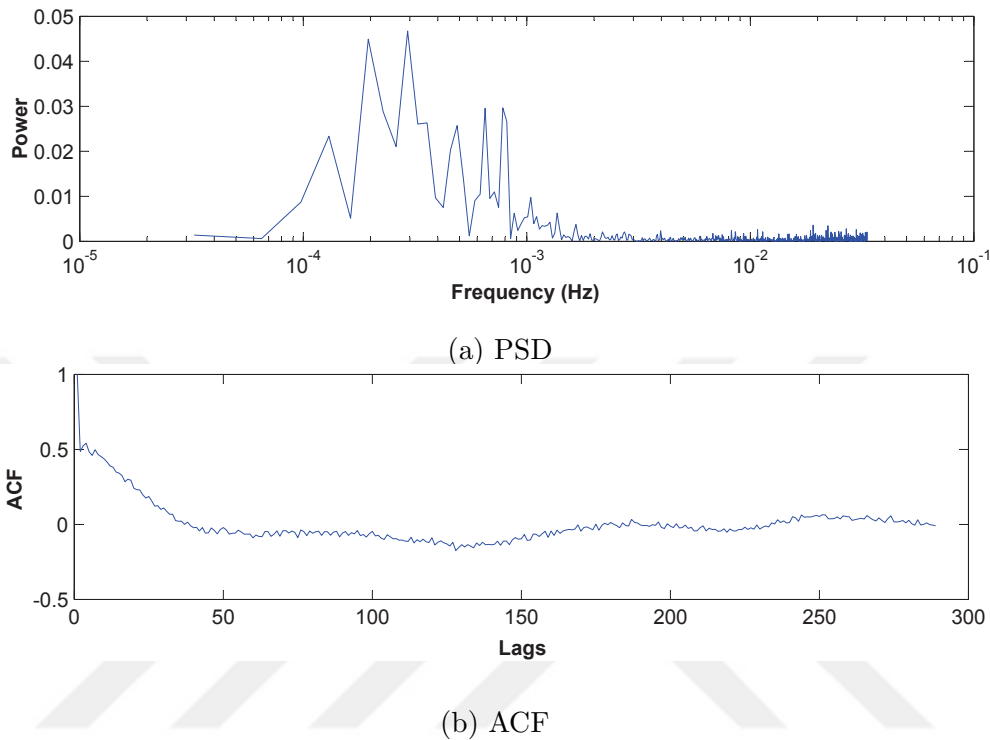
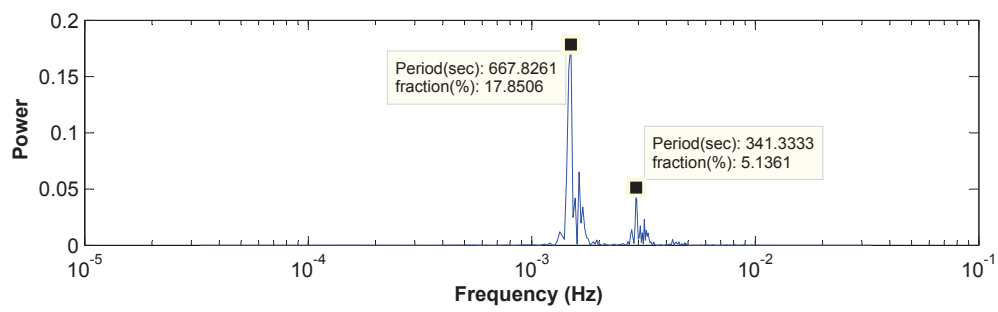


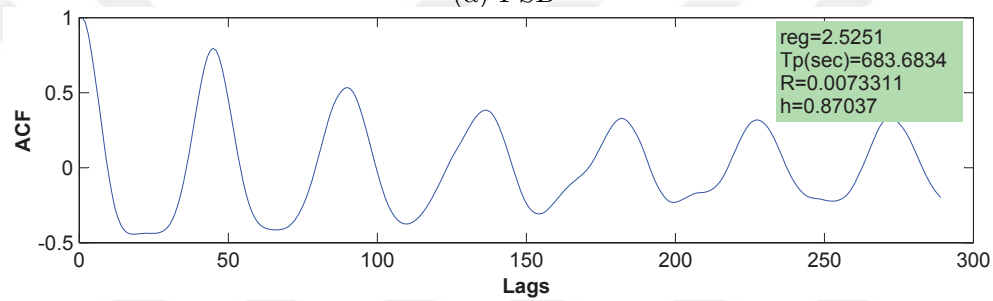
Figure 5.50: Oscillation Analysis of PC5 for Segment 18

TC1: This controller adjusts the reactor inlet temperature by manipulating the flow rates through the exchanger E5 and the by-pass line. As shown in Table 5.2, performance of the loop is stable over the analysis period. However, the average grade is low. The oscillation analysis of the loop shows that it has intermittent, slightly regular oscillations. Figure 5.52 gives the oscillation analysis of TC1 for segment 1. The PSD of the signal shows some frequencies dominating the signal with strengths of 11.36% and 7.68%. Similarly, the ACF of the signal is regular with $reg = 1.7759 > 1$. There is not a single frequency but multiple frequencies affect the loop. Similar results are also seen for the other segments. Especially, the periods around 850-950s are observed frequently for the other segments. The reasons behind these oscillations are discussed in the following sections.

TC3: Similar to TC1, this controller adjusts the feed inlet temperature of column C1 by manipulating the flow rates through the exchanger E4 and the by-pass line.

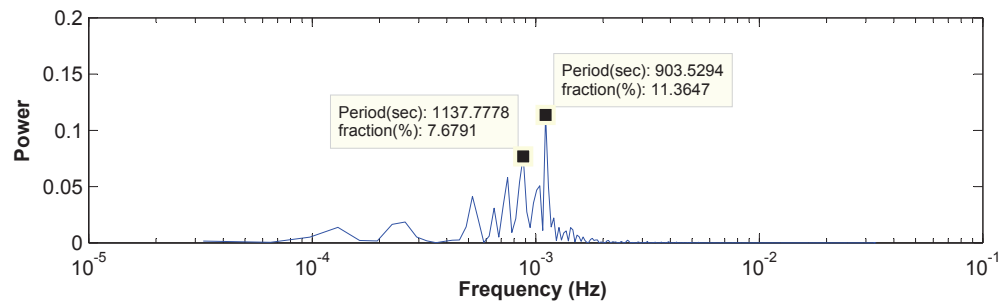


(a) PSD

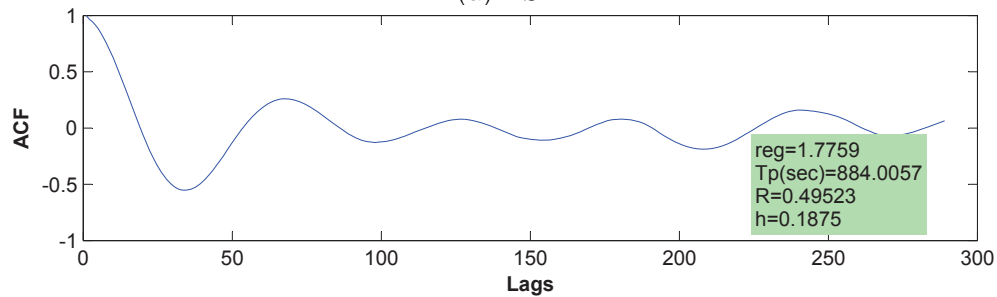


(b) ACF

Figure 5.51: Oscillation Analysis of PC6 for Segment 1



(a) PSD



(b) ACF

Figure 5.52: Oscillation Analysis of TC1 for Segment 1

This controller is also above moderate with an average grade of 0.6929. The oscillation analysis of the loop showed that there are some frequencies common in most of the segments. Figure 5.53 shows an example from segment 8. As Figure 5.53a implies,

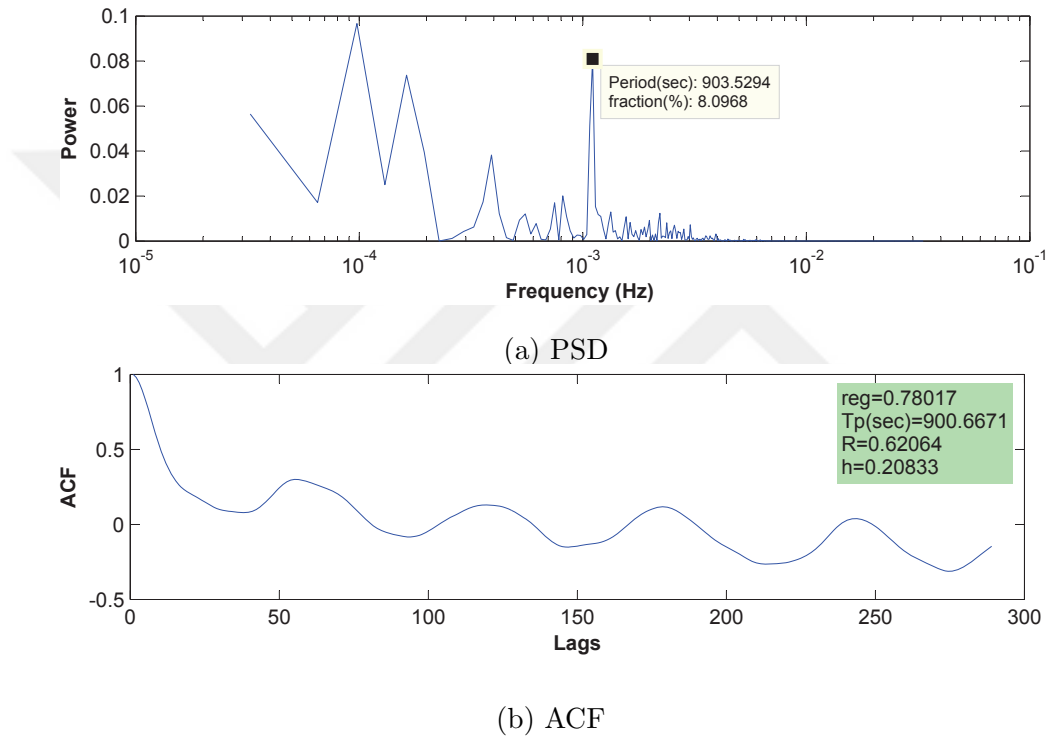


Figure 5.53: Oscillation Analysis of TC3 for Segment 8

the oscillation with the period of 903.53s covers the 8.1% of the signal. However, the lower frequencies around 10^{-4} destroy the regularity of the ACF in Figure 5.53b with $reg = 0.78017 < 1$. On the other hand, decay ratio (R) is successful to capture the oscillation with $R = 0.62064 > 0.5$. In other segments, the same structure is observed. The details are discussed in the following sections.

Table 5.3 summarizes all the oscillation analyses for the loops discussed above. It gives whether the analysis of the loops indicate significant peaks or not. The period ranges of the oscillations are also given for the loops having significant peaks.

Table 5.3: Oscillation Analysis Summary

Loop Name	Average Grade	Significant Peaks?	Period Range (sec)
FFC1	0.5106	yes	870-910
FFC2	0.5464	intermittent	>600, >2000
FC1	0.8552	yes	870-910
FC2	0.8973	no	-
FC3	0.8651	intermittent	180-210
FC4	0.9637	no	-
FC6	0.9831	no	-
FC7	0.9333	no	-
FC8	0.9020	no	-
FC9	0.4258	not exact frequencies	870-910, >1000
LC1	0.7817	yes	870-910
LC2	0	-	-
LC3	0.3100	no	-
PC1	0.4719	intermittent	870-910, >2000
PC2	0.8999	intermittent	100-180
PC3	0.3647	yes	100-120
PC4	0	-	-
PC5	0.8594	no	-
PC6	0.0035	yes	667, 341
TC1	0.5338	intermittent	870-910, >1000
TC2	0	-	-
TC3	0.6929	intermittent	870-910, >1000

As the table indicates, loops FFC1, FC1, LC1, PC3 and PC6 have significant oscillations. On the other hand, FFC2, FC3, FC9, PC1, PC2, TC1 and TC3 have intermittent oscillations. For FFC1, FC1, FC9, LC1, PC1, TC1 and TC3, there exists a common period range of 870-910. This result signs a possible plant-wide oscillation problem and to be questioned in the following sections. Other than that, there are different period ranges for FFC2, FC3, PC2, PC3 and PC6. At first glance, it seems that they have independent oscillations. These are also to be questioned in the following sections.

5.2.3 Non-Linearity Detection

For non-linearity detection, bispectral analysis (3.3.1) and surrogate analysis (3.3.2) were applied simultaneously for the loops and their corresponding segments in which oscillations were detected in 5.2.2. Analyzed loops are LC1, FC1, FFC1, FFC2, FC3, FC9, PC1, PC2, PC3, PC6, TC1 and TC3. For bispectral analysis, segment length was chosen as 64. For number of DFT points, 128 was selected. The segments are overlapped with 45%. Hanning window was used to smooth the edges of the segments. The bicoherence graphs are filtered with correction factor κ as discussed in 3.3.1. True Nyquist frequency was used to limit the frequency axis. For surrogate analysis, the parameter of the samples per segment (S) was adjusted to fit between 7-25 by down-sampling the process data with the integer multiplications of real sampling ($T_s = 15s$). Other than that, all suggested parameters given in Table 3.3 were used. Finally for surrogate data generation, random phases method was used.

LC1, FC1 and FFC1: Oscillation analysis given in Table 3.1 showed that this structure has a common oscillation within the range of 870-910s. In 5.2.2, segment 4 was given as an example for this structure. Figure 5.54 shows the bicoherence of LC1 for segment 4, and Table 5.4 gives the non-linearity analysis results. Table 5.4 shows that LC1 has some non-Gaussianity. However, the loop does not have non-linearity since NLI is low and $NPI < 1$. In addition, although there are some little peaks over the principle domain, the bicoherence graph (Figure 5.54) does not indicate a

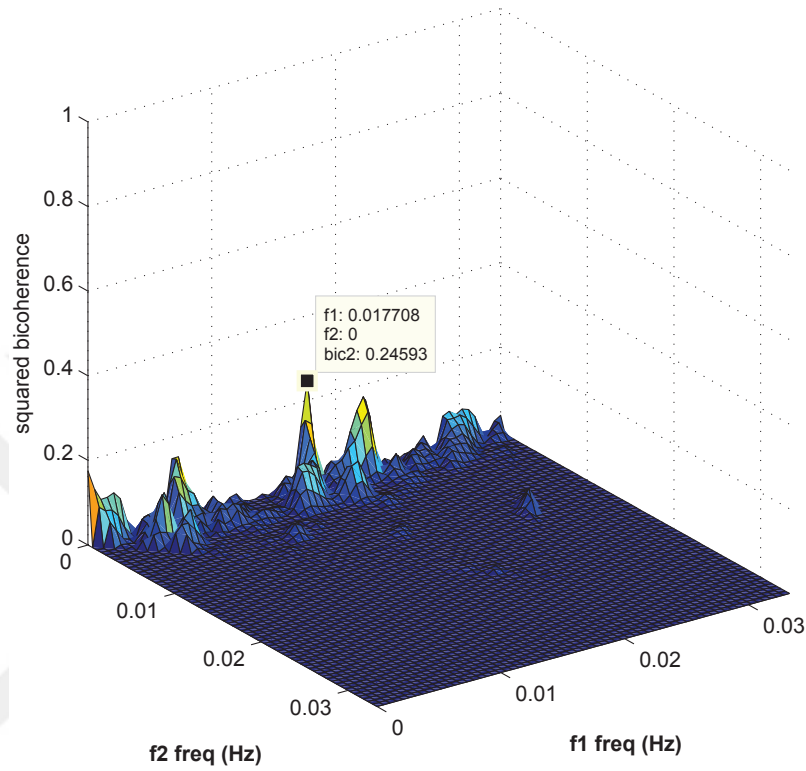


Figure 5.54: Squared Bicoherence of LC1 for Segment 4

Table 5.4: Non-linearity Analysis of LC1 for Segment 4

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.017708, 0)	0.246	0.1306	0.0110	0.3368

strong frequency interaction. Similarly, Figure 5.55 shows the bicoherence of FC1 for the same segment, and Table 5.5 gives the non-linearity analysis results. Similar to

Table 5.5: Non-linearity Analysis of FC1 for Segment 4

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0010417, 0.0010417)	0.148	0.1082	0.0042	-0.9476

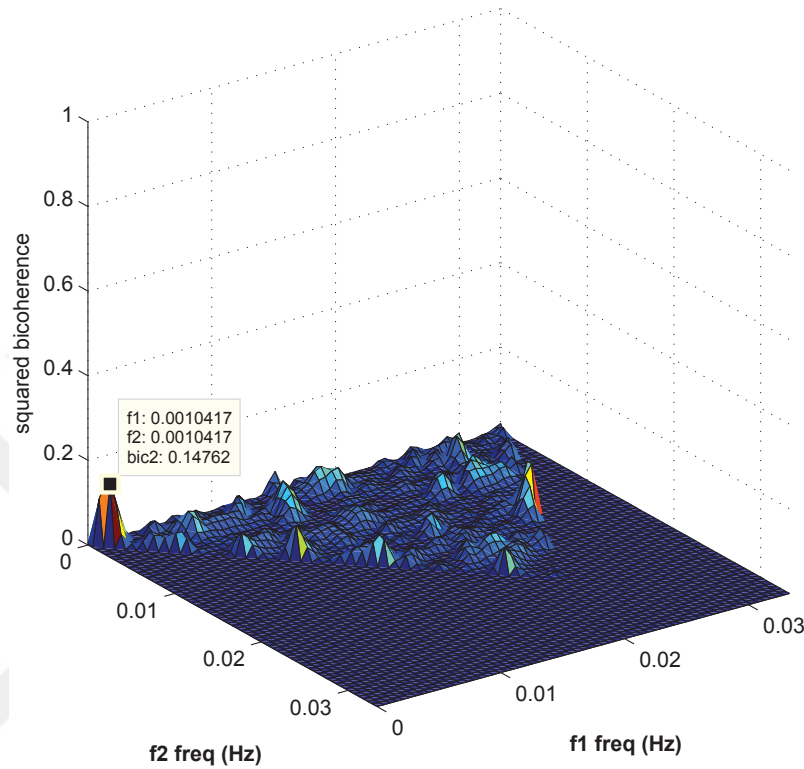


Figure 5.55: Squared Bicoherence of FC1 for Segment 4

LC1, FC1 has also some non-Gaussianity. However, NLI index is low. Furthermore, $NPI < 1$ validates that result. On the other hand, the frequency pair of (0.0010417, 0.0010417) is close to the range of 900s which discloses the frequency components observed in 5.2.2. Finally, Figure 5.56 shows the bicoherence graph of FFC1 for the same segment and Table 5.6 shows the non-linearity analysis. Table 5.6 states that similar to LC1 and FC1, FFC1 also has some non-Gaussianity. However, the loop does not suffer from non-linearity. This shows that, LC1-FC1-FFC1 structure is slightly skewed from the normal distribution, but does not have non-linearity problem. On the other hand, there is a common frequency range affecting the structure. This result leads to question a possible plant-wide oscillation and is analyzed further in the plant-wide disturbance detection section.

FC4 and FFC2: In this structure, there are intermittent oscillations only for FFC2. Figure 5.57 shows the bicoherence graph for one of the segments having

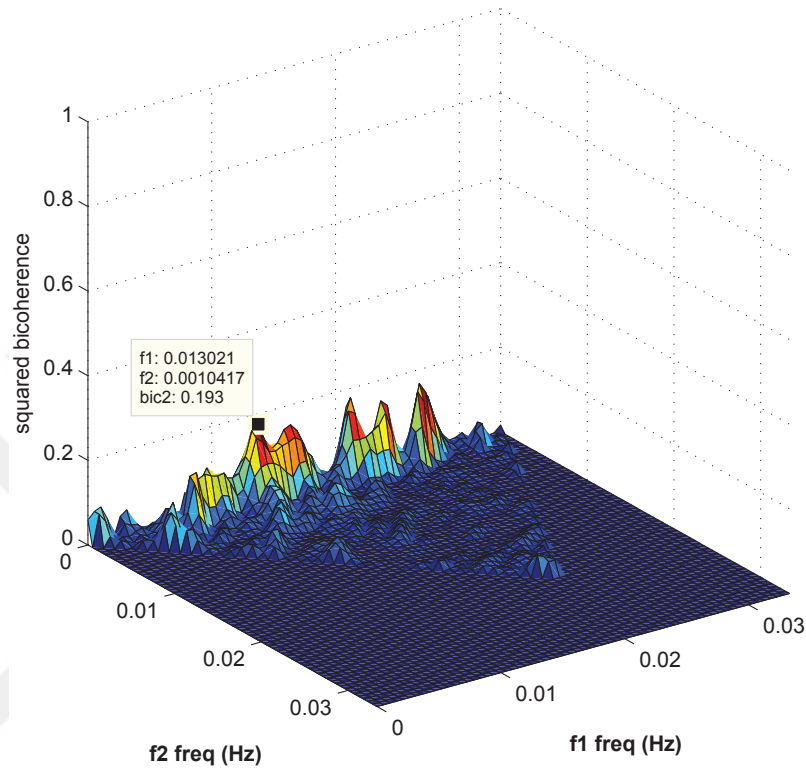


Figure 5.56: Squared Bicoherence of FFC1 for Segment 4

Table 5.6: Non-linearity Analysis of FFC1 for Segment 4

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.013021, 0.0010417)	0.193	0.1312	0.0208	0.2669

intermittent oscillations, segment 48, and Table 5.7 shows the results of non-linearity analysis for the same segment. Table 5.7 indicates that the loop does not have non-

Table 5.7: Non-linearity Analysis of FFC2 for Segment 48

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.011979, 0.0057292)	0.2	0.1251	0.0098	-0.5882

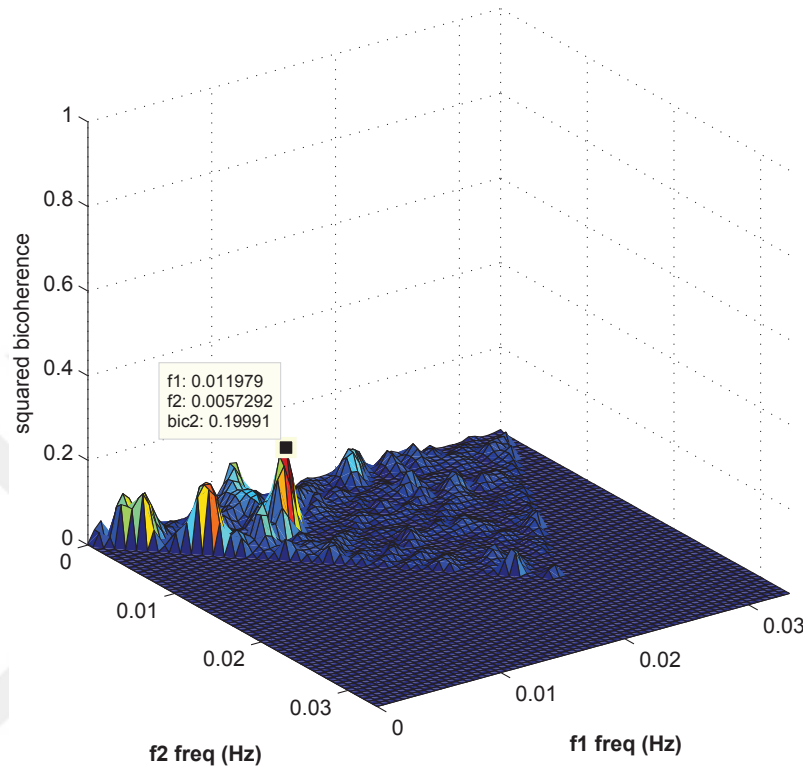


Figure 5.57: Squared Bicoherence of FFC2 for Segment 48

linearity problem. Rather, the loop has some deviations from the normal distribution since NGI is significant with 0.1251.

LC3 and FC3: In this structure, FC3 has some intermittent oscillations, whereas LC3 does not show at all. Figure 5.58 represents the bicoherence graph of LC3 for segment 3, and Table 5.8 shows the results of non-linearity analysis. According to

Table 5.8: Non-linearity Analysis of FC3 for Segment 3

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0026042, 0.0010417)	0.225	0.1395	0.0087	0.0688

Figure 5.58 and Table 5.8, the loop has non-Gaussianity but not non-linearity. The possible reasons of intermittent oscillations are discussed in the following sections

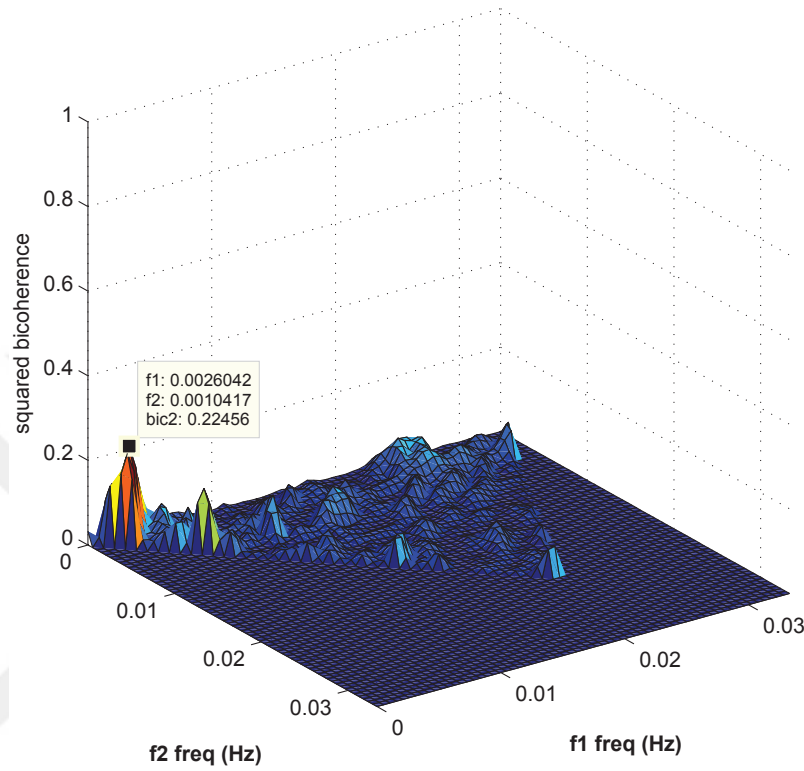


Figure 5.58: Squared Bicoherence of FC3 for Segment 3

with details.

FC6, FC7, FC8 and FC9: Among these loops, the only loop with oscillations is FC9. Figure 5.59 shows the bicoherence graph of FC9 for segment 12, and Table 5.9 shows the results of non-linearity analysis. Figure 5.59 shows that there are some

Table 5.9: Non-linearity Analysis of FC9 for Segment 12

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.011979, 0.0010417)	0.168	0.1134	0.0123	1.0081

peaks over the graph. However, interactions seem to be weak. NGI and NLI given in Table 5.9 verify that interpretation. On the contrary, $NPI = 1.0081 > 1$ implies that the loop has some non-linearities. This result is questioned in 5.2.4.

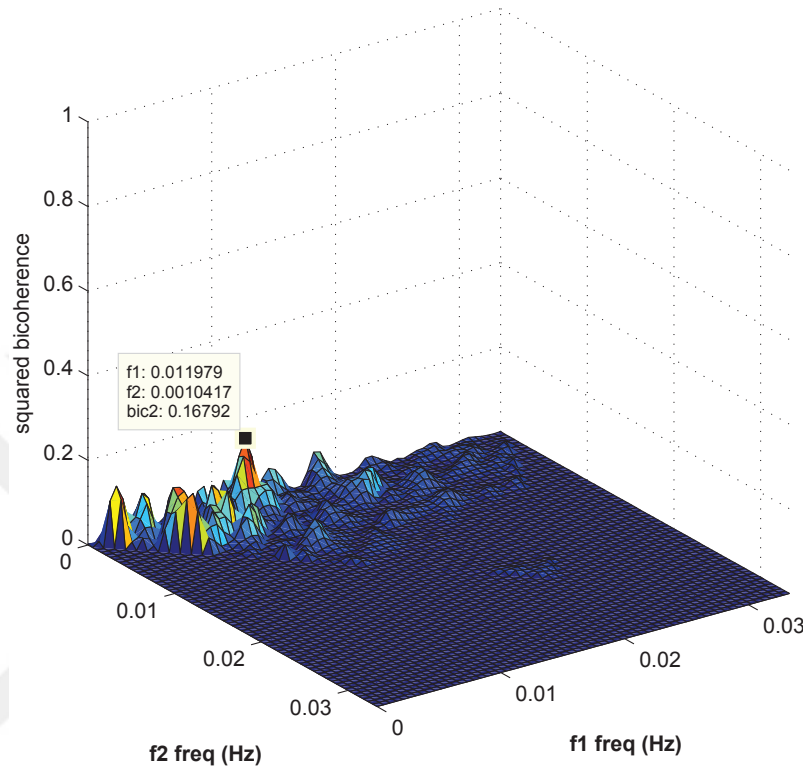


Figure 5.59: Squared Bicoherence of FC9 for Segment 12

PC1: As given in Table 5.3, PC1 has intermittent oscillations with changing frequencies. One of the representative segments is segment 7. Figure 5.60 shows the bicoherence graph for this segment, and Table 5.10 gives the results of non-linearity analysis. The results show that intermittent oscillations are not induced from non-

Table 5.10: Non-linearity Analysis of PC1 for Segment 7

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0, 0)	0.168	0.1107	0.0093	-0.2214

linearities. Rather, the loop has some non-Gaussianity.

PC2: This is one of the controllers having intermittent oscillations again. In oscillation detection section (5.2.2), segment 13 was selected as an example. Here,

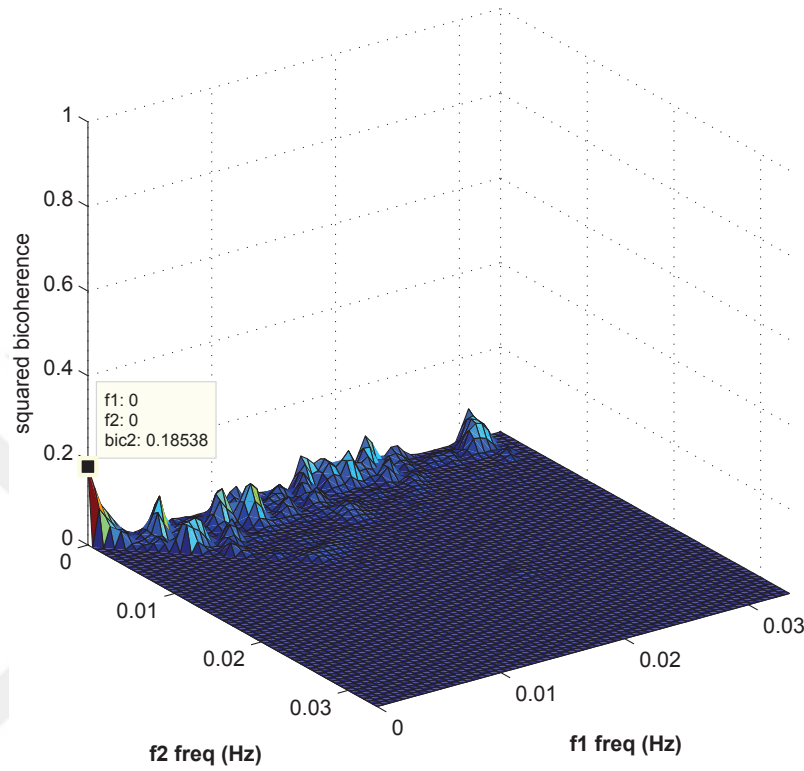


Figure 5.60: Squared Bicoherence of PC1 for Segment 7

Figure 5.61 shows the bicoherence graph for segment 13, and Table 5.11 gives the results of non-linearity analysis. Figure 5.61 indicates that the loop has low frequency

Table 5.11: Non-linearity Analysis of PC2 for Segment 13

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0015625, 0)	0.895	0.2863	0.0092	-1

interactions. However, these are not significant; since although NGI is significant, NLI is low. In addition, NPI given in Table 5.11 is -1 , which shows that the loop is not suffering from non-linearities.

PC3: As given in Table 5.3, this controller has an oscillation within the range of 100-120s for almost all the segments. Figure 5.62 gives an example from segment 2,

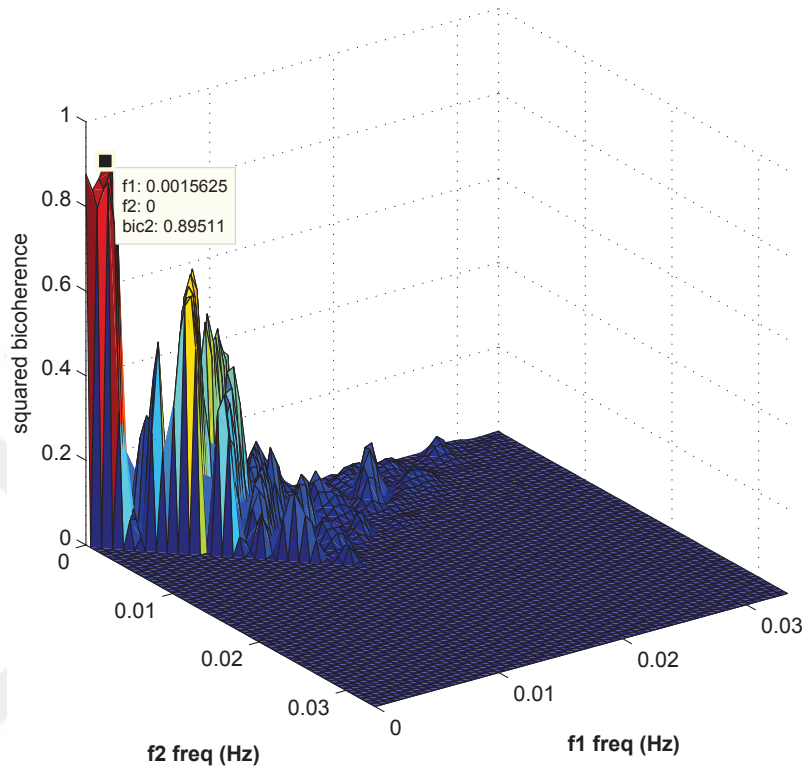


Figure 5.61: Squared Bicoherence of PC2 for Segment 13

and Table 5.12 summarizes the results of non-linearity analysis. Figure 5.62 shows

Table 5.12: Non-linearity Analysis of PC3 for Segment 2

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.009375, 0.0010417)	0.210	0.1325	0.0194	2.5376

that there are some peaks in low frequency region, however maximum bicoherence value is not high. NGI value given in Table 5.12 implies that the loop has non-Gaussianity but not non-linearity, since NLI is low. On the other hand, NPI value shows that the loop has strong non-linearity. Detailed analysis is done in the following sections.

PC6: This loop is the lowest performing loop among the whole list as given

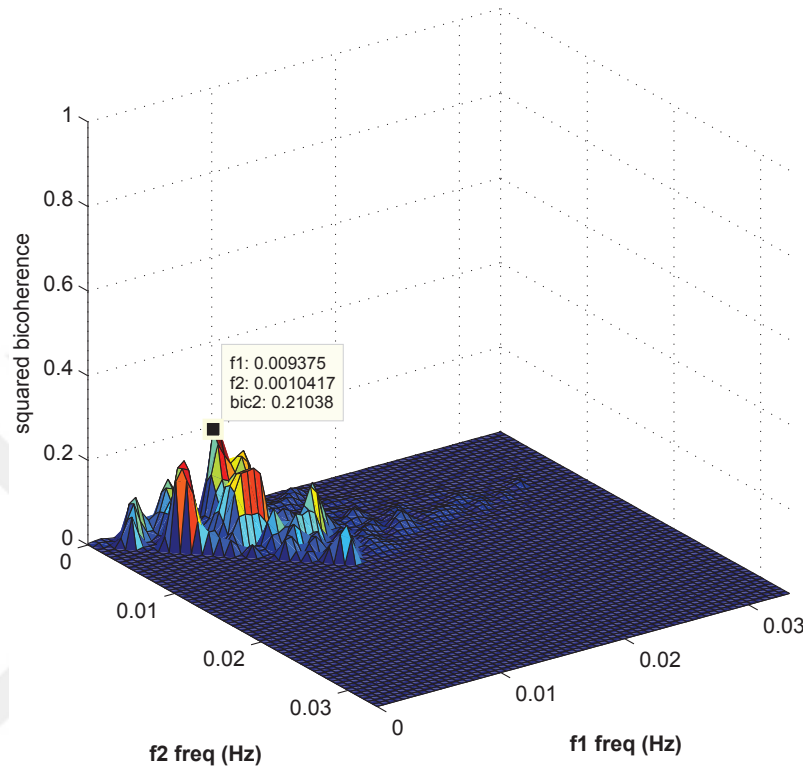


Figure 5.62: Squared Bicoherence of PC3 for Segment 2

in Table 5.2. In all segments, oscillations are observed and reported in Table 5.3. Preliminary analysis indicated a possible stiction problem and this interpretation are investigated. Figure 5.63 shows the bicoherence graph for segment 1, and Table 5.13 summarizes the results of non-linearity analysis. Both Figure 5.63 and Table 5.13

Table 5.13: Non-linearity Analysis of PC6 for Segment 1

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0083333, 0.0015625)	0.959	0.4283	0.1976	1.8309

imply that the loop has strong non-linearities. However, the maximum bicoherence value does not create a single peak but shows a region of frequencies. The loop should be analyzed for stiction.

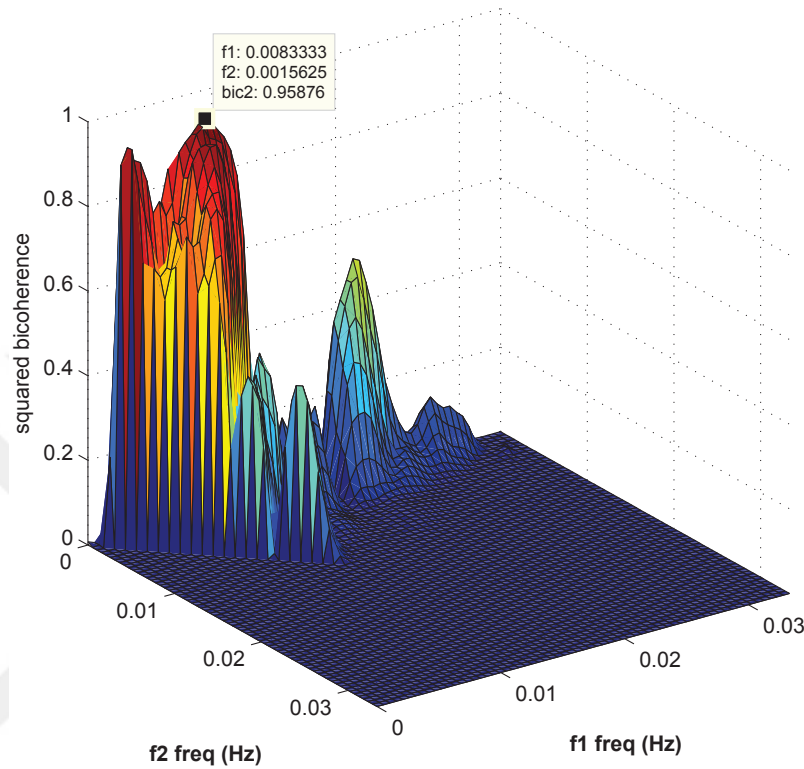


Figure 5.63: Squared Bicoherence of PC6 for Segment 1

TC1: In oscillation detection, intermittent oscillations were observed in this loop. Segment 1 was one of the examples. Figure 5.64 shows the bicoherence graph for segment 1, and Table 5.14 summarizes the results of non-linearity analysis for the given segment. Figure 5.64 and Table 5.14 imply that there is not any non-linearity in the loop.

Table 5.14: Non-linearity Analysis of TC1 for Segment 1

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0072917, 0)	0.135	0.1082	0.0128	-0.5094

TC3: This loop also showed intermittent oscillations in oscillation detection. Segment 8 was selected as an example. Figure 5.65 and Table 5.15 give the non-

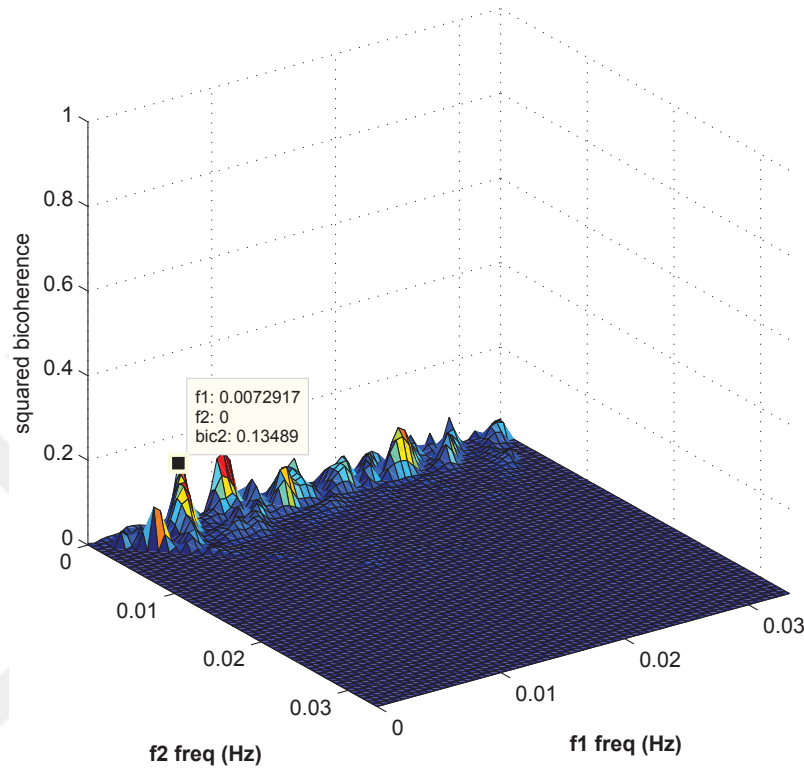


Figure 5.64: Squared Bicoherence of TC1 for Segment 1

linearity analysis. The analysis shows that the loop has some non-Gaussianity but not non-linearity. Table 5.15 summarizes the results.

Table 5.15: Non-linearity Analysis of TC3 for Segment 8

frequency pair	$\hat{bic}_{max}^2$	NGI	NLI	NPI
(0.0015625, 0.0010417)	0.253	0.1374	0.0120	0.3289

Table 5.16 summarizes the non-linearity analysis given above. According to the analysis, loops FC9, PC2, PC3 and PC6 are candidates of non-linearity problem. In addition, the loops with oscillations show changing amounts of non-Gaussianity, which implies that these loops are skewed from normal distribution. In the table, the loops marked with "*possible*" mean that either of the methods could capture the non-

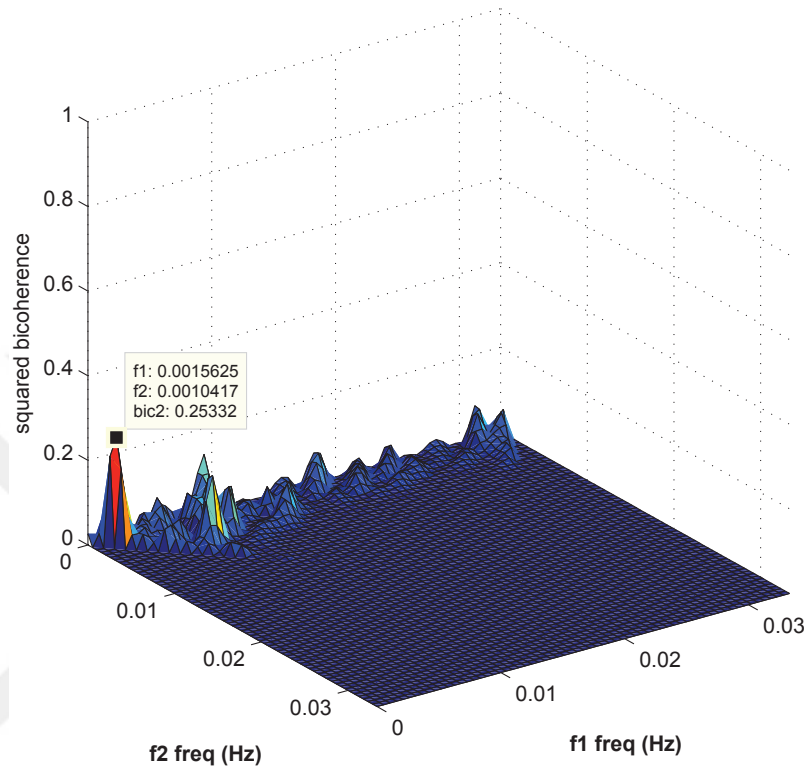


Figure 5.65: Squared Bicoherence of TC3 for Segment 8

linearity, whereas the ones marked with *"yes"* mean that both of the methods could capture the non-linearity in the loop. The analysis also showed that the frequency of 0.0010417 Hz (=960s) is a common component of frequency pairs obtained in the bicoherence graphs. It is known that obtained frequencies in the method of bispectral analysis are not exact. For this reason, the method of PV-OP mapping analysis, which is based on bispectral analysis, requires to use filter. Besides, in this analysis a pre-filter was not used. Therefore, the components obtained in frequency pairs may not be exact also. Knowing that fact, the period of 960s might be relevant to the frequency band of 870-910s which is obtained in the oscillation detection section. Furthermore, for the loops signed with *"possible"*, it is seen that the methods conflict. In the stiction detection section, that result is discussed.

Table 5.16: Non-linearity Analysis Summary

Loop Name	Average Grade	Oscillation	Non-linearity
FFC1	0.5106	yes	no
FFC2	0.5464	intermittent	no
FC1	0.8552	yes	no
FC2	0.8973	no	-
FC3	0.8651	intermittent	no
FC4	0.9637	no	-
FC6	0.9831	no	-
FC7	0.9333	no	-
FC8	0.9020	no	-
FC9	0.4258	not exact frequencies	possible
LC1	0.7817	yes	no
LC2	0	-	-
LC3	0.3100	no	-
PC1	0.4719	intermittent	no
PC2	0.8999	intermittent	possible
PC3	0.3647	yes	possible
PC4	0	-	-
PC5	0.8594	no	-
PC6	0.0035	yes	yes
TC1	0.5338	intermittent	no
TC2	0	-	-
TC3	0.6929	intermittent	no

5.2.4 Stiction Detection and Quantification

In stiction detection, non-linearity detected loops (FC9, PC2, PC3 and PC6) given in 5.16 are analyzed. For that purpose, both curve-fitting analysis (3.4.1) and PV-OP mapping analysis (3.4.2) were applied simultaneously. For simplicity, in PV-OP mapping analysis, described Wiener filter was used.

FC9: For this loop, surrogate analysis showed that there is a non-linearity problem in the loop with $NLI > 1$. On the other hand, bispectral analysis did not indicate a significant non-linearity. Figure 5.66 shows the curve-fitting analysis of FC9 for a portion of the segment 12. For the given segment, the result of $SI_{cf} = 0.5823 < 0.6$ falls into no decision region of the method. Unfortunately, PV-OP mapping analysis

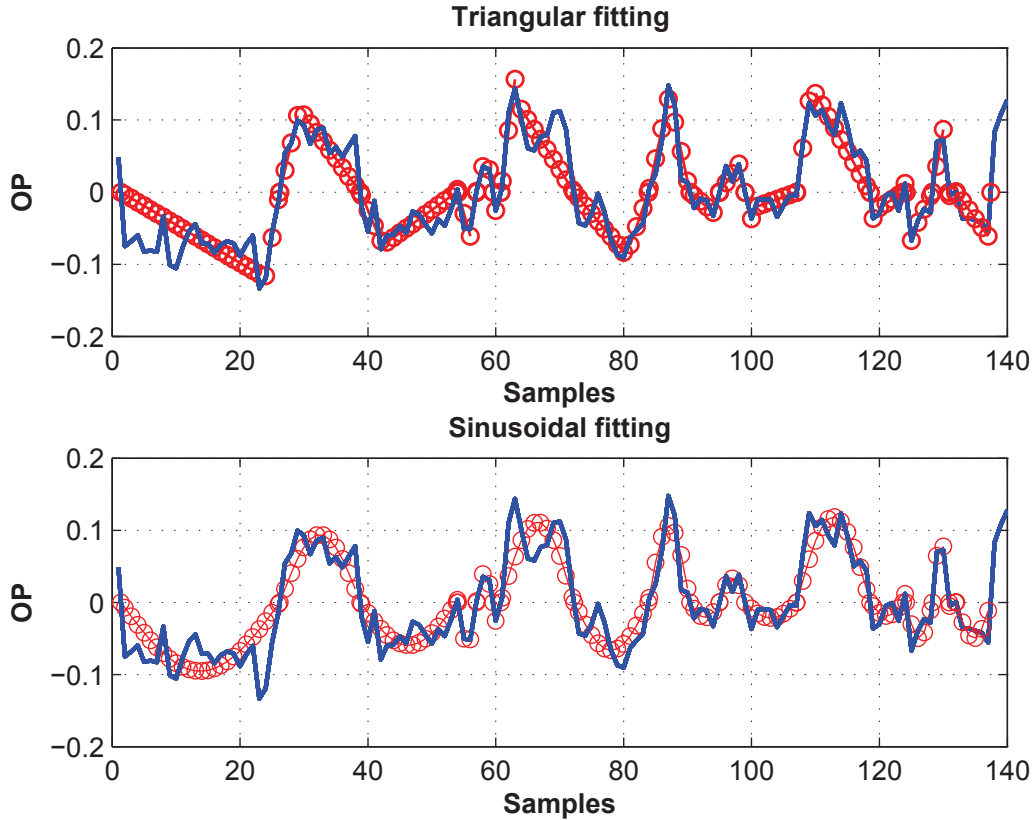


Figure 5.66: Curve-Fitting Analysis of FC9 for Segment 12

could not be done, because the data points did not produce an ellipse as Equation 3.39 requires in 3.4.2.

PC2: In this controller, two of the non-linearity detection algorithms produced

different results. Figure 5.67 shows curve-fitting analysis of FC9 for a portion of the segment 13. Analysis showed that $SI_{cf} = 0.5493 < 0.6$ and a certain decision cannot be made. Similar to FC9, PV-OP mapping analysis did not produce an ellipse for this loop.

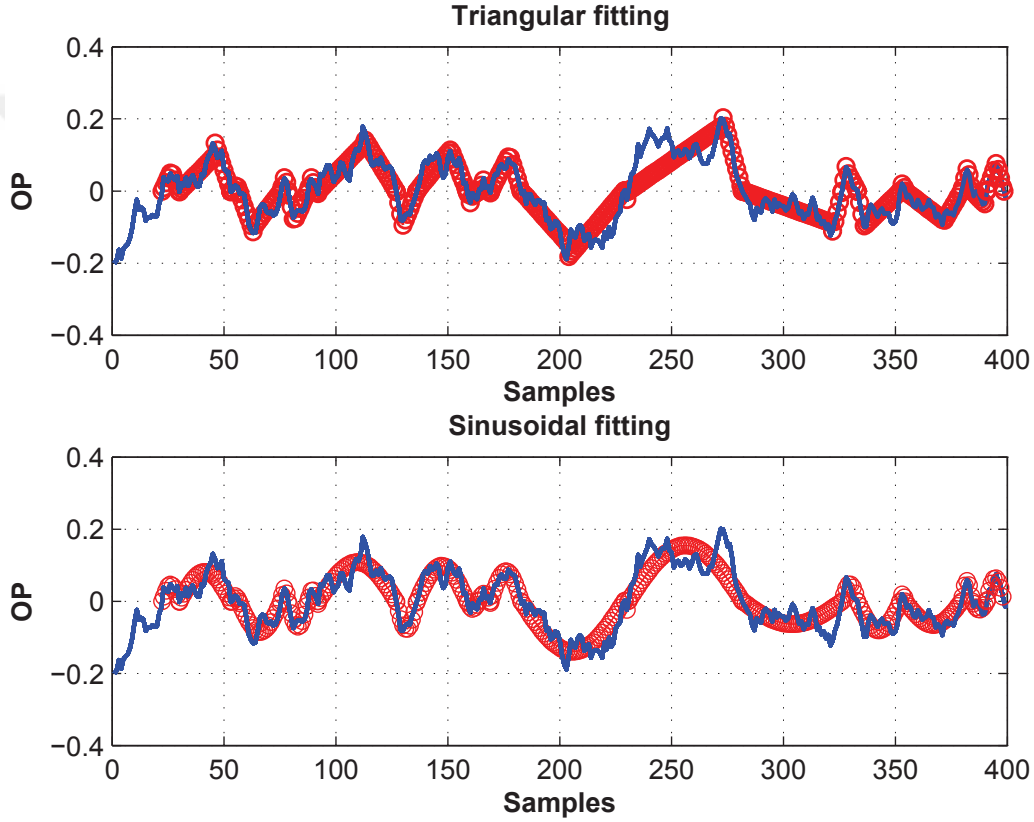


Figure 5.67: Curve-Fitting Analysis of PC2 for Segment 12

PC3: As Table 5.12 indicates, there are some non-linearities in the loop. However, bispectral analysis did not verify that. Following Figure 5.68 shows the curve-fitting analysis for segment 2. The analysis show that $SI_{cf} = 0.5673 < 0.6$ which falls into no decision region.

PC6: The non-linearity analysis shown in Table 5.16 showed that two of the methods agree on the non-linearity problem in this loop. In addition, the oscillation analysis in Figure 5.51 gave some indications about stiction problem. Figure 5.69 shows the curve-fitting analysis which results in $SI_{cf} = 0.9530 > 0.6$. The calculated

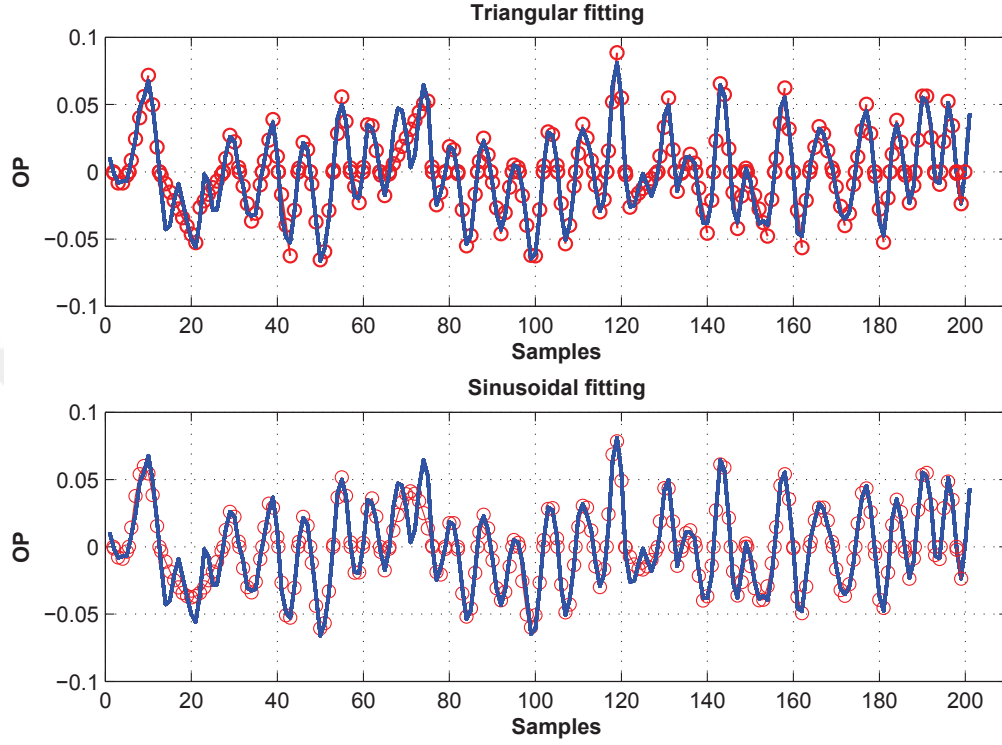


Figure 5.68: Curve-Fitting Analysis of PC3 for Segment 2

index clearly shows that the loop suffers from the stiction problem. Similar results are also obtained for PV-OP mapping analysis as shown in Figure 5.70. The analysis showed that $stiction = 1.56\%$ and $hysteresis = 0.003\%$ with 89.2% goodness-of-fit. In the analysis, the confidence ellipses are obtained with $f = 1.5$. In this loop, both of the methods detected stiction.

Table 5.17 summarizes the stiction detection analysis. As the table indicates, PC6 has a stiction problem. For the loops marked with "*possible*", both of the analysis methods did not indicate a stiction problem. The possible reasons are discussed in the following sections.

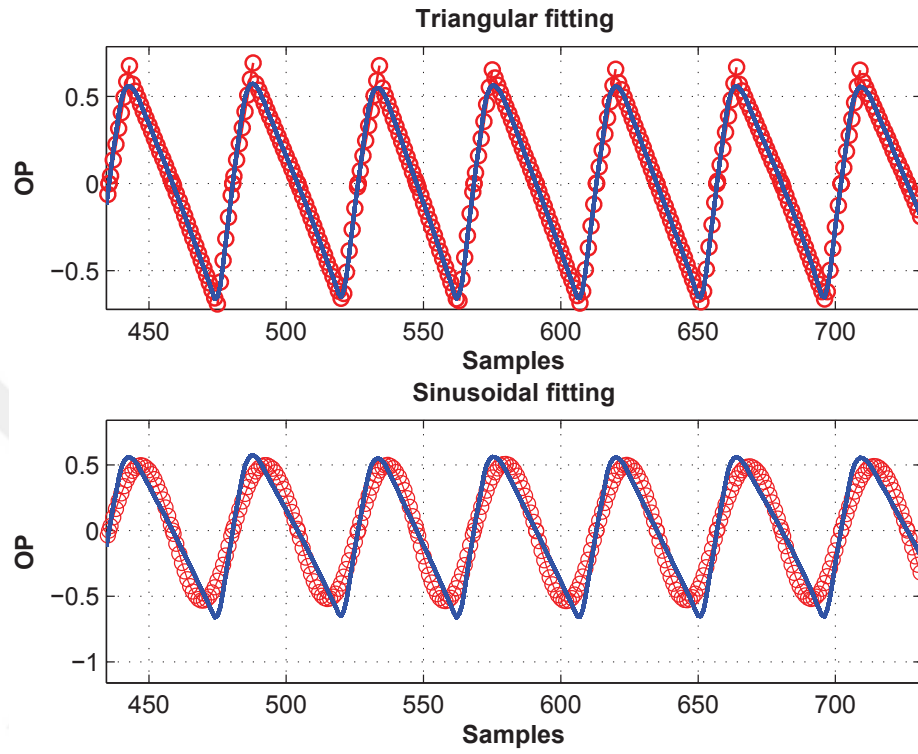


Figure 5.69: Curve-Fitting Analysis of PC6 for Segment 1

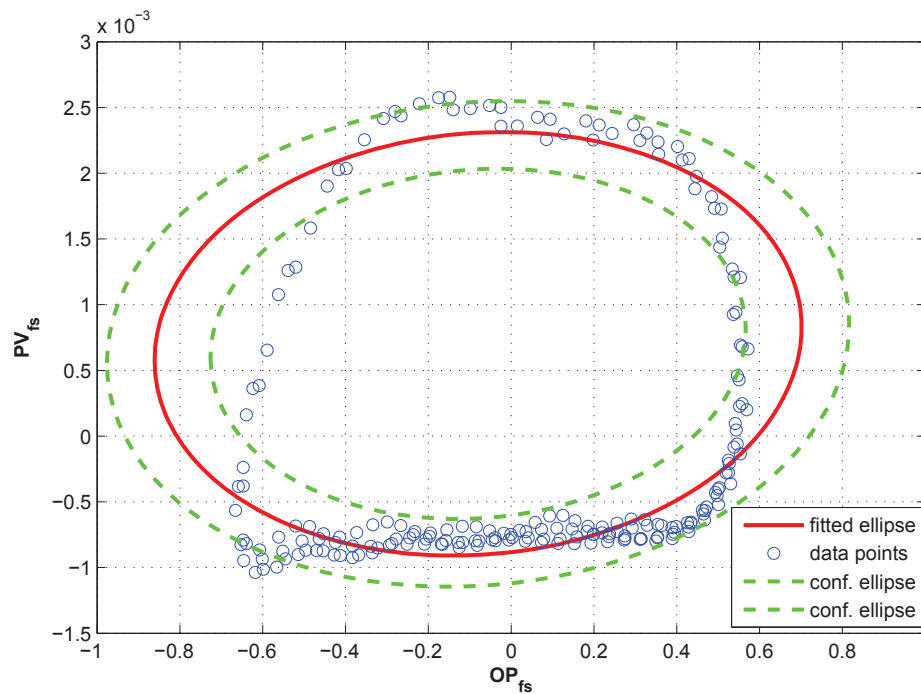


Figure 5.70: PV-OP Mapping Analysis of PC6 for Segment 1

Table 5.17: Stiction Detection Summary

Loop Name	Average Grade	Oscillation	Non-linearity	Stiction
FFC1	0.5106	yes	no	-
FFC2	0.5464	intermittent	no	-
FC1	0.8552	yes	no	-
FC2	0.8973	no	-	-
FC3	0.8651	intermittent	no	-
FC4	0.9637	no	-	-
FC6	0.9831	no	-	-
FC7	0.9333	no	-	-
FC8	0.9020	no	-	-
FC9	0.4258	not exact frequencies	possible	no
LC1	0.7817	yes	no	-
LC2	0	-	-	-
LC3	0.3100	no	-	-
PC1	0.4719	intermittent	no	-
PC2	0.8999	intermittent	possible	no
PC3	0.3647	yes	possible	no
PC4	0	-	-	-
PC5	0.8594	no	-	-
PC6	0.0035	yes	yes	yes
TC1	0.5338	intermittent	no	-
TC2	0	-	-	-
TC3	0.6929	intermittent	no	-

5.2.5 Controller Tuning Assessment

The assessment of controller tuning was done by calculating the IRAI as described in 2.5. During the analysis period, it is known that no controller has been tuned. Therefore, average tuning indices and their standard deviations were calculated. Table 5.18 summarizes the results of average IRAI values for each loop. Table 5.18 shows

Table 5.18: Controller Tuning Assessment Summary

Loop Name	Average Grade	Oscillation	Non-linearity	Stiction	Average IRAI	σ_{IRAI}
FFC1	0.5106	yes	no	-	0.78	0.15
FFC2	0.5464	intermittent	no	-	0.69	0.23
FC1	0.8552	yes	no	-	0.49	0.22
FC2	0.8973	no	-	-	0.44	0.25
FC3	0.8651	intermittent	no	-	0.35	0.12
FC4	0.9637	no	-	-	0.32	0.17
FC6	0.9831	no	-	-	0.33	0.17
FC7	0.9333	no	-	-	0.43	0.20
FC8	0.9020	no	-	-	0.47	0.23
FC9	0.4258	not exact frequencies	possible	no	0.91	0.18
LC1	0.7817	yes	no	-	0.68	0.22
LC2	0	-	-	-	-	-
LC3	0.3100	no	-	-	0.97	0.10
PC1	0.4719	intermittent	no	-	0.66	0.22
PC2	0.8999	intermittent	possible	no	0.30	0.11
PC3	0.3647	yes	possible	no	0.22	0.05
PC4	0	-	-	-	-	-
PC5	0.8594	no	-	-	0.51	0.25
PC6	0.0035	yes	yes	yes	0.56	0.25
TC1	0.5338	intermittent	no	-	0.35	0.07
TC2	0	-	-	-	-	-
TC3	0.6929	intermittent	no	-	0.48	0.19

that FFC1, FC9 and LC3 are sluggish with $IRAI > 0.7$. Besides that FFC2, LC1 and PC1 are optimum but close to sluggish. On the other hand, FC4, FC6, PC2 and PC3 are aggressive with $IRAI < 0.35$. In addition, FC3 is optimum but close to aggressive. Finally, loops FC1, FC2, FC7, FC8, PC5, PC6, TC1 and TC3 are optimally tuned.

5.2.6 Plant-wide Disturbance Detection

In the plant-wide disturbance detection, spectral envelope method given in Chapter 4 was used. Instead of divided data segment, whole data for each day was analyzed. For cascaded control structures, SP data of the slave loop was also analyzed in addition to PV and OP. Smoothing degree was chosen as 2. Then, the obtained spectral envelope graph for each day was visually analyzed and the peaks were extracted. Finally, for the corresponding frequencies, $TestStat$ and OCI values were calculated with $cL = 99.9\%$ and $\chi^2_{0.001,2} = 13.816$. Figure 5.71 shows the spectral envelope of day 1.

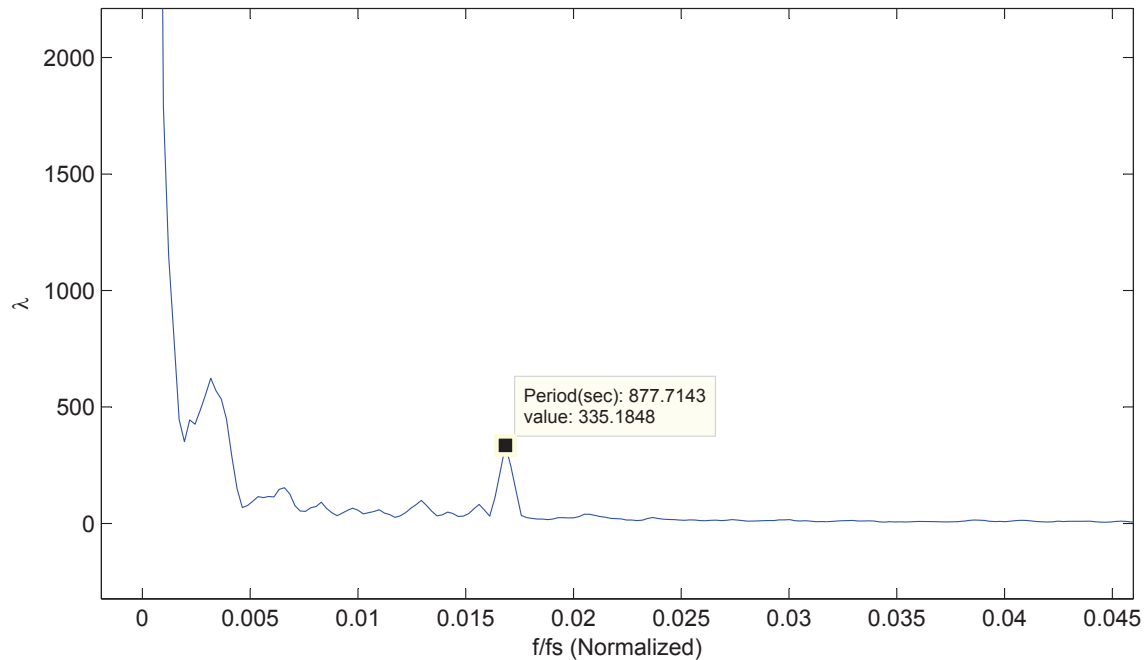


Figure 5.71: Spectral Envelope for Day 1

The figure states that among the loops, a common period with 877.71s exists. After detecting the peak, *TestStat* and *OCI* values were calculated for the corresponding frequency. With the given *cL*, there exists an oscillation if $TestStat > 13.816$. In addition, the loop variables with $OCI > 1$ become the root cause of the oscillation. The results are given below in Tables 5.19 and 5.20. The results show that a considerable amount of the loops have oscillation at period of 877.71s. These are FFC1, FC1, FC3, FC4, FC6, LC1, LC3, PC1, PC3, PC5, TC1, and TC3. This shows that a disturbance affects most of the loops. *OCI* values given in the tables signal TC1 and LC1 as the possible root causes with $OCI_{TC1.PV} = 2.05$ and $OCI_{LC1.PV} = 1.79$, respectively. In addition with $OCI \approx 1$, PC1 and TC3 are also closer candidates. Similar results were also observed for the other days with changing root cause candidates among these 4 loops. Table 5.21 gives the summary of the whole analysis period for these loops. In the table, only days with significant spectral envelopes are given.

Table 5.21 points out that TC1 is the most frequent possible root cause and should be investigated first. In addition, the results presented in the table are meaningful in terms of process. Variations in the reactor (C3) temperature cause to change the properties of the effluent. Accordingly, the effluent temperature controller TC3 tries to stabilize the temperature of the column inlet stream. Correspondingly, this stream enters the column and changes the column dynamics (C1). One of the important dynamics is the column top pressure which is controlled by PC1. Apparently, the vapour-liquid traffic inside the column changes. As a result, the liquid volume in C4 which is controlled by LC1, changes. These variations propagate towards the other loops and create a plant-wide disturbance.

Table 5.19: Spectral Envelope Analysis for Day 1 with Period=877.71s

Loop Name	Average Grade	TestStat	OCI	Comments
FFC1	0.5106	SP: 204.696	SP: 0.43	Oscillation for SP, PV, OP
		PV: 223.398	PV: 0.36	
		OP: 212.424	OP: 0.38	
FFC2	0.5464	PV: 0.273	PV: 0.01	No oscillation
		OP: 1.443	OP: 0.03	
FC1	0.8552	PV: 269.017	SP: 0.31	Oscillation for SP, PV, OP
		SP: 201.446	PV: 0.31	
		OP: 202.592	OP: 0.31	
FC2	0.8973	PV: 5.236	PV: 0.21	No oscillation
		OP: 5.183	OP: 0.22	
FC3	0.8651	PV: 35.119	SP: 0.11	Oscillation for SP, PV, OP
		SP: 31.302	PV: 0.12	
		OP: 41.922	OP: 0.10	
FC4	0.9637	PV: 6.224	PV: 0.25	Oscillation for OP
		OP: 20.925	OP: 0.32	
FC6	0.9831	PV: 7.080	PV: 0.12	Oscillation for OP
		OP: 18.254	OP: 0.13	
FC7	0.9333	PV: 12.528	PV: 0.30	No oscillation
		OP: 4.777	OP: 0.13	
FC8	0.902	PV: 5.648	PV: 0.15	No oscillation
		OP: 9.021	OP: 0.15	
FC9	0.4258	PV: 10.953	PV: 0.45	No oscillation
		OP: 10.433	OP: 0.09	

Table 5.20: Spectral Envelope Analysis for Day 1 with Period=877.71s (cont'd)

Loop Name	Average Grade	TestStat	OCI	Comments
LC1	0.7817	PV: 378.927 OP: 201.446	PV: 1.79 OP: 0.31	Oscillation for PV, OP
LC2	0	-	-	-
LC3	0.31	PV: 81.537 OP: 31.302	PV: 0.21 OP: 0.11	Oscillation for PV, OP
PC1	0.4719	PV: 205.474 OP: 167.526	PV: 0.95 OP: 0.25	Oscillation for PV, OP
PC2	0.8999	PV: 11.968 OP: 5.101	PV: 0.17 OP: 0.07	No oscillation
PC3	0.3647	PV: 48.072 OP: 43.902	PV: 0.18 OP: 0.45	Oscillation for PV, OP
PC4	0	-	-	-
PC5	0.8594	PV: 69.206 OP: 124.945	PV: 0.42 OP: 0.14	Oscillation for PV, OP
PC6	0.0035	PV: 2.543 OP: 7.496	PV: 0.11 OP: 0.18	No oscillation
TC1	0.5338	PV: 196.873 OP: 190.563	PV: 2.05 OP: 0.20	Oscillation for PV, OP
TC2	0	-	-	-
TC3	0.6929	PV: 27.613 OP: 2.238	PV: 0.90 OP: 0.04	Oscillation for PV

Table 5.21: Spectral Envelope Analysis Summary for 1-month Period

<i>Days</i>	TC1.PV	LC1.PV	PC1.PV	TC3.PV
<i>1</i>	2.05	1.79	0.95	0.90
<i>2</i>	1.72	1.47	1.23	1.24
<i>5</i>	1.87	1.74	0.84	0.83
<i>6</i>	1.78	1.73	0.93	0.93
<i>7</i>	1.40	1.32	0.80	1.06
<i>10</i>	1.73	1.92	1.05	1.00
<i>11</i>	1.52	1.87	0.85	1.21
<i>12</i>	0.30	1.21	1.76	1.00
<i>13</i>	2.02	1.57	1.10	1.09
<i>15</i>	1.15	2.00	1.22	1.13
<i>16</i>	1.28	1.94	1.08	0.52
<i>22</i>	2.25	1.38	0.74	1.08
<i>26</i>	1.80	1.51	1.34	1.24
<i>27</i>	2.03	1.32	0.87	1.55

Chapter 6

DISCUSSIONS AND CONCLUSIONS

In this study, the main components of a CPM tool were discussed extensively. In the components, several proposed algorithms in the literature were surveyed. The algorithms were also examined with real plant data. For the tests, a refinery unit with 22 control loops was selected. Among those, 2 of the loops (TC2 and PC4) were in control structure revision. In addition, LC3 was switched to manual mode by the plant operators. Thus, below analysis was done only for remaining 19 auto loops. According to performance assessment, the loops are categorized into four: *best*, *good*, *fair*, and *poor*. Table 6.1 shows that 47% of the loops are performing "best", whereas 16% is

Table 6.1: Industrial Loop Categories

Category	Grade Interval	Percent in Total
Best	0.8 - 1.0	47%
Good	0.6 - 0.8	11%
Fair	0.4 - 0.6	26%
Poor	0.0 - 0.4	16%

"poor". In addition, Figure 6.1 shows that approximately 67% of the poor loops are oscillating. Similarly for the fairly performing loops, intermittent oscillations are significant with 60%. As expected, for the best performing loops, only 33% of the loops have either consistent or intermittent oscillations. The oscillation analysis revealed that there are some significant oscillations with changing periods from 100s to 2000s. Indeed, the analysis showed that there are some loops oscillating in a common period

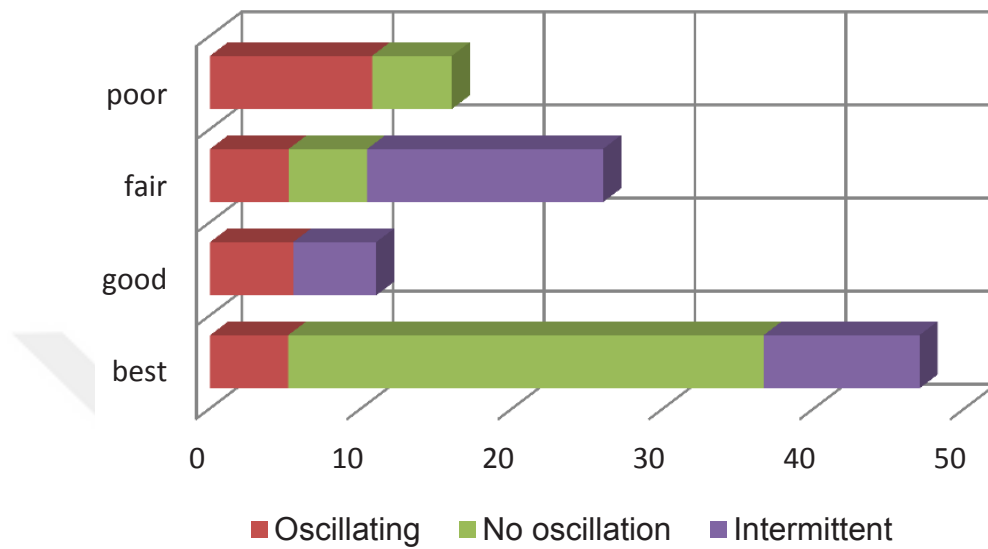


Figure 6.1: Oscillation Analysis Summary for All Categories

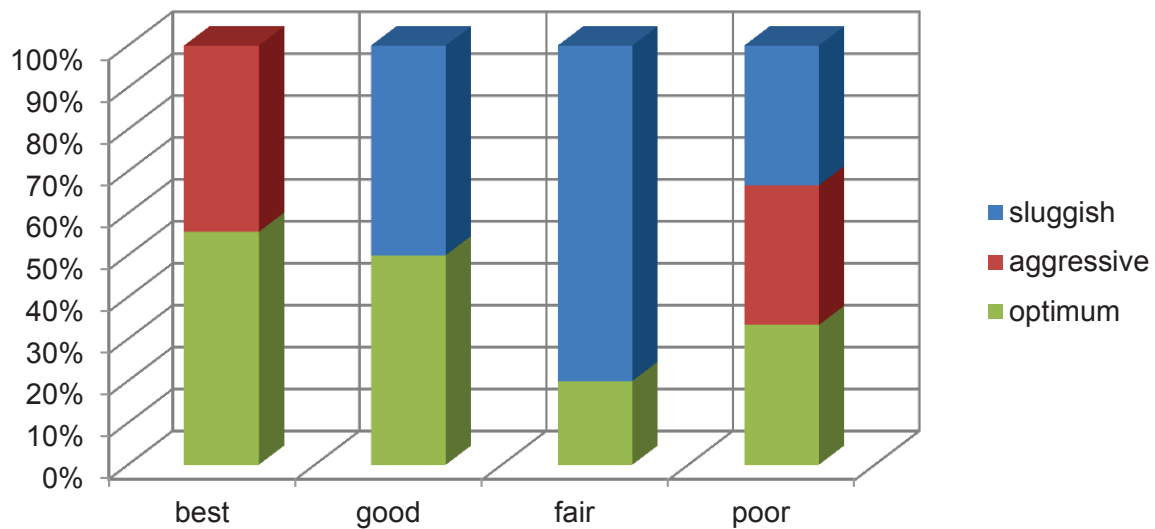


Figure 6.2: Tuning Analysis Summary for All Categories

of 870-910s. This fact was investigated with a plant-wide analysis method. Besides the oscillation analysis, Figure 6.2 shows the percentages for aggressively, sluggishly and optimally tuned loops. The figure shows that for the categories of fair and poor, considerable amount of the loops are not optimally tuned. Surprisingly, the percent

of aggressively tuned controllers for the category of best is 44. However, it is known that 2 of the loops from this category (FC4 and FC6) are close to optimal range. As expected, the percentage of optimally tuned controllers for the categories of fair and poor are 20% and 33% respectively. Related with the oscillation analysis results, it is concluded that the loops PC2 and PC3 are oscillating because of aggressive tuning. Furthermore, among 19 loops, 4 of them (FC9, PC2, PC3, and PC6) are possible candidates of non-linearity problem. However, stiction problem was only detected for PC6. Fortunately, the loop is not critical for the process.

In addition to SISO analysis for each PID controller, the whole control structure was analyzed with the method of spectral envelope. The analysis showed that TC1, LC1, PC1, and TC3 are possible candidates for the plant-wide oscillations occurring at the period of 877.71s. This fact was also verified in terms of process physics. However, during the analysis period, the candidates could not be examined by the control engineers. In the light of these analyses, some plant test were proposed to control engineers and listed as a future work.

As discussed in Chapters 2, 3 and 4, the study contains lots of different algorithms to analyze PID control loops. The algorithms were selected based on several surveys. First, the published features of various commercial products were investigated. Some of the popular products in the market are *Control Performance Monitor*[®] (formerly Matrikon CPM) by Honeywell, *Loop Performance Manager*[®] by ABB, *PlantTriage*[®] by Metso Expertune, *Aspen PID Watch*[®] by AspenTech, *MD^{Pro}*[®] in PCTP by Shell-Yokogawa, and *Tune Wizard*[®] by PAS. Then, some literature surveys were done to see the main requirements in CPM applications. After that, each analysis block (as given in the proposed algorithm, Figure 1.6) in the applications were surveyed separately. The methods were examined and coded with Matlab[®].

The examination showed that each method studied has some advantages and disadvantages. In addition to that, there are some key concepts in the CPM algorithm. These are discussed below within their categories:

- **Data Gathering and Pre-Processing:** Today, with the concepts of *Big Data*

and *Internet of Things*, data gathering is progressively becoming popular and fortunately easier. Furthermore, these concepts bring the fast and efficient data analysis capabilities together [Qin, 2014]. However, today in most of the plants, conventional data storage technologies are being used. In general, the plants have historian databases for different in-house services. The data collection can be done either from these historians sampled previously or from OPC servers with the required sampling rates. In this study, it is seen that collecting as frequent data as possible make users to get more reliable results. Generally, depending on the process dynamics, plants can change the sampling rate accordingly. In addition, any kind of data compression or quantisation should be avoided [Jelali, 2013; Choudhury et al., 2008]. Thus, the term pre-processing in the algorithm means the elimination of non-numeric data caused by various database faults.

- **Statistical Metrics:** As given in 2.2, several statistical metrics can be used to monitor the performance of the control loops. They are easy to calculate in terms of both computational load and reasonable user requirements. Apparently, they do not show the root causes but give indications about possible problems [Burch, 2004]. CPM users can create their own KPIs to monitor the loops.
- **Performance Assessment:** Although MVC is not a realistic benchmark, today it remains its popularity in industrial use. A recent survey covering different CPM users worldwide showed that MVC is accepted as a useful benchmark with 25% [Bauer et al., 2016]. There are 2 fundamental reasons for that. First, it requires the specific time delay of the loop, which may be non-trivial to determine. This requirement was addressed by several studies. The master thesis done by Björklund [2003] is one of them. It discusses the time delay estimation techniques extensively. Second disadvantage of using MVC as a benchmark is its sensitivity to non-stationary signals [Bauer et al., 2016]. In case of any non-stationary behavior, the index may give highly pessimistic results as expe-

rienced in the industrial case study. This fact was recently addressed via DFA (detrended fluctuation analysis) [Srinivasan et al., 2012; Pillay and Govender, 2014]. Other than that, commercial software providers have their own benchmarks in addition to MVC. Having that fact, MVC keeps its persistence.

- **Pre-filtering:** The analysis blocks of oscillation, non-linearity and stiction detection in the algorithm are mostly based on frequency analysis. Therefore, the researchers propose using pre-filters to remove high frequency noise and low frequency set-point changes [Jelali, 2013; Jelali and Huang, 2010; Choudhury et al., 2008; Ordys et al., 2006]. During the industrial case study presented, any pre-filter was not used.
- **Oscillation Detection:** In order to detect oscillations, there are lots of methods in the literature. In this study, industrially most popular ones are discussed. The examination showed that there is not a single method valid for all the cases. For example, one of the most robust and informative methods is the regularity of auto-covariance function (3.2.4). However, it is seen that in case of multiple oscillations, the regularity is lost. This may require a prior analysis of PSD of the control error signal. For the estimation of PSD, one should also be careful with the selection of number of DFT points. Inappropriate selections might result spurious spectral components. Having that, it is said that a combination of methods is useful to automate oscillation detection. Besides that, during the analyses, it is seen that for some loops, oscillations are intermittent. In this case, batch analysis of the data might not be sufficient; because, the spectral components change with respect to time. One approach for this problem is wavelet analysis. By decomposing signal into wavelets, one can analyze the change of frequencies along the time axis [Matsuo et al., 2004].
- **Non-linearity Detection:** It is an important requirement in CPM applications, since non-linearities are not desired in the processes. Unfortunately, very low amount of participants (approximately 25%) in the survey of Bauer et al. [2016] state that these analyses are useful. However, the participants also state

that non-linearities such as stiction and saturation are frequent problems faced. Thus, it can be said that non-linearity analyses are still too complex to follow. In this study, two popular algorithms are discussed. During the examination, it is seen that both bispectral analysis based on detection of phase coupling and surrogate data analysis based on surrogate data generation are sensitive to non-stationary data. This fact puts a constraint to automate these analyses. Careful data pre-treatment may be required for these analyses.

- **Stiction Detection and Quantification:** Detecting stictions in control valves is a valuable outcome of CPM applications. In the literature, this problem was addressed and studied extensively. However, there is still room for improvement because of false detections. Recently, Hammerstein models are being developed to detect stiction. Nevertheless, it brings computational complexities and considerable amount of developing effort [Jelali and Huang, 2010]. In this study, two different methods were discussed. Curve-fitting analysis is relatively easy to implement, whereas PV-OP mapping requires more complex computations such as ellipse fitting algorithms.
- **Controller Tuning Assessment:** Controller tuning assessment is also a popular topic in CPM applications [Bauer et al., 2016]. Conventionally, the control engineers try to keep the base-layer regulatory control healthy. Therefore, usually they do periodic base-layer enhancement studies. Before these studies, it is valuable to know about controller behavior. Deterministic tuning assessment was also addressed extensively [Visioli, 2006; Visioli and Zhong, 2011; Spinner et al., 2014]. However, in this study, an impulse response based algorithm was examined. It is seen that selection of number of impulse response coefficients is an important parameter. The examination suggests that the number of coefficients can be selected based on the approximate settling time.
- **Plant-wide Disturbance Detection:** Usually, industrial processes are controlled with lots of controllers. In some cases, the number of loops might go to hundreds or thousands [ABB, 2008]. In addition, in complex processes, the

process units are connected each other in upstream & downstream connections. A disturbance occurring in a single loop can propagate and affect the other loops. Therefore, detection of the root cause plays an important role in CPM applications. In the literature, there are several algorithms developed. A very comprehensive review of the methods was done by Duan et al. [2014]. The research examines some of the methods such as spectral envelope, adjacency matrix, Granger causality, transfer entropy and Bayesian networks. Furthermore, the study discusses the strengths and weaknesses of these methods. However, in this study, only spectral envelope method was applied. During the examination, it is seen that increasing the resolution of the envelope and the amount of analysis data increase the computation time. For the other methods requiring more samples (Granger causality, transfer entropy etc.), the computation time is expected to be even more. Therefore, development of efficient and fast algorithms are still remains its popularity.

Briefly, CPM puts a great value on process control applications. It enables that starting from plant operators to control engineers and even to operations management, company personnel can monitor the control assets and detect possible problems. In that framework, the popularity of CPM seems to increase greatly. It is stated that companies benefit from CPM applications by integrating them to company workflows. Therefore, integration of efficient and easy to implement algorithms producing easily interpretable metrics plays very important role. This thesis covers possible algorithms, discussing their robustness, strengths and weaknesses.



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Appendices

Appendix 1

DATA FOR INDUSTRIAL LOOPS

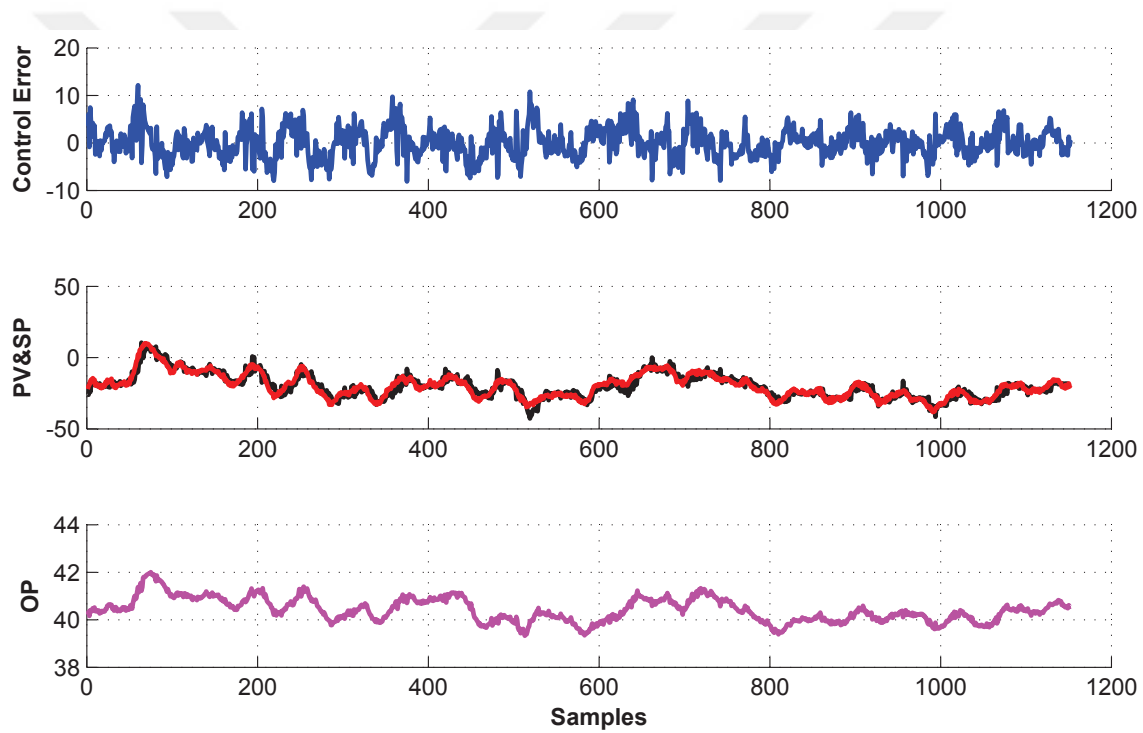


Figure A.1: Process Data for FFC1 in Segment 4

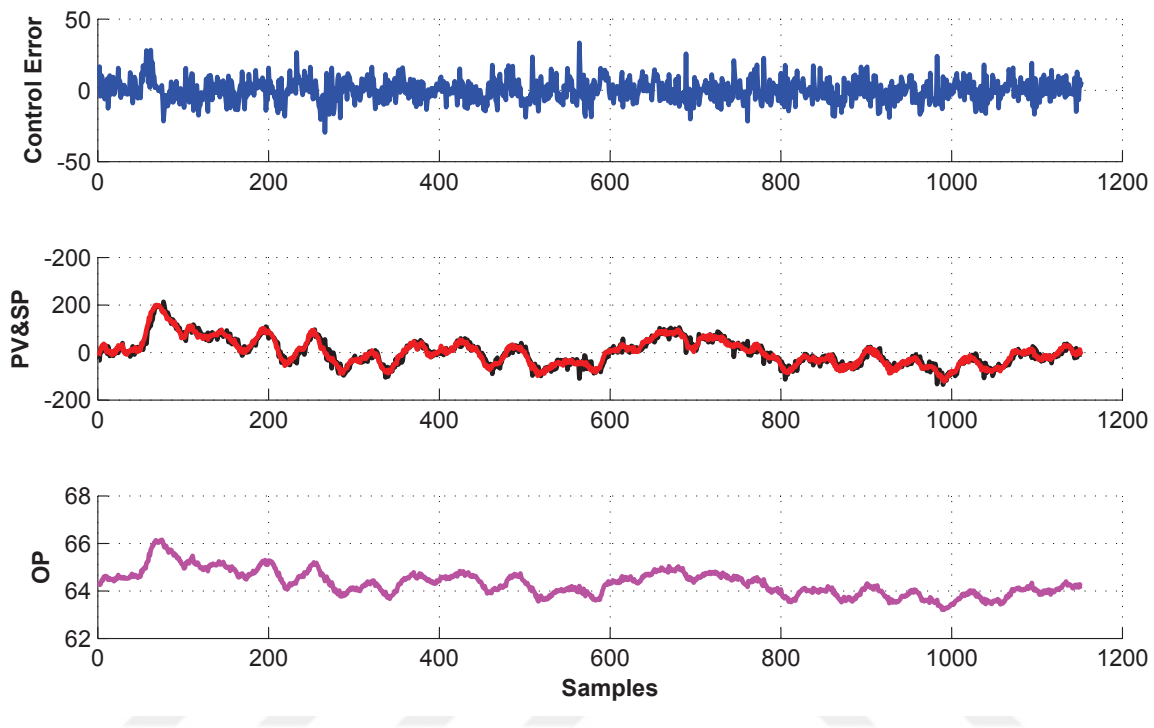


Figure A.2: Process Data for FC1 in Segment 4

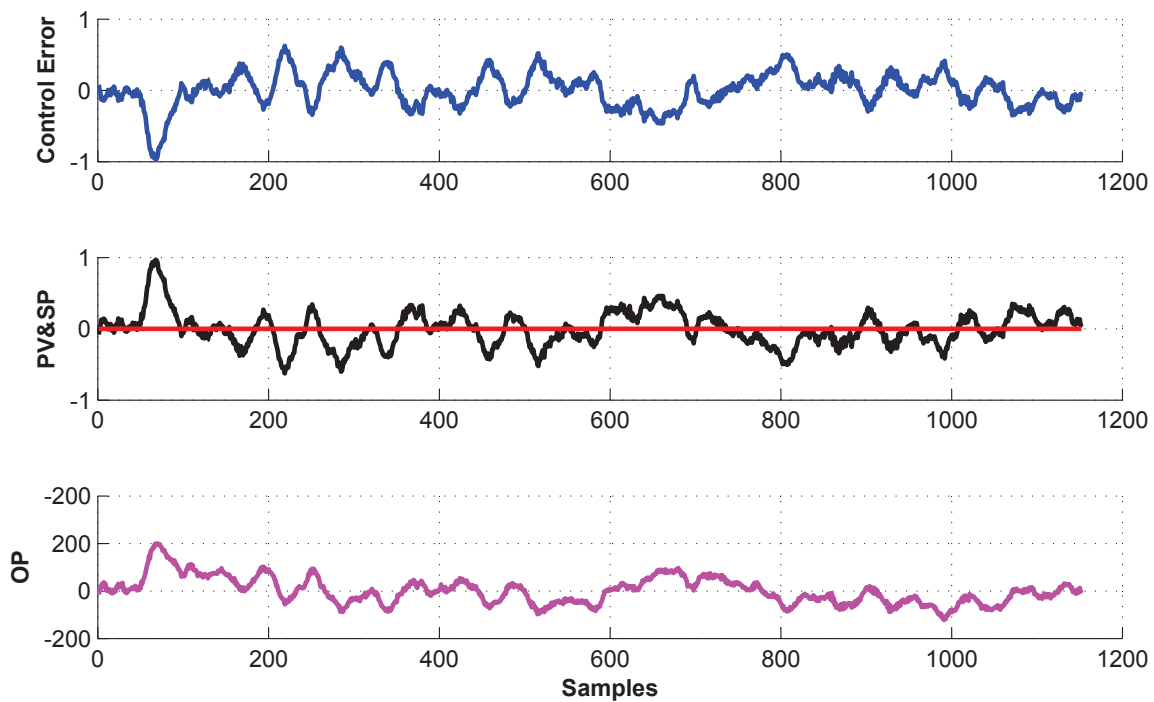


Figure A.3: Process Data for LC1 in Segment 4

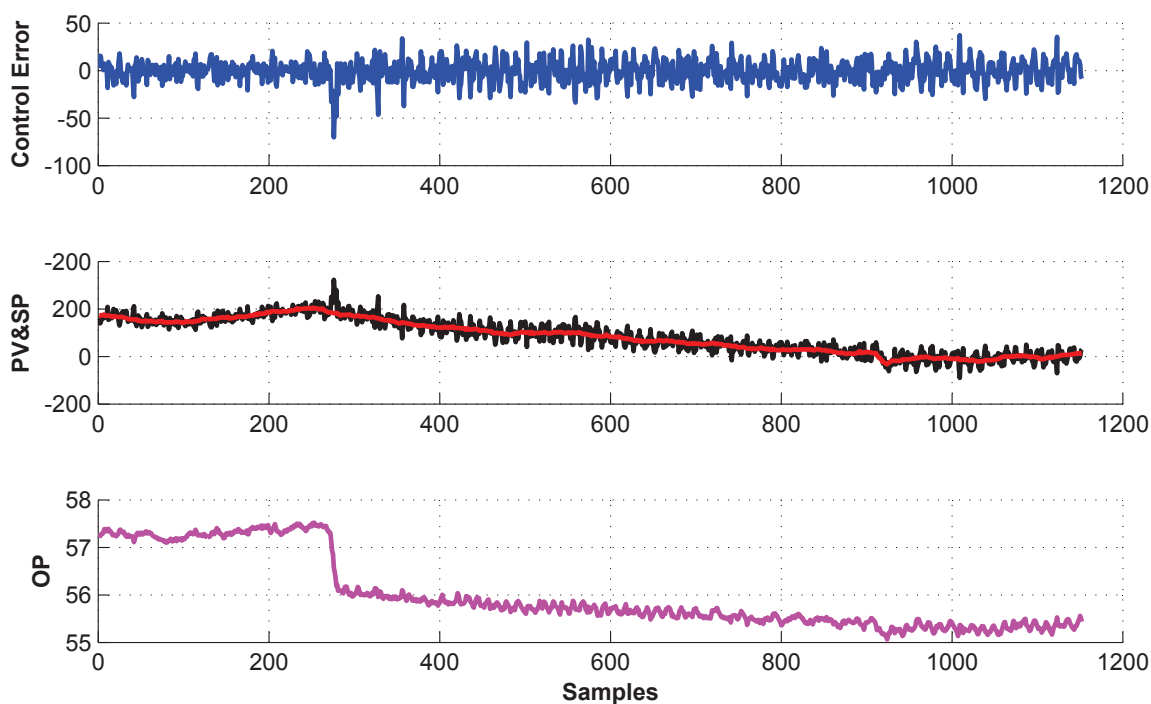


Figure A.4: Process Data for FC3 in Segment 3

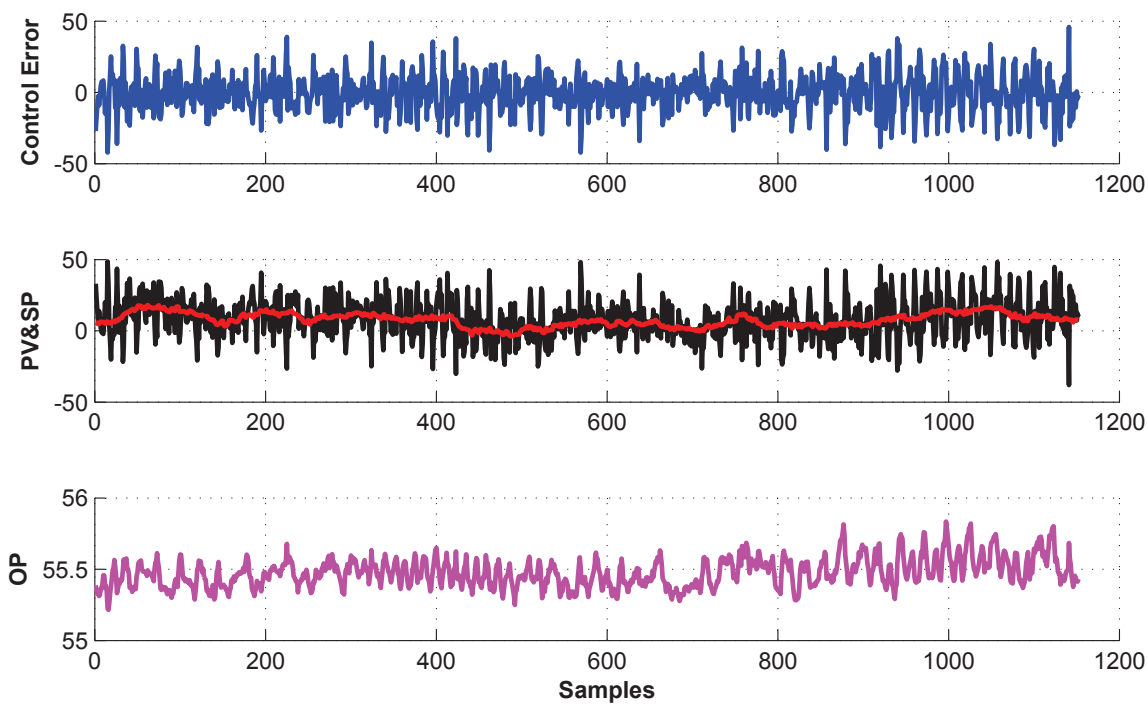


Figure A.5: Process Data for FC3 in Segment 4

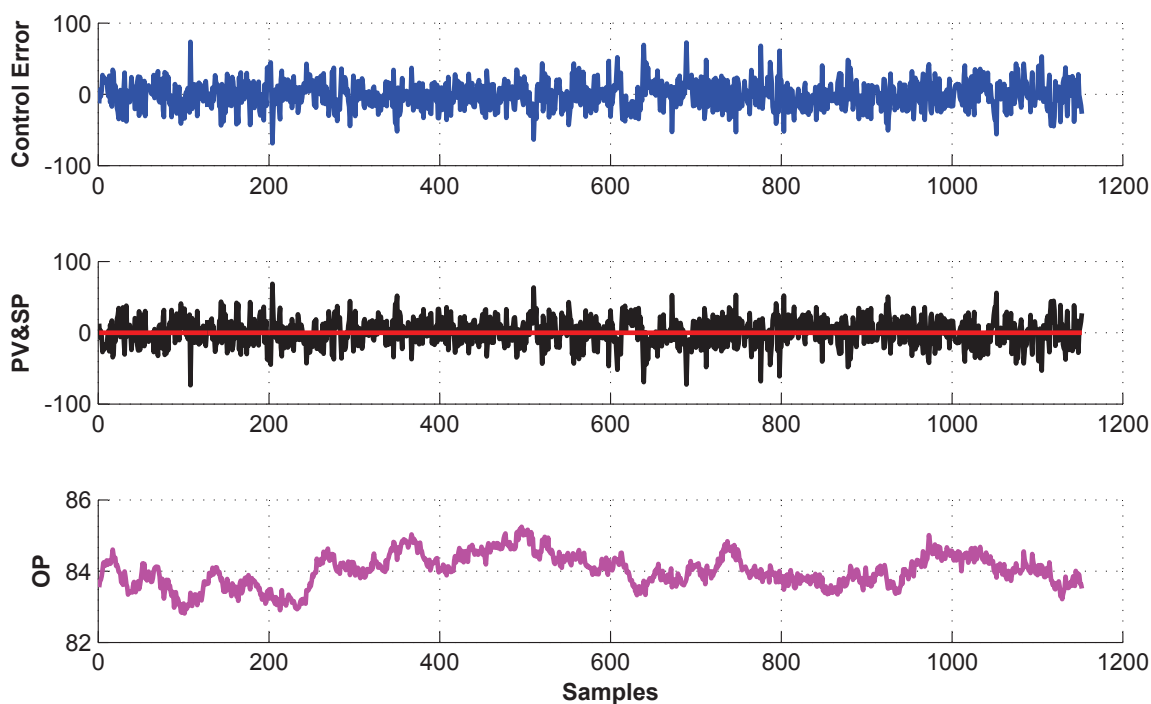


Figure A.6: Process Data for FC4 in Segment 1

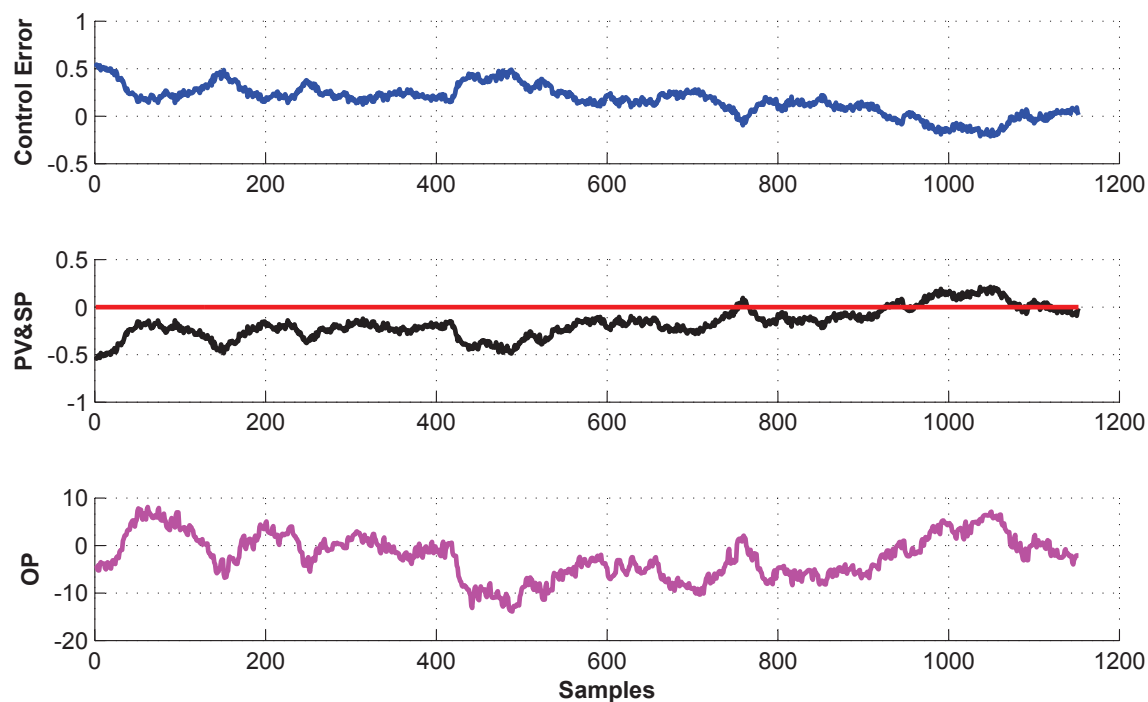


Figure A.7: Process Data for LC3 in Segment 4

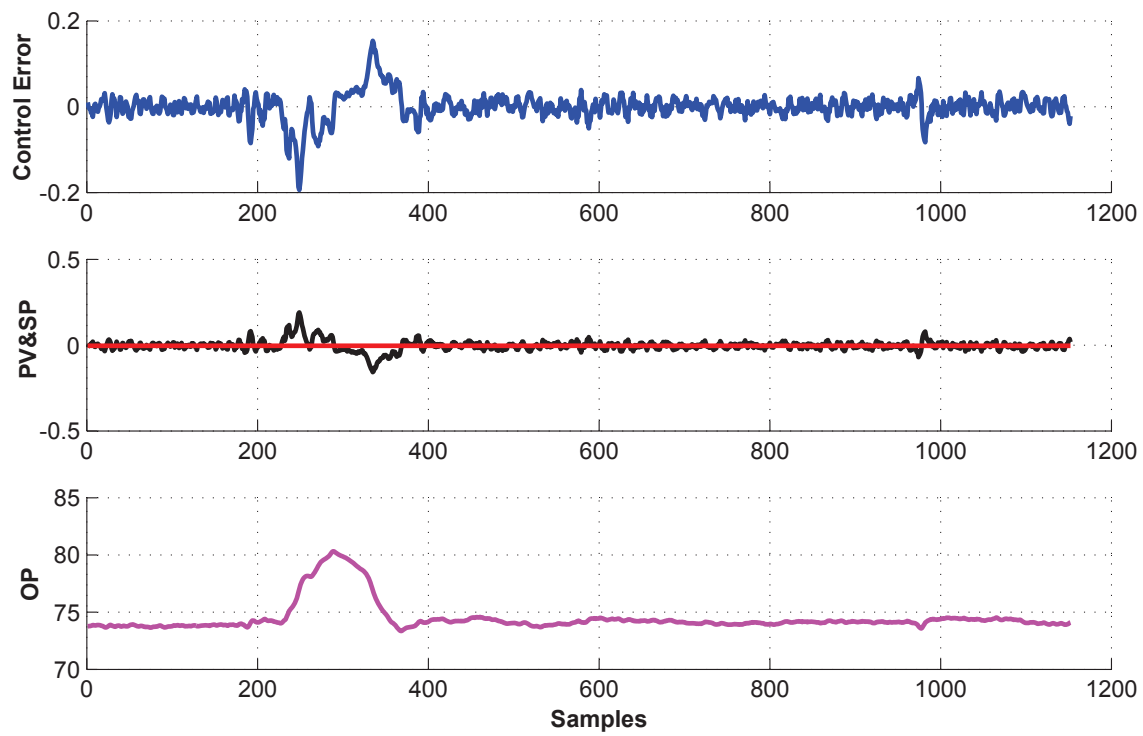


Figure A.8: Process Data for PC2 in Segment 92

VITA

Mehmet Yağcı was born in Kırcaali in Bulgaria on May 2, 1989. Right after his birth, his family has migrated to Turkey. After that, he graduated from Çanakkale Science High School in 2007. Then, he received his B.Sc degree in Chemical Engineering from Middle East Technical University (METU), Ankara, Turkey in January 2013. There, he served as *computer assistant* for 3 years at Department of Modern Languages. In addition, he took responsibilities in *METU Balkan Society* as *Public Relations* during 2009-2010 and *President* in 2010-2011. Right after his graduation, he joined M.Sc program at METU. During that year, he drew the figures and wrote up the chemical formulas in the book titled "*Chemistry, Materials and Properties of Surface Coatings*" by Prof. Güngör Gündüz. In 2013, he joined to TPRAŞ, a private petroleum refinery corporation in Turkey as *R&D Engineer*. There, he involved in several research projects covering both European Union and TBİTAK funded. In 2014, he joined to Koç University to follow his M.Sc in Chemical and Biological Engineering with the supervision of Prof. Yaman Arkun. He received his M.Sc degree in June 2016. He is currently working as *Modelling and Control Chief Engineer* at TPRAŞ. His main projects and research areas are covering performance analysis of control loops, dynamic and steady state process modelling, optimum control of refinery processes and signal processing for process control framework.



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This thesis contains 116 sources, 128 figures and 26 tables.