PROCESS ENHANCEMENT THROUGH INTEGRATED STATISTICAL AND AUTOMATIC PROCESS CONTROL TECHNIQUES

BY

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Dedicated to my Parents

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Praise be to the lord of the worlds, the Almighty for having guided me towards the right path. May peace be upon Mohammed, the last of the messengers.

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THESIS ABSTRACT

FULL NAME: MUNEEB AKRAM MUHAMMAD AKRAM

TITLE OF STUDY: PROCESS ENHANCEMENT THROUGH INTEGRATED STATISTICAL AND AUTOMATIC PROCESS CONTROL TECHNIQUES

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Process Enhancement is the key to achieve production targets and to improve product quality. Statistical Process Control and Automatic Process Control are considered as two sets of toolkits for this enhancement. The major focus of *SPC* is on process monitoring, while that of *APC* is on process adjustment. Due to the knowledge gap between the advocates of these two methods, they were initially thought to be in conflict with each other, and their integrated use was totally out of question, until their advocates realized the fact about the techniques applied by these methods being complementary rather than been contradictory.

In this thesis, we will present different enhancement schemes which are based on dual application of *SPC* and *APC* techniques. Starting by conducting literature survey and covering technical background on our topic, moving to effective initial setting of the process parameters, passing by proper selection of control parameters, then proceeding towards process monitoring and assessment schemes; all of that will be our work path. All previous topics will be the building blocks for our suggested fuzzy integrated *SPC/APC* scheme that results into obtaining enhanced level of: process quality, performance, as well as robustness.

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خلاصة الرسالة

إسم الطـــالب : منيب أكرم محمد أكرم

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يعتبر تعزيز العمليات المفتاح الأساسي لتحقيق أهداف الإنتاج و تحسين جودة المنـــتج، و تعتـــبر عمليـــات التحكم الإحصائي و عمليات التحكم الآلي مجموتان من الأساليب لتحقيق ذلك التعزيـــز. دور عمليـــات التحكم الإحصائي يركز على رصد العمليات، في حين أن دور عمليات التحكم الآلي يكمن في تكييفهـــا. بسبب الفجوة المعرفية بين مبتكري هذه الأساليب، كان يعتقد في البداية أنهما متباعـــدتان عـــن بعـــضهما البعض، و دمج تقنياتهما كان أبعد ما يكون عن التساؤل، لحين إدراك مبتكريها أن التقنيات المتبعة بواســـطة هذه الأساليب مكملة لبعضها و ليست متناقضة.

في هذه الرسالة، سوف نقوم بدراسة مجموعة من الخطط لتعزيز العمليات مبنية على إستخدام التقنيات المتبعة بواسطة عمليات التحكم الإحصائي و الآلي معاً؛ بدأ من تغطية الجوانب الفنية حول الموضوع، إنتقالاً إلى الإعداد الأولي لمتغيرات العملية، مروراً بالإعداد السليم لمتغيرات التحكم، ثم المضي قُدماً تجاه عملية الرصد و التقييم، كل هذا سيكون مسار عملنا. كل المواضيع السابقة ستكون اللبنات لبناء مخطط مدمج بين تقنيات عمليات التحكم الإحصائي و الآلي مبني على ستخدام المنطق الغامض لتعزيز مستوى الجودة، الأداء، و المتانة.

درجة الماجستير في العلوم

جامعة الملك فهد للبترول و المعادن

الظهران، المملكة العربية السعودية

فبراير ٢٠١١ م

CHAPTER 1

INTRODUCTION

1.1 Background:

Today, and more than ever, with the growing complexity of today's processes along with the increasing demand on optimum product quality and enhanced plant performance, the need arises for the development of integrated techniques that satisfy these requirements while maintaining a high robustness level against different operating conditions. Generally, each process needs to be analyzed by examining its inputs and outputs to determine the required actions for its enhancement. The output from a process is that which is transferred to somewhere or someone. In order to produce an output which meets the requirements, it is necessary to define, monitor and control the inputs to the process. Process Enhancement refers to moving a process from its current state to another state of higher performance. But in order to enhance a process, several underlying elements need to be considered and addressed, such as:

- *Process Parameters Setting:* refers to the initial setting of its parameters which includes selecting the optimum values for: process mean (set-point), production run length (process running duration before shutdown), and specification limits (allowable level of quality deviation).
- *Process Quality:* refers to a statistical measure of the conformance to specification for the products generated by a process.
- *Process Performance:* refers to the degree of effectiveness of a process in satisfying the requirements, which is usually determined from a process study conducted over an extended period of time under normal operating conditions.
- *Process Robustness:* refers to its in-sensitivity to variation in external factors.
- *Process Control:* refers to using collected data about a process to control its output and it includes the use of control techniques such as *SPC* and *APC*.

The first step toward process enhancement is to initialize its setting properly before heading it up into operation. This is accomplished by proper selection of process parameters which include: optimum process mean, production run length, and specification limits. An effective optimization model for this problem should incorporate the use of quality loss functions (for maintaining the desired quality level on target) and process cost indices (for minimizing the overall cost). But as the process is placed into operation and starts its interaction with its surrounding, it may no longer maintain its stability. Its control parameters may need to be changed to keep it insensitive to noise factors, or it might need to operate with different gain parameters once a certain set-point has been reached. These problems could be resolved by applying the use of Robust Design, which aims to make the process less sensitive to noise factors, and Gain Scheduling, which provides satisfactory control for different operating points of the system by modifying the gain parameters depending on the states of the system.

Once the process is brought to be under control and continue its operation, monitoring and evaluation part needs to be considered. The objective behind that is to enable tracking and fixing problems before they can cause in producing poor quality products and result into financial loses. Monitoring could be achieved by applying the use of control charts, while performance needs to be measured against some kind of benchmark from which the performance of the system could be evaluated. Although the human side could be useful in resolving these issues, real industrial process running at fast production rate result into high dimensionality data which makes it difficult for a human operator to monitor them processes, analyze their output data, evaluate their performance, find reasons behind degradation, select the proper controller to handle the operation … etc. All of this calls the need for having a systematic strategy which can translate the human way of decision making and its knowledge about the process into machine language. A suggested solution is apply the use of Fuzzy Logic (*FZL*), which is close to the human way of thinking and reasoning and provides means for modeling and dealing with the approximate and inexact nature of the real world.

Process control is no less than an attempt to cancel out the effect of a fundamental physical law (the second law of thermodynamics) which implies that if left to itself, the entropy or disorganization of any system can never decrease and will usually increase. Statistical Process Control and Automatic Process Control are two complementary approaches to combat this law. Generally, each one has the reduction of variability and maintaining the quality level on target as their objectives. However each seeks to accomplish these objectives in different ways. *SPC* attempts to remove process abnormalities using process monitoring, while *APC* attempts to compensate them through process adjustment.

Initially, *SPC* and *APC* took their origin from different industries (discrete part manufacturing and continuous process industry, respectively), and have been applied by different professionals (Statisticians and Control Engineers, respectively). MacGregor (1988) noted that a control engineer, who is primarily involved with *APC*, typically has more experience with process fundamentals, process dynamics and control theory. On the other hand, a quality engineer or an applied statistician, who is primarily involved with *SPC*, has more experience with statistics, analysis of data, and design of experiments. Box and Kramer [11] and Box and Luceño [12] also noted this knowledge gap. Traditionally, the results of Deming's funnel experiment [21] have been used to demonstrate what will happen when one tampers with a stable process [56], which leads to an obvious question: When do we need to adjust the process? And when should we leave it alone? Based on the experiment and the remarks made by Deming, some quality consultants took the extreme view that a process should never be adjusted and that *SPC* charts are always sufficient. Lately, MacGregor [51] analyzed the experiment in detail and provided further useful information. Based on his analysis, the answer to the previous question is that *SPC* will tell the decision maker when to look for assignable causes and make process adjustments, and when to leave the process alone. However, for an unstable process (i.e. process with a drifting mean or subjected to disturbances) applying an *APC* action will always outperform the no control situation.

SPC is traditionally applied to processes that vary about a fixed mean, and where successive observations are viewed as independent. It seeks to reduce variability by detecting and eliminating assignable causes of variation. *SPC* can be viewed as a top-down tool which is usually driven by upper management as part of a company wide quality improvement policy. The role of *SPC* is to change the process when assignable causes occur. *SPC* does not control the process, but performs a monitoring function that signals when control is needed (identification and removal of root causes).

On the other side, *APC* is usually applied to processes in which successive observations are related over time, and where the mean drifts dynamically. It seeks to reduce variability by transferring it from the output variable to a related process input (controllable) variable. It actively reverses the effect of process disturbances by making regular adjustments to manipulatable process variables. *APC* is usually discussed in the framework of a process with a drifting mean, and the objective of the process adjustment is to keep the output quality characteristic on target. *APC* is viewed as a bottom-up procedure driven by process control or manufacturing engineers. The role of *APC* is to continuously adjust the process to counteract ongoing forces that will cause the process to drift off-target if compensations are not made. *APC* does not remove the root or assignable causes; it uses continuous adjustments to keep process variables on targets.

1.2 Thesis Objectives:

In this thesis, we are mainly concerned with integrating statistical and automatic control techniques towards forming unified strategies and schemes to handle the previous issues related to process enhancement by applying the use of techniques from both areas. We envision that the application of integrated *SPC/APC* techniques to any system will result into having better quality for the output product, maintain its performance, and keep it insensitive against external factors. The main objectives of the thesis are as follows:

1. Develop a Trine Model the can be used for joint determination of optimum values of process parameters including: process mean, production run length, and specification limits under mixed quality loss function.

2. Apply the use of robust design methodology to determine the optimum value of control parameters so that the controller maintains the process on target with low variability while keeping the performance robust against the external factors.

3. Apply the use of gain scheduling to modify the control parameters depending of the state of the system to maintain its stability.

4. Set a Robust Gain-Scheduled methodology that includes the utilization of previous two techniques.

5. Develop an *SPC* controller which is based on the constrained controller principle and incorporated with quadratic quality loss function and apply its use for process control as well as a standard benchmark from which performance evaluation could be conducted.

6. Construct a unified scheme that combines between the use of *SPC* and *APC* techniques of process monitoring and performance evaluation from which thorough assessment could be resulted.

7. Develop an integrated scheme that combines between the utilization of *SPC* and *APC* techniques under Fuzzy Logic interaction from which enhanced level of process quality, performance, and robustness results.

1.3 Organization of the Thesis:

This thesis is organized as follows. In the next chapter, preliminaries on *SPC* and *APC* techniques are outlined and literature review related to the issues facing their integration, along with the strategies followed to overcome the contraventions between them are discussed. Different models for optimum determination of process parameters under mixed quality loss function are developed in chapter three. Chapter four presents a robust gain-scheduled methodology for proper setting of control parameters. Chapter five suggests a unified *SPC/APC* scheme for process monitoring and performance evaluation. An integrated *SPC/APC* scheme under *FZL* interaction is presented in chapter six. Conclusions and recommendation for future work are given in Chapter seven. To make the thesis self informative, illustrative examples, case studies, graphs ... etc. are provided throughout its body. Furthermore, Matlab codes, Simulink diagrams and calculation tables used throughout this thesis are supplied in Appendices.

CHAPTER 2

BACKGROUND AND LITERATURE SURVEY

2.1 Overview:

Statistical Process Control and Automatic Process Control are two complementary approaches that have been used widely to improve product quality and process productivity. *SPC* is mainly used for process monitoring, while *APC* is used for process adjustment. *SPC* reduces process variability by detecting and eliminating special causes of process variation, while *APC* reduces variability by adjusting the process to keep the output on target. Both *SPC* and *APC* were initially thought to be in conflict with each other, but in recent years, many researchers have shown their interest in integrating their techniques to reduce total variability of the process. They have found that the techniques used in those two methods are complementary rather than contradictory. A considerable amount of work has appeared in the literature about methods that combine *SPC* and *APC* techniques for the same process. In this chapter, we will cover preliminaries on *SPC* and

APC and outline the major techniques applied by both. Literature survey related to the issues facing their integration will be outlined. We will also summarize different strategies followed in literature to achieve their integration.

2.2 Statistical Process Control:

Statistical process control is defined as a collection of tools and techniques that provide a system of quality control, which can be used to monitor, control, and improve a process. Its purpose is to control the process in an ideal status with respect to product specifications and to achieve process stability and to improve its capability by reducing variability. *SPC* uses the process information from samples to identify process shifts and initiate timely remedial actions. *SPC* aims to maintain the process in an ideal status and to keep product quality loss minimal during production. Another objective of *SPC* is to monitor the performance of a process over time, in order to detect any unusual events that may occur. Improvements in the process and product quality can be achieved by finding the assignable causes for these events and eliminating them and by improving the process or its operating procedures.

SPC is comprised of three sets of activities: understanding the process, understanding the causes of variation, and eliminating the sources of variation. In understanding a process, the process is typically mapped out and monitored using control charts, which are used to identify variation. When the process is stable and does not trigger any of the detection rules for a control chart, process capability analysis is performed to predict the ability of the current process to produce conforming (within specification limits) product in the future. When excessive variation is identified by the control chart detection rules, or the process capability is found to be lacking, additional effort is exerted to determine causes of that variance by using the tools. Once the causes of variation have been quantified, effort is spent in eliminating those causes that are both statistically and practically significant. Figure 2.1 shows the flow chart for a traditional *SPC* [5, 54, 55].

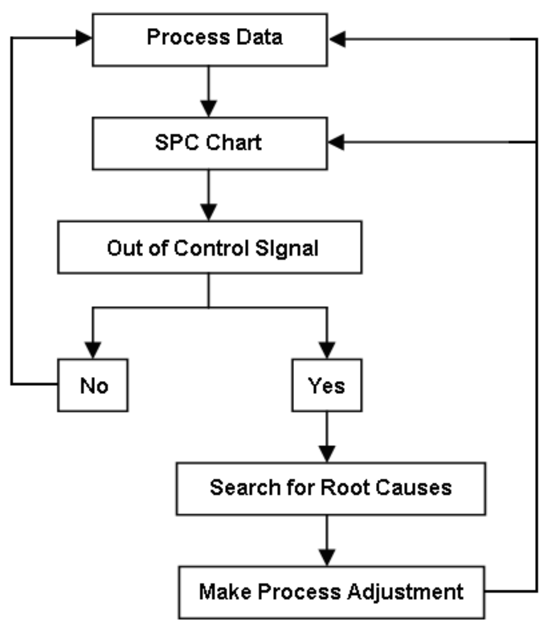


Figure 2.1: Flowchart for traditional *SPC*

2.2.1 SPC Tools:

The *SPC* strategy in stabilizing a process is to standardize procedures and raw materials and to use hypothesis-generating tools to track down and eliminate causes of trouble. These tools often called magnificent seven (Figure 2.2) include: [5, 55]

1. *Flow Chart:* used to show the steps that a product follows from the beginning till the end of the process, which helps to locate the value added parts of these steps from the unnecessary ones in which extra cost, material and labor are required.
2. *Pareto Diagram:* used to display the relative importance or size of the problem to determine its priority, which helps to concentrate effort on the most serious one.
3. *Cause and Effect Diagram:* used to develop the relationship between an effect and all possible causes influencing it (also known as fishbone diagram).
4. *Scatter Plot:* used to study the relationship between two variables (also known as X-Y plot) and to give visual assessment of the local tendencies of data points, which helps to identify the type of statistical analysis needed for the data.
5. *Control Chart:* used to determine if a process is in control or not and can also be used to monitor its performance.
6. *Check Sheet:* is a pre-printed table layout that facilitates data collection and helps in organizing it for subsequent analysis.
7. *Histogram:* used to display the distribution of data through collecting the data points and organizing them into evenly spaced numerical sub-groupings then showing the frequency of values in each subgroup.

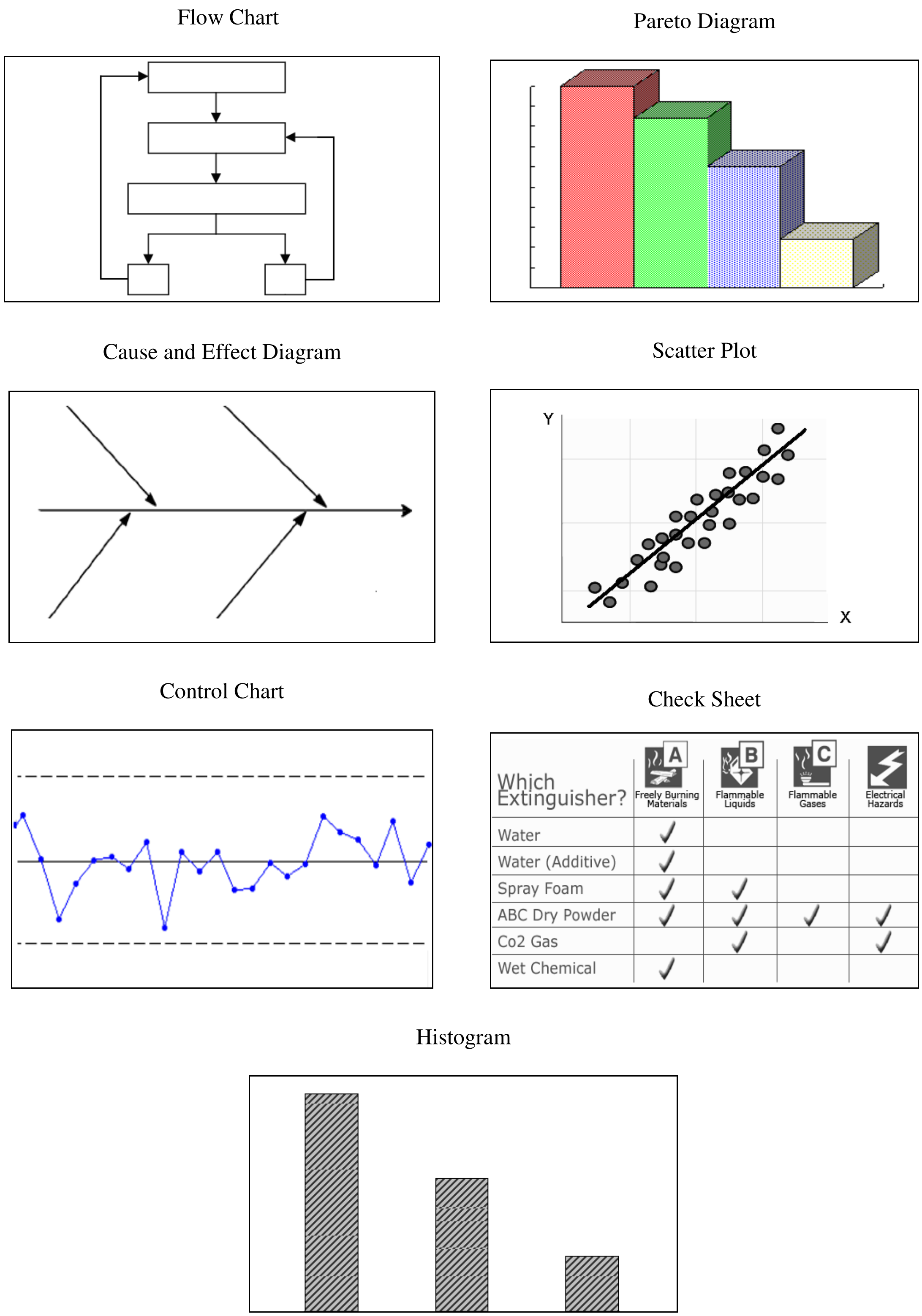


Figure (2.2): *SPC* tools

2.2.2 Shewhart Control Charts:

A control chart is a graph of quality measurement plotted against time with control lines superimposed to show statistically significant deviations from normal levels of performance (Figure 2.3). It was invented in 1924 by Shewhart who stated that *SPC* with control charts is mainly used for three objectives: process monitoring and surveillance, process parameter identification, and process variation reduction [32, 55].

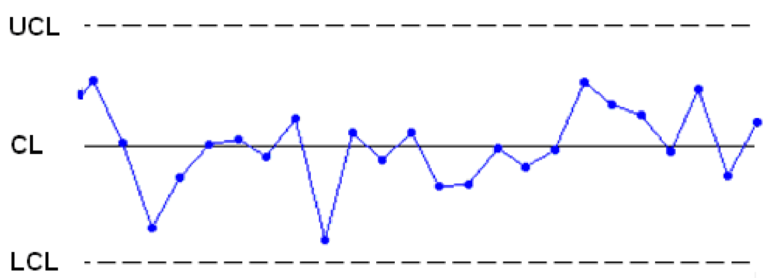


Figure 2.3: Typical control chart

Two common types of Shewhart control are the x-bar and s charts. When dealing with a variable quality characteristic, it is necessary to monitor its mean value as well as its variability. The x-bar chart is an approach for controlling the mean quality level of the process, whereas, the s chart is used for monitoring the process variability, by calculating the standard deviation of each subgroup. Given a sample of size n, its standard deviation is defined as: [32, 55]

$$s = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{2.1}$$

where x_i is the ith observation and $\bar{x}$ is the average of n observations. For m preliminary samples, the average mean and average standard deviations are respectively:

$$\bar{\bar{x}} = \frac{1}{m}\sum_{i=1}^{m}\bar{x}_i \qquad \bar{s} = \frac{1}{m}\sum_{i=1}^{m}s_i \tag{2.2}$$

Accordingly, the control parameters for the $\bar{x}$ chart are written as:

$$UCL = \bar{\bar{x}} + A\bar{s} \qquad CL = \bar{\bar{x}} \qquad LCL = \bar{\bar{x}} - A\bar{s} \tag{2.3}$$

While the parameters for the s chart are given by:

$$UCL = C\bar{s} \qquad CL = \bar{s} \qquad LCL = B\bar{s} \tag{2.4}$$

The factors A, B, and C for the $\bar{x}$ and s control charts, for different values of n, are listed in Table 2.1 [55].

Table 2.1: Factors for the X-bar and *s* control charts

n	*A*	*B*	*C*
2	2.659	0	3.267
5	1.427	0	2.089
10	0.975	0.284	1.716
15	0.789	0.428	1.572

2.3 Automatic Process Control:

APC is primarily envisioned as a mean for reducing manufacturing costs by reducing payroll expenses and increasing production rates. Applying *APC* not only increases the production rate, but also results in a low scrap rate (rejected product). Moreover, the improved quality of the end product is frequently achieved, since it can be adjusted to produce products closer to tolerances. *APC* uses algorithms relating process inputs to process outputs to automatically compensate for process perturbations by manipulating selected input variables. *APC* is an effective method for regulating a process about its mean (target) value since it continuously implements control action after new observations. *APC* is a useful tool in Continuous Processing Industries, where process data is collected at high rates using on-line computers. Applying *APC* is very successful for processes that need to be operated under extreme conditions or have features that render them beyond the capability of human operators. Other cases include situations where the degree of complexity of control is excessive, or where certain control features are too critical to trust the human capabilities [23, 69].

2.3.1 Feedback Control System:

Feedback is one of the foundations of Control Engineering [23]. The word "Feedback" was introduced in the 1920s by radio engineers to describe parasitic positive feeding back of the signal from the output of an amplifier to the input circuit. The first automatic feedback controller used for an industrial process was the flyball governor, developed by James Watt in 1769, for controlling the speed of a steam engine. Within a feedback control system (Figure 2.4), a cause (input) and an effect (output) are compared and their difference is used to alter the effect. The feedback loop starts with a sensor, which measures the output of the process (i.e., temperature, pressure … etc.) and sends it to the transmitter, which takes that output and converts it into a signal (known as feedback signal) strong enough to be transmitted to the controller. After comparing the feedback signal with the desired target to be achieved by the process, the difference (known as error signal) is sent to the controller (known as the brain of the control system), which determines the control signal to be fed to the process [23, 36, 69].

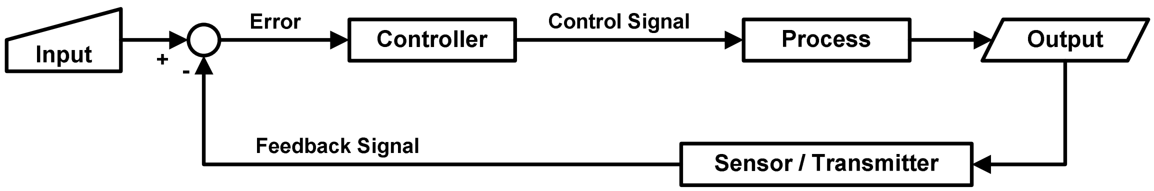


Figure 2.4: Feedback control system

For illustration, consider a room air cooling system from which it is desired to maintain the room temperature at 22^{o}C. An air-conditioner is used for cooling and its thermostat is set to allow fluctuations between 21~23^{o}C to avoid having unit cycle on and off too frequently. Figure 2.5 shows the components of this feedback control system.

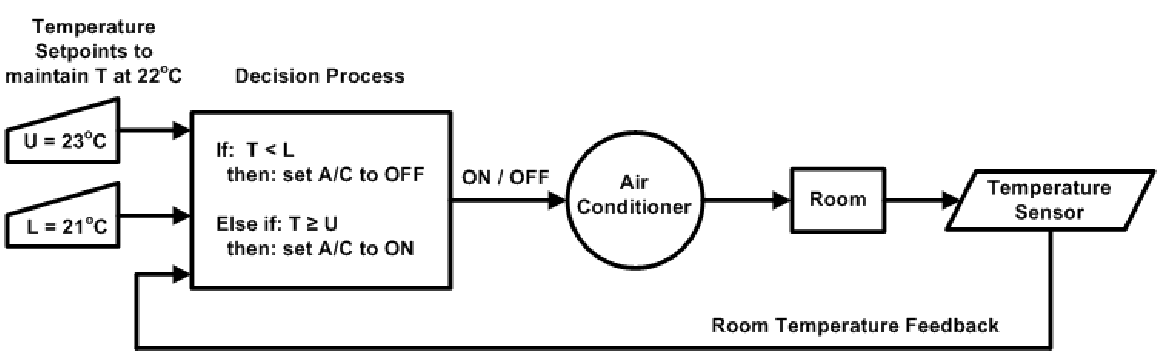


Figure 2.5: Feedback control system for an air conditioning system

2.3.2 Proportional Integral Derivative Controller:

The Proportional Integral Derivative (*PID*) is the most common controller found in industry. Studies have indicated that approximately 95% of control loops are of *PID*-type. This is due to the simplicity of its control law, few count of tuning parameters, and the familiarity of engineers and operators to its design and operation. *PID* control is based on the present (*P*), past (*I*), and future (*D*) control errors. Block diagram for a *PID* controller is shown in Figure 2.6.

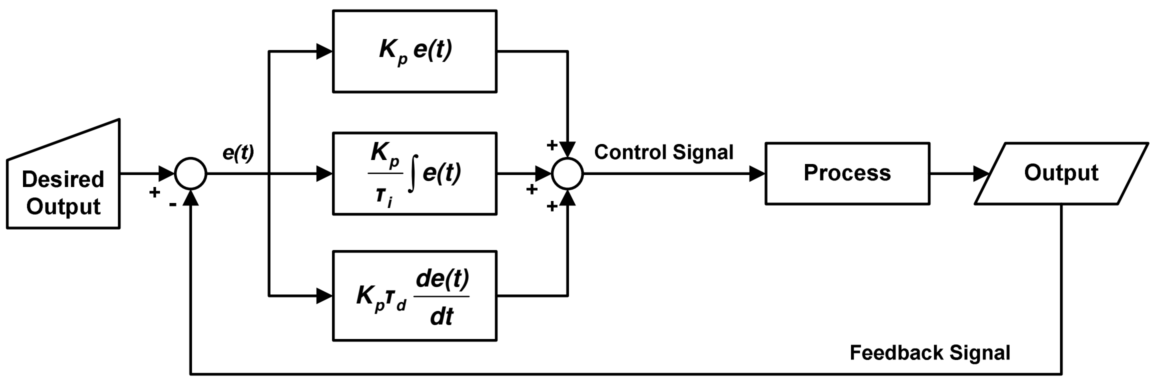


Figure 2.6: Block diagram of a *PID* controller

The *PID* controller is used for a wide range of problems, including process control, motor drives, magnetic and optic memories, automotive, flight control, instrumentation, etc. It can come in different forms such as: standard single-loop controller, software component in programmable logic controllers and distributed control systems, built in controller in robots and *CD* players [5, 12, 45]. The controller form in time domain is expressed as follows:

$$u(t) = K_p e(t) + \frac{K_p}{\tau_i} \int_0^t e(t)dt + K_p \tau_d \frac{d}{dt} e(t) \tag{2.5}$$

where K_p is the proportional gain constant, $u(t)$ is the control action, τ_i is the integral time constant, τ_d is the derivative time constant, and $e(t)$ is the error given as the output deviation from target of controlled variable. The discrete time equivalent for a *PID* controller is as follows:

$$u(t) = K_p \left[e(t) + \frac{T}{\tau_i} \sum_{k=0}^{t} e(k) + \frac{\tau_d}{T} \big(e(t) - e(t-1) \big) \right] \tag{2.6}$$

where T is the time constant.

2.4 SPC Versus APC:

Most professionals initially thought about *SPC* and *APC* methods to be effective in their respective industries only, which are discrete item manufacturing for *SPC* and continuous processing for *APC*. The reason behind this native assumption was that both methods were employed by distinctly different professionals; statisticians for *SPC* and engineers for *APC*. Box and Kramer [11] mentioned that *SPC* originated from the parts industry, while the *APC* had its origin from the process industry. They gave several reasons for the disparities between the two industries, and gave means for controlling critical process variables. Vander Weil et al. [78] stated that *SPC* and *APC* have for the most part developed in isolation from one another. Messina [54] studied *SPC* and *APC* control schemes and compared their philosophies (Table 2.2) and concluded that quality and process engineers have nothing in common.

Table 2.2: *SPC* compared with *APC*

		SPC	*APC*
Philosophy		Minimize variability by detection and removal of process upsets	Minimize variability by process adjustment to counteract its upsets
Application		Expectation of process stationary	Expectation of continuous process drift
Deployment	*Level*	Strategic	Tactical
	Target	Quality characteristics	Process parameters
	Function	Detecting disturbances	Monitoring setpoints
	Cost	Large	Negligible
	Focus	People and methods	Equipment
Correlation		None	Low to high
Results		Process improvement	Process optimization

Moreover, some aspects of controversy used to arise between *SPC* and *APC*. The practitioners of *SPC* criticized that *APC* compensates disturbances rather than removing them, and it conceals the information. On the other side, *APC* practitioners in turn argued that *SPC* charts are inefficient for regulating a process, and in coping well with fast system dynamics [5, 11, 52, 59]. Despite these controversies, several papers appeared in literature suggesting integration between the two. Generally, it is aimed that integration yields a process that effectively regulates the process to target using *APC*, while providing effective process monitoring and removal of assignable causes using *SPC* (Figure 2.7) [45, 38, 43, 44, 58, 77, 78].

Musheng and Yu [57] stated that *SPC* and *APC* play different roles in manufacturing process quality control. While *APC* method can properly control parameter changes during the manufacturing process to meet quality requirements, *SPC* can predict and control stability of the manufacturing process and discover its control state as soon as possible. Therefore, using an integrated *SPC/APC* control technology can better ensure the quality of products. Messina [54] referred to Macgregor's [52] suggestion of using stochastic control to bridge between the two fields. Vander Weil et al. [78] advocated using integrated tools from both fields to yield quality improvement by: removing sources of variability, and compensating for predictable process deviations from target.

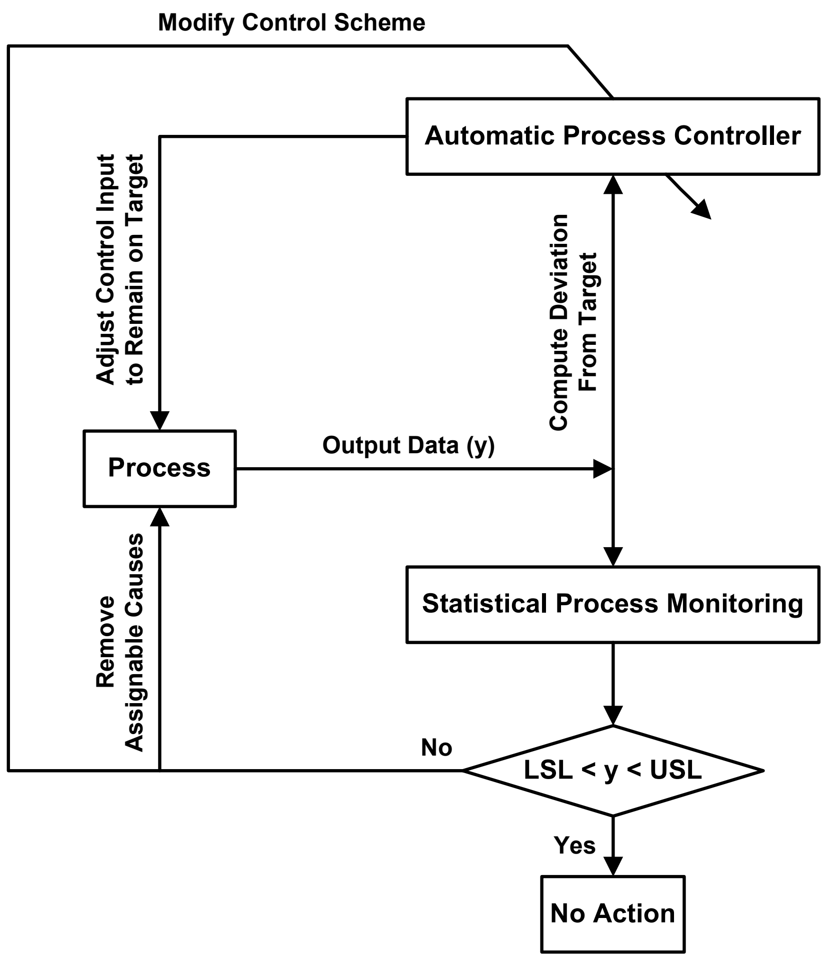


Figure 2.7: Relating *SPC* with *APC*

2.5 Integrating SPC with APC:

Integrating *SPC* with *APC* is an emerging area that has attracted both academia and industry. Montgomery et al. [56] stated that in many chemical and process plants and in computer integrated manufacturing environments, combining *SPC* and *APC* is an important tool ready for use in the quality improvement process. MacGregor [52] was the first who suggested to the *SPC* community that *SPC* charts could be used to monitor the performance of a controlled system. Park [60] mentioned that noises could be compensated by *APC*, while assignable causes could be detected by S*PC*. However, when both noises and special causes occur during operation, an Integrated Process Control (*IPC*) action, in which simultaneous application of *SPC* and *APC* procedures is involved will be needed for controlling the process. Despite the importance of integration, joint implementation of both has received little attention in literature. Main integration strategies found in literature are summarized briefly in the following subsections.

2.5.1 Integrating for Reducing Variation Causes:

Shewhart [67] classified process variation into two categories: special cause and common cause variation. He pointed out that special cause variation can be eliminated by implementation of *SPC* methods through identification and elimination of the root cause of the process changes. On the other hand, common cause variation is inherent in the process and it is generally difficult to be reduced by *SPC* methods. However, if the common cause variation is modeled as an auto-correlated process, it could be reduced by implementation of *APC* methods through feedback or feedforward control schemes.

Box and Kramer [11] gave an excellent comparison between the complementary roles of *SPC* monitoring schemes and of *APC* in dealing with the dynamic nature of quality variables. They suggested that it is possible to reduce both the special cause and common cause variations by applying *SPC* methods to monitor the output of an *APC* controlled process. In practice, when an *APC* control scheme is applied to reduce the systematic variation, it also compensates unintentionally against (special cause) process shift at the same time. This makes it difficult to apply standard *SPC* methods to detect the process shift. However, the authors pointed out that it is important to identify this type of process shift so that the engineer can understand and eliminate the root cause and thus improve the long-term performance of the process.

Wiklund [81] presented an economic model for the evaluation of different adjustment policies based on different process mean estimates for a constant process that experiences random-size shifts. He showed that adjusting the process by an amount equal to the observed mean deviation at the time of an alarm is the worst strategy. On the other hand, adjustments based on the estimated normal distribution perform better in general.

Park [60] considered noises and special causes as two major sources of variation that make the process level move away from the target. Since noises can not be removed from the process, the effective way of minimizing their effect is by compensating the process by an *APC* action. On the other hand, since special causes could be removed from the process if they are detected, the effective way of monitoring the process is to detect them quickly by an *SPC* scheme and eliminate them from the process. However, when noises are inherent to the process and special causes can occur during its operation, simultaneous application of *SPC* and *APC* procedures is needed for controlling the process, which is called *IPC*. In his work, he split the process into two parts: in-control (*IC*) process and out-of-control (*OC*) process. He referred *IC* to a normal process in which no special cause occurred, and *OC* to an abnormal process in which a special cause has occurred. For such a process, usual approach for the *IPC* procedure is to adjust the process by *APC* first, then control the adjusted process by an effective *SPC* monitoring scheme. He mentioned that the controller, which is optimal for the *IC* process is not optimal for the *OC* process. For that, he developed statistical models for the process level, the process adjustment, and the observed deviation; and expressed them as linear filter models. To illustrate how to consider the *IPC* procedure in manufacturing practice, he cited an example for a manufacturing process of Vary Large Scale Integrated (*VLSI*) circuits. The example showed that the implementation of *IPC* in the *VLSI* manufacturing industry can improve the quality of the wafers by achieving a uniform thickness.

2.5.2 Integrating for Disturbance Rejection:

MacGregor [51,52] reviewed the basic concepts of stochastic control and *SPC* charts. He pointed out their similarities and cited the reasons for lack of interference between them. He indicated that there are two types of process disturbances: stochastic and deterministic. Stochastic disturbances result from random variations that occur continuously in many processes, while the deterministic disturbances occur due to sudden step or ramp changes in a load variable at any particular instant of time. For describing a process with a drifting mean, he used the following model:

$$y_t = u_{t-1} + n_t + e_t \tag{2.7}$$

where y_t is the process output at time t, u_{t-1} is control action taken after the $(t-1)^{st}$ observation, n_t is the disturbance at time t, e_t is an independent random variable for white noise with mean zero and variance σ_e^2. The quantities n_t for the disturbance were assumed to follow an autoregressive process of order one *AR*(1) as:

$$n_t = \phi\, n_{t-1} + a_t \tag{2.8}$$

where a_t is a random variable with mean zero and variance σ_a^2, and $-1 < \phi < 1$. The control action was based on using the Minimum Mean Square Error (*MMSE*) controller discussed by Box and Jenkins [10] and was suggested to be:

$$u_t = \phi\, u_{t-1} - (\phi - \theta)\, y_t \tag{2.9}$$

where $0 \leq \theta \leq 1$ is the moving average parameter for auto regressive moving average *ARMA*(1,1) model, resulted when *AR*(1) model for n_t is combined with the white noise term e_t. He concluded that the *MMSE* controller will always out perform the no control situation, except for some extreme cases.

Montgomery et al. [56] described and illustrated a simple method of integrating *APC* and *SPC*, by using MacGregor's [51] model of the funnel experiment and showed the potential effectiveness of this new approach when assignable causes occur in a general situation. They supported the claim that *SPC* can detect assignable causes from the output rapidly, while *APC* can effectively keep the process on target. In their work, they investigated how Macgregor's system operates when additional assignable causes occur. They used the average squared deviation from the target as a performance measure. They pointed out that the model is robust to the misspecification of the disturbance model. They concluded that integrating *SPC* with *APC* by applying *SPC* to the output deviation from target results in reducing overall variability if the system experiences certain assignable causes.

Tsung and Shi [76] developed an integrated design methodology for a run-to-run *PID* controller and *SPC* monitoring for the purpose of process disturbance rejection. The process disturbance was assumed to be an *ARMA*(1,1) process. A detailed procedure was developed to design a *PID* controller that minimizes process variability. The performance of the *PID* controller was discussed and the Average Run Length (*ARL)* performance was also studied. A joint monitoring of input and output based on Bonferroni's approach was designed for the controlled process. Their proposed framework for the integrated design of *PID* and *SPC* strategies is shown in Figure 2.8.

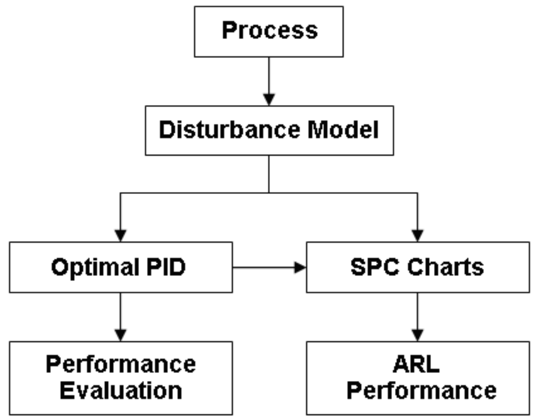


Figure 2.8: Integrated framework for *PID* and *SPC* strategies

This framework works by following the following steps:

- Given process disturbance model, a set of *PID* control parameters can be selected from the design maps, which minimize the process variability.
- *PID* evaluation plots can then be used to provide an assessment of the *PID* controller performance.
- A Joint *SPC* monitoring algorithm which is based on Bonferroni's approach can be obtained using provided equations.
- The obtained *SPC* performance can be evaluated according to its *ARL* using the provided *SPC* evaluation plots.

They concluded that successful integration of the *APC* and *SPC* approaches will provide better quality control and process improvements in manufacturing. However, lack of research on the integrated design of those tools has proven to be a barrier to the implementation of the concept.

2.5.3 Applying SPC for Monitoring and APC for Controlling:

English and Case [27] attempted to integrate *SPC* and *APC*, by using *SPC* as a feedback filter, taking control action only when the out of control signal was given. The drawback in their work was in not using any control algorithm and only applying feedback compensation whenever an alarm was given by the *SPC* chart. Moreover, whenever an out of control signal was given, compensatory action was taken without having any attempt made to identify and remove the cause of process upset, which does not serve the purpose behind using *SPC*.

Palm [59] provided a review of *APC* and *SPC* and the approaches taken in pursuit of both. He used the example of the effect of oven temperature on the golden-brownness of cookies to outline how much each method of process control might improve the process. In his example, he used *APC* for process regulation and *SPC* for process monitoring. He concluded that neither approach alone would have done well without the help of the other. Vander Weil et al. [78] introduced the term Algorithmic Statistical Process Control (*ASPC*) as an integrated approach for quality improvement and provided a technical description of this concept. They attempted to integrate feedforward/feedback control, while monitoring the complete system to identify and remove special causes by conducting research on a real process. In their work, the process under study was for batch polymerization, in which the quality variable of interest was the intrinsic viscosity of the polymer. In their application, they followed a four-step procedure which is illustrated below:

1. Develop a time series transfer-function model for the process output that includes the effect of past performance, control actions and other relevant process characteristics.
2. Based on pertinent costs, design a control rule for the estimated model.
3. Along with installing the control rule, place *SPC* charts to monitor the closed-loop process. The *SPC* charts should signal if the process and controller are no longer operating as expected from the identification and estimation stage.
4. When monitoring signal occurs, conduct search for the assignable cause and remove it if feasible.

In their study, changes to the chief quality characteristic (viscosity) were made by adjusting a compensatory variable (amount of catalyst). A *MMSE* control algorithm was developed for the process, and the closed loop output was monitored by a Cumulative Sum (*CUSUM*) chart. They reported that *ASPC* resulted in 35% reduction in viscosity variation and virtual elimination of off-specification material.

Janakiram and Keats [38] explained the differences between *SPC* and *APC* in simple terms and showed the challenges behind their integration for parts/hybrid industries. They presented a simple case of an integral controller to show the application of a *MMSE* controller to a stochastic process. The adjustment in terms of *MMSE* using integral control was calculated as:

$$X_t = -\left(\frac{\lambda}{g}\right)\sum_{j=1}^{t} e_j \tag{2.10}$$

where g is the gain, λ is the Exponentially Weighted Moving Average (*EWMA*) parameter, and e_j is the output deviation from the target. They also presented a case study of integrating *SPC* and *APC* for process monitoring and control for parts/hybrid industries in which they studied a powder loading operation for an automobile air-bag initiator. They used X-bar and R charts for monitoring the average powder weight at fixed intervals. They recommended monitoring the manipulatible variable, since it will provide valuable information on the process output. Their study demonstrated the successfulness of integrating *SPC* and *APC* for process control. They recommended further research on *MMSE* control and multivariate control.

Nembhard and Mastrangelo [58] used the term *IPC* to describe a policy that uses both *APC* and *SPC*. They stated that *APC* can refer to many forms of feedback and feedforward regulation, while *SPC* can refer to many forms of monitoring tools such as Shewhart charts and *EWMA* charts. For their *IPC* mechanism, they used Proportional Integral (*PI*) controller to provide the *APC* component and a Moving Center-line Exponentially Weighted Moving Average (*MCEWMA*) chart to provide the *SPC* component. They implemented their mechanism by developing a simulation model using Simulink, which is a program for simulating dynamic systems. They concluded that *IPC* design develops adjustment policies to: reduce the length of the transient period, decrease the out-of-control points and lower the variation.

Jiang and Tsui [44] developed an economic model for *SPC* monitoring of *APC* controlled processes. They also developed an economic loss-based criterion, the Average Quality Cost (*AQC*), to evaluate the performance of *SPC* charting methods. The *AQC* and the traditional average run length of three common *SPC* charts were investigated and compared. They stated that when the feedback control is a *MMSE* control scheme and the underlying process can be perfectly estimated, the outputs of the control system are independent, and identically distributed. When a constant (step) mean shift of magnitude μ occurs, the control action can compensate the mean shift and result into an independent process output with a dynamic mean value. When the *MMSE* control scheme is applied to *AR*(1) process, the means of the process output before and after the shift occurrence are:

$$\mu_t = \begin{cases} 0 & \text{at} \quad t < 0 \\ \mu & \text{at} \quad t = 0 \\ (1\text{-}\phi)\mu & \text{at} \quad t > 0 \end{cases} \tag{2.11}$$

It follows that the total cost of a production cycle (denoted as the total quality cost) consists of two parts: the in-control cost and the out-of control cost as:

$$L_T = L_{in} + L_{out} \tag{2.12}$$

where L_{in} is the in-control cost, L_{out} is the out of control cost, and L_T is the total quality cost. By assuming the adjustment cost to be negligible, and averaging the total quality cost over the entire production cycle, the *AQC* was obtained from:

$$L_A = \frac{L_T}{(1/p) + ARL_1} \tag{2.13}$$

where ARL_1 is the average run length when the process is out-of-control, and L_A is the average quality cost. They applied the *AQC* criterion to compare three common *SPC* charts: the Individual Shewhart Chart (*IS* chart), the *EWMA* chart, and the combined *EWMA*–Shewhart charts (*CES* chart), under *AR*(1) and *ARMA*(1,1) processes. They found that the *AQC* criterion was generally consistent with the *ARL* criterion except when the *APC* control action significantly compensates the process shift. When this happens, the performance of the control chart will depend critically on the size of the diagnosis cost. They concluded that the *AQC* criterion is generally consistent with the ARL criterion and gives more economic information than the *ARL* by providing an integrated measure to evaluate the performance of an *SPC* chart.

Jiang and Tsui [43] showed that traditional *SPC* techniques could be applied to monitor *APC* controlled process for reducing assignable cause process variation. They compared the monitoring of the process output with monitoring of the control action of *MMSE* and *PI* controlled process. In their work, *ARMA*(1,1) models were used as disturbance represented by:

$$D_t = \phi D_{t-1} + a_t - \theta a_{t-1} \tag{2.14}$$

where D_t is the process output, and parameters $|\phi| < 1$ and $|\theta| < 1$ were chosen to guarantee that the process is stationary and invertible. They used the *MMSE* controller defined by Box and Luceño [12] as:

$$X_t = \phi X_{t-1} + (\phi - \theta) e_t \tag{2.15}$$

where e_t is the process output, X_t is the control action. Accordingly, the output of the *MMSE* controlled *ARMA*(1,1) process was expressed as:

$$e_t = D_t - X_{t-1} + \eta_t \tag{2.16}$$

where η is a shift parameter. They derived the transient (t = 0) and the steady state ($t = \infty$) mean shifts for both the output and the control action. They mentioned that when the mean shift magnitude is large (at 4 or 5 standard deviations of the output), it is expected that monitoring the output is more efficient than monitoring the control action. However, when the shift magnitude is small (less than 3 standard deviations of the output), monitoring the control action will be more efficient. For the case of a *PI* controller, they expressed it as follows:

$$X_t = k_p e_t + k_i \sum_{k=0}^{t} e_k \tag{2.17}$$

where k_p, k_i are the proportional and integral constants. They derived the mean shifts for the output and the control action for the cases of a pure-*P* controller (k_i = 0), and a general *PI* controller. They mentioned that when the process is controlled using a pure-*P* controller, there will be no difference in monitoring the output or the control action. However, when a general *PI* controller is used, the mean shift of the output converges to zero, due to the integral component, which makes difference between monitoring of the output and the control action. In that situation, monitoring the control action is more efficient than monitoring the output. For illustration, they used the example of a mechanical system consisting of a mass, a dashpot, and a spring. Moreover, they illustrated how signal-to-noise ratios summarize partial information about the chart performance under mean shift detection and help to select the appropriate control chart for monitoring.

2.5.4 Integrating by Applying Control Action:

Box et al. [13] showed that when the feedback control scheme is *MMSE* and the underlying process can be perfectly estimated, the outputs of the control system are independent and identically distributed. When a constant (step) mean shift of magnitude l occurs, the control action can compensate the mean shift and result into an independent process output with a dynamic mean value.

Box and Luceño [12] compared *APC* and *SPC* and studied their applicability. They also explained the nature and importance of the proportional *PI* controller and how it may be adopted to *SPC*. They used the following general *PI* control scheme:

$$gX_t = k_0 + k_1 e_t + k_2 \sum_{i=1}^{t} e_i \tag{2.18}$$

where X_t is the setting of the input variable, and e_t is the deviation at the output, and g is a regression coefficient. But, instead of considering the level X_t of the input variable at time t, they considered the adjustment $x_t = X_t - X_{t-1}$ to be made at time t, which was written as:

$$x_t = -(G/g)\left[e_t + P(e_t - e_{t-1})\right] \tag{2.19}$$

where G = - k_2 and P = k_1/k_2. They pointed that the choice of the parameters of the control scheme are expected to depend on the nature of the disturbance and the dynamics of the process. In their work, they used a time-series analysis to predict the value of disturbance at t+1 and used this value to find the adjustment needed in the input variable. They stated that it makes sense to do nothing unless a deviation from the norm occurs, which is so large with very small probability of being due to chance. By contrast, feedback adjustment is appropriate when the normal state of the process is unstable.

2.5.5 Integrating by Minimizing Quality Deviation:

Capilla et al. [14] described a case study of integrating *SPC* and *APC* approaches in a polymerization process and showed that the use of both *SPC* and *APC* techniques can outperform the use of either of them alone. They developed and compared the effectiveness of several regulation strategies to reduce polymer viscosity deviations from target. They derived controllers using the constrained Minimum Variance (*MV*) criterion. Their case study involved a commercial scale polymerization process that produces large volumes of polymer (high density of polyethylene) used in consumer products. The key quality characteristic was polymer viscosity measured by Melt Index (*MI*). The viscosity variation at time t was represented by the following model:

$$\nabla MI_t = w_1 \nabla T_{t-1} + w_2 \nabla T_{t-2} + a_t \tag{2.20}$$

where ∇T_{t-1} is the temperature adjustment at time t-1, w_1 and w_2 are the transfer function model parameters, and the set $\{a_t\}$ contains independent variables following normal distribution $N \sim (0\ , \sigma_a^2)$. Three controllers were derived, namely: Clarke's Constrained Controller (*CCC*), Minimum Mean Square Error Controller (*MMSEC*), and a Two-Step-Ahead Forecasting Controller. The *CCC* was derived by minimization over the performance index:

$$Min: \quad \left\{ \left(MI_{t+1/t} - \text{Target} \right)^2 + r\left(\nabla T_t \right)^2 \right\} \tag{2.21}$$

where r is a Lagrangian multiplier. The resulted change in control action was:

$$\nabla T_t = \frac{-e_t}{\left(w_1 + \frac{r}{w_1}\right) + w_2 B} \tag{2.22}$$

where e_t is the output error for the adjusted process, and $B = -\left[w_1 + \left(r / w_1\right)\right] / w_2$. For the *MMSE*C, the control algorithm was obtained by considering as a special case of *CCC* when $r = 0$, which yields:

$$\nabla T_t = \frac{-e_t}{\left(w_1 + w_2 B\right)} \tag{2.23}$$

The Two-Step-Ahead Forecasting Controller was based on the *MMSE* criterion by focusing on MI_{t+2} leading into the following control rule:

$$\nabla T_t = \frac{-e_t}{\left(w_1 + w_2\right) + w_2 B} \tag{2.24}$$

The performances of the: *MMSEC*, *CCC*(0.02), and *CCC*(0.05) were compared with: the situation when actual control was done by process operators (MANUAL), and simulated situation in which no *APC* action was used (NO APC) by setting *T* fixed. Results are compared in Figure 2.9. These results indicated that, although operators were doing a good job, the feedback algorithms reduced the variability even more and gave better control strategy, independent of the particular rules of each process operator. In their work, they proposed different monitoring schemes (*SPC* component) and analyzed their performance and effectiveness. They also studied the performance and adequacy of the regulation schemes when assignable causes affect the process by simulation.

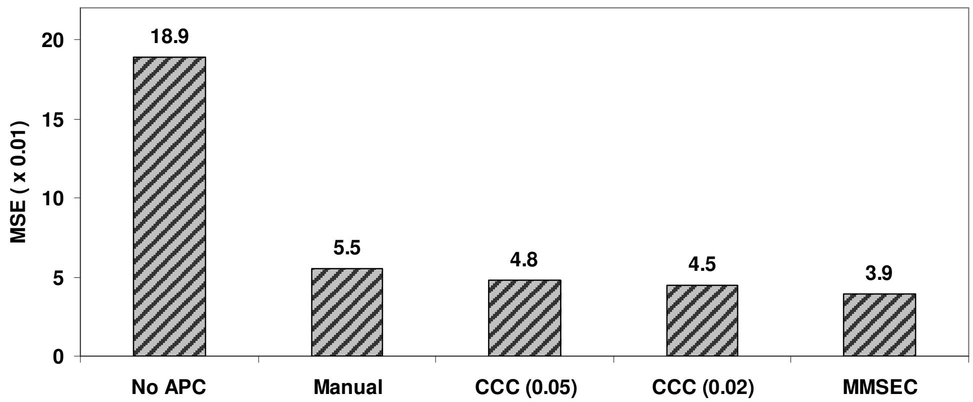


Figure 2.9: MSE of the output MI under different control strategies

They concluded that a combined *SPC* and *APC* procedure can provide important reduction in the long term, because it signals and helps to identify disturbances.

Duffuaa et al. [24] proposed a scheme to integrate *SPC*, *APC* and Taguchi's Quality Engineering (*TQE*) and presented two models for implementing their proposed scheme. Both models employed the concept of Taguchi's quadratic loss function to determine whether to take an *APC* action, by comparing the cost of the control action to the cost of quality. In the first model, they found the most economical control limits for the X-bar chart to ensure that *APC* will be done only when it is more economical. In the second model, they focused on the variance of the process and found its value for which the cost of quality loss will be more than the cost of taking the *APC* action. They used a case study to compare these two models with a model from literature where *SPC* and *APC* have been integrated. Their results showed 25% saving by using the first model, while 30% saving by the second model for the case under consideration.

2.5.6 Integrating by Optimizing Existing Processes:

Vander Weil and Tucker [77] used a polymerization process as a basis for a four step approach to integrate *SPC* with *APC* and suggested that at least every one would be interested in detecting the change in the mean square error (*MSE*) of the controlled variable. The presented steps were listed as follows:

1. Modeling
2. Model identification and estimation
3. Control rule design
4. Process monitoring

The drawback in their schema was in it being not as general as might be required for achieving an integrated *SPC/APC* system on a different process. Slocomb [68] extended these steps and established a six-step procedure to set up an integrated system of *SPC* and *APC* on a new or existing system. His suggested six-steps were as follows:

1. Disturbance Identification and Modeling: This involves open loop data collection at steady state. Here, the steady state implies that all input variables are at their nominal operating values and no changes are made to them over the duration of experiment, only disturbances are allowed to enter the process. This allows identifying disturbance models affecting the system.
2. Process Evaluation: At this step, decision is made whether to continue with the integration of *SPC* with *APC*. This is determined based on the type of disturbances that affect the controlled variables to be stationary or non-stationary and whether they are in a form that can be monitored using control charts.

3. Process Dynamics Identification and Modeling: The reaction curve method is the most popular one for identifying dynamic models. The method consists of introducing a step change into the process input and fitting the resulting change in the output to a First Order Plus Dead Time (*FOPDT*) model.
4. Choice of Automatic Process Control: This involves identification of a suitable automatic control scheme to regulate the process outputs.
5. Choice of Charting Variables and Charting Procedures: After having the automatic process control determined, the next step deals with introducing *SPC*, which involves determining suitable variables for process monitoring and type of control chart to be used.
6. Continuous Process Improvement: At this step, the goal is to achieve a process whose disturbances follow *SPC* model with small variance.

2.5.7 Integrating by Applying Intelligent Techniques:

Jiang and Farr [42] used the integrated concepts of *SPC* and *APC* to combine Soft Computing (*SC*) technique and statistical analysis technique to modularize the relationship between process output and process input for yielding optimality and improving process quality. In their study, they intended to construct a Multi Input Multi Output (*MIMO*) process control system with soft computing methods for prediction and parameter control and detailed the internal operation for each subsystem and relationship among one another. They used Chemical Mechanical Polishing (*CMP*) as an example to evaluate the performance of the *MIMO* process control system. They showed that beside correct prediction and diagnosis for the noise due to system deviation, it effectively controlled process input and output as well as achieved process optimization. From their study, the following results were reported:

- After verification of the *CMP* simulation process, soft computing proves to be effective for *MIMO* process system.
- The application of integrated artificial neural network and genetic algorithm in soft computing performs better than single artificial neural network system.
- The soft computing method can be used to prevent complicated mathematical operation process and facilitates practical applications in achieving the goal of process control.

Musheng and Yu [57] outlined the features of the *SPC* and *APC* method during manufacturing quality control putting forward a process control system that integrates the *SPC* and *APC* method. They studied the informational interface technique, the intelligent integration technique and the harmonious control technique for the two methods and then analyzed the integrated technique and the quality guaranteed technique for the two methods through a specific manufacturing process example. They stated that application of this technique not only guarantees the need for the individual parameter, but also for the distribution regulation for the group with same parameter. Since manufacturing process is a complex system, its control capability can be improved by using an appropriate control scheme. From their study, following conclusions were reported:

- *APC* can control individual process parameters with a higher precision, but it can not control the distribution rule for those parameters, nor predict the control state of itself and manufacturing process that it is controlling. Since *SPC* is opposite to *APC*, they can learn from others strong points to offset their weakness and bring more control effect.
- Combination of *SPC* and *APC* system can keep the process under control no matter whether it is stimulated by an assignable cause or a random disturbance.
- Optimization method of controlling manufacturing process is the intelligent integration of *APC* and *SPC*. Intellectualized methods can be employed based on the difference of control object, such as artificial intelligence, fuzzy control, artificial neural net and expert system … etc.

2.6 Gaps in Recent Work:

Despite all previous work and the efforts spent to integrate *SPC* with *APC*, it did not cover all the areas, and many gaps were left out. Throughout this thesis, we will consider these work gaps which mainly include the following:

a. Dual Monitoring and Control:

Most of integration strategies found in literature have applied the use of *APC* techniques for process regulation and using *SPC* techniques for monitoring, while others derived

SPC controllers based on the *APC* loop information and applied their use alone; which does not give a real meaning of integration. The need arises for a unified scheme that combines dual usage of the techniques followed by both.

b. Application of Robust Design Principles:

A system is said to be robust when it is insensitive to variation sources that could come from outside or inside the system. Its main purpose is to minimize variability of the system and to make it less sensitive to noise factors. Applying robust design principles can wield improved and more efficient procedure for integrating *SPC* with *APC* and result in maintaining the performance under critically damped conditions.

c. Account for Performance Deterioration:

The assumption in most current work was that the *APC* system would maintain its original performance characteristic over time. However, in reality and like most systems, controllers are subject to wear and tear and may experience an increasing failure rate during their service life. To obtain economic feasibility, it is recommended to include the effect of performance deterioration over time. Another extension could be made in identifying the appropriate time for maintenance and replacement of the *APC* system.

CHAPTER 3

JOINT DETERMINATION OF PROCESS PARAMETERS

3.1 Introduction:

Most of the recent work found in literature solved the problem of determining the optimum values of process parameters by considering one or jointly two parameters using separate models under different assumptions. In this chapter, we will develop a Trine Model that can be used for joint determination of three process parameters, namely: optimum process mean, production run length and specification limits, under mixed quality loss function for processes that are subject to deterioration over time. We will summarize the recent related literature and outline the technical information required for this work. In this work, the problem will be tracked in two ways: by minimizing the total loss and by maximizing the net profit. For achieving that, we will develop different models that can be used to determine optimum values for process parameters and our analysis will lead to the development of the Trine Model. Numerical examples parallel to each model will be presented to illustrate their use in determining the desired optimum parameter value. Sensitivity analysis for different process parameters will also be presented to study their effects on the net profit in the view of satisfying the manufacturing requirements.

3.2 Background:

Determination of optimum process parameters, which include: process mean (target), production run length and the specification limits, is one of the most important decision making problems which encounters in a wide variety of industrial processes. Selecting the optimal values for process parameters is critically important since it has a large impact on both the manufacturer and customers. Moreover, it affects the process defective rate, processing cost, scrap cost, and rework cost [62, 73]. The problem of finding optimal values for these parameters can be resolved by:

- Minimizing: by using the loss as an objective function for the optimization model.
- Maximizing, by having the profit function as an objective.

The initial work on this problem began with Springer [70] who considered the problem of determining the optimum process mean with specified upper and lower specification limits. Many researchers have extended this problem by finding optimum values for different parameters under different assumptions. Some of previous work concerned about setting optimum process mean only [8, 15], while other was about joint determination of optimum process mean and production run [62, 16], and some about determining optimum production run and initial settings of process parameters [61]. Most of previous work was based on the assumption of the stability of the process and that the process mean remains unchanged over time. However, in most real cases the process may deteriorate from its initial state (being in-control) to another state (out-of-control), which explains the importance for including the deterioration effect into consideration [17].

3.2.1 Optimum Process Mean Problem:

The initial setting of the process mean is an important decision since it does not only affect the output rate of conforming units but also affects other manufacturing decisions such as finished products and raw material lot sizing policies. Setting the process mean to a very low level can reduce manufacturing cost but it will increase rejection cost (due to formation of more nonconforming products) and return cost (due to high customer dissatisfaction). On the other hand, setting the process mean to a very high level can reduce the rejection cost and the return cost, but it will increase the manufacturing cost. [73] Research has been continuing from the 1950s to solve this targeting problem under various conditions. Main categories for research conducted in this area felt under three conditions:

1. Use of Specification Limits: The determination of the optimal process mean with specified upper and lower specification limits can be determined based on a cost function, such as a step loss function where a normal distribution with known standard deviation is assumed for the measured quality characteristic and fixed costs are assumed for producing items below the lower specification limit and above the upper specification limit as done by Springer [70]. On the other hand, as done by Bettes [8] who modeled the process mean by setting a fixed lower specification limit and an arbitrary upper specification limit. He included a constant reprocessing cost based on step loss function for overfilled and under-filled cans. This problem was also solved by Wen and Mergen [80] based on minimizing the costs of falling below the lower specification limit and exceeding the upper specification limit.

2. Use of Different Strategies for Disposing Defective Items: Hunter and Kartha [37] presented a model to determine optimal process mean under the assumption that the products meeting the requirement are sold in a regular market at a fixed price, while the underachieved products are sold at a reduced price in a secondary market. They assumed that the quality characteristic is normally distributed with a known standard deviation. They considered a linear function for the net income of accepted products and a constant cost for rejected products and expressed the net income as the sum of the income from conforming items, the income from the rejected items, and the giveaway cost. Golhar [29] developed a model for the optimal process target with the assumptions that an over specification product can be sold in the regular market while an under specified one can be reprocessed (e.g. emptied and refilled) with an additional cost. This model was further modified by Golhar and Pollock [30] who treated both upper specification limit and process mean as control variables. Ladany [48] solved the problem for determining the most economic position of a manufacturing process by considering unequal revenue from undersized and oversized items.

3. Use of Quality Loss Functions: Cho and Leonard [20] presented a piecewise linear quality loss function for product to be roughly proportional to the deviation of the quality characteristic from its specification limit. Chen [18] used a mixed quality loss function which was composed of a quadratic loss function to express the loss within the specification limits and a piecewise linear loss function to express the loss outside the specification limits. Teeravaraprug and Cho [75] extended Taguchi univariate loss function to a multivariate quality loss function.

3.2.2 Optimal Production Run Length Problem:

In many industrial situations, the process mean may shift from an in-control state to an out-of-control state as a result of the occurrence of an assignable cause (such as leakage, chipping or malfunctioning mounting). Moreover, the processes generally deteriorate as a result of ageing. This can be either an increase or a decrease in the product quality characteristic (known as a drift) which eventually causes the process to move to an out of-control state. Because of this inevitable deterioration, the process could be classified into two states:

- In-Control State: A process is said to be at in-control state if it is working with its natural variability, producing an output within the accepted quality level it was designed for.
- Out-of-Control State: A process is said to be at an out-of-control state if it is operating outside its tolerance or producing a nonconforming output.

In literature, the assumption in almost all current work is that the process will maintain its original performance characteristic over time. However, in most real situations, the opposite is true. As the process moves to an out-of control state, the proportion of defective items will increase to a point where it is economical to terminate the process and carry out the restoration action. However, these actions are usually expensive and result into loss of production time; therefore they are not recommended to be done until it is economically wise to do so [17, 62, 73]. Main categories for research done in this area felt under three conditions.

1. Inclusion of a Shift: Arcelus et al. [4] considered non-negative shifts in process mean and variance. They assumed that the shift occurred at the beginning of the production cycle and treated the defective items (whether oversized or undersized) as worthless items. Arcelus and Banerjee [3] extended the previous model to include possible rewards for defective items.

2. Inclusion of a Drift: Hall and Eilon [31] assumed that the process exhibited a linear trend in the process mean (had a constant variance) and exhibited a positive constant drift with time. Taha [72] presented a procedure for determining the optimal production run of a cutting tool considering the tool wore with time which causes the machine to produce more defective items. Gibra [28] established decision rules for resetting process mean due to a drift or due to the occurrence of an assignable cause. In his work, he considered the case of nonlinear positive drift in the process mean.

3. Use of Quality Loss Functions: Jeang and Yang [41] addressed the problem of optimal cutting tool replacement models with both symmetrical and asymmetrical quality loss. Al-Fawzan and Rahim [1] modified Jeang and Yang's [41] model to include an age dependent salvage value and maintenance cost in the formulation. Rahim and Tuffaha [62] applied quadratic quality loss function when the quality characteristic lied between the specification limits.

3.2.3 Optimal Specification Limits Problem:

The general concept of specifications is that items must meet some limits for being conforming. Usually, the specification limits are selected according to some technical criteria. However, in view of the economic character of a manufacturing process, it makes sense to select the specification limits using some economic criteria. Kapur and Wang [47] described the use of the normal and log-normal quality characteristic to design the optimum specification limits based on Taguchi's quadratic quality loss function. They pointed out that: "suppose we can't improve the present process, then a short term approach to decrease variance of the units shipped to the customer is to put specification limits on the process and truncate the distribution by inspection". Kapur and Cho [46] addressed problems related to the application of the quality loss function in the economic design of specification limits. Chen and Chou [19] presented a solution for jointly designing the economic manufacturing quantity, type-1 continuous sampling plan and specification limits aiming to minimize the incurred cost under imperfect quality.

3.2.4 Quality Loss Functions:

The quality loss function is a way to quantify the quality cost of a product on a monetary scale when a product or its production process deviates from the desired value for one or more key characteristics. It relates the quality characteristic of a product to its quality performance. Taguchi [71] redefined the product quality to be the total loss to society, including the loss to the producers and the loss to customers. He pointed out that loss always incurs when a product's functional quality characteristic deviates from its target value, regardless of how small the deviation is. He indicated that quality loss should be measured in monetary units and it is incurred at any deviation from its target value. Taguchi characterized this loss or cost as a quadratic function and the quality loss in his approach was given by:

$$L(y) = \begin{cases} k\left(y - \tau\right)^2 & \text{for } LSL \le y \le USL \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

where y is the measured quality characteristic, τ is the target value, and k is the quality loss coefficient which is given by:

$$k = \frac{C_r}{\Delta^2} \tag{3.2}$$

where C_r is the rejection cost per unit, and Δ is the tolerance.

The advantage of applying quadratic quality loss function is that losses could be evaluated in terms of bias (the distance of the target value and the process mean) and process standard deviation. Other forms of quality loss functions are listed below: [74]

a. Step Loss Function: It assumes zero cost for the quality falling within the specification limits and a fixed cost when it falls outside these limits as shown in Figure 3.1.

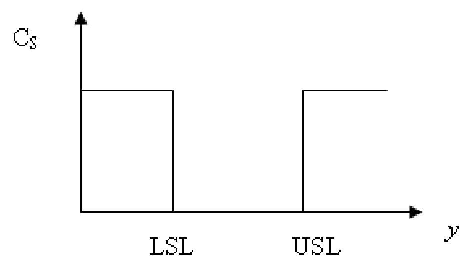


Figure 3.1: Step loss function

$$C_S(y) = \begin{cases} C_{RL} & if \;\; y < LSL \\ 0 & if \;\; LSL \le y \le USL \\ C_{RU} & if \;\; y > USL \end{cases} \tag{3.3}$$

where C_S is the nonconformance cost, C_{RL} is the rejection cost for falling below the LSL, C_{RU} is the rejection cost for exceeding the USL and y is the measured quality characteristic.

b. Piecewise Linear Loss Function: It assigns a zero cost when falling within the specification limits and linearly varying costs for deviating outside a shown in Figure 3.2.

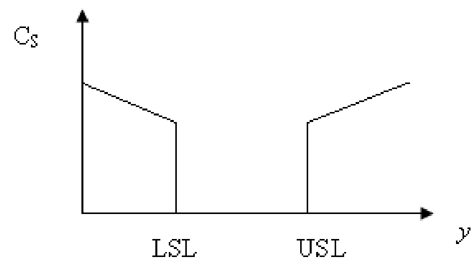


Figure 3.2: Piecewise linear loss function

$$C_S(y)=\begin{cases} C_{RL}(LSL-y) & \text{if } y<LSL \\ 0 & \text{if } LSL\le y\le USL \\ C_{RU}(y-USL) & \text{if } y>USL \end{cases} \tag{3.4}$$

where C_{RL} is the rejection cost for falling lower than the lower specification limit, and C_{RU} is the rejection cost when exceeding the upper specification limit.

c. Mixed Quality Loss Function: It is viewed as a combination between different quality loss functions. In our work, it is resulted from combining a step loss function with a quadratic loss function as shown in Figure 3.3.

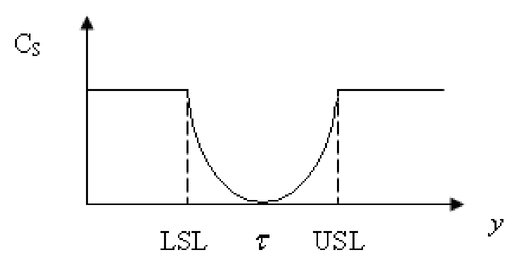


Figure 3.3: Mixed quality loss function

$$C_S(y)=\begin{cases} C_{RL} & \text{if } y<LSL \\ k\left(y-\tau\right)^2 & \text{if } LSL\le y\le USL \\ C_{RU} & \text{if } y>USL \end{cases} \tag{3.5}$$

where C_S is the cost for nonconformance, C_{RL} is the rejection cost for falling lower than the lower specification limit, C_{RU} is the rejection cost when exceeding the upper specification limit, y is the measured quality characteristic, τ is the target value, and k is the quality loss coefficient.

3.3 Models for Optimum Process Parameters Determination:

3.3.1 Review of Wen & Mergen's Model:

Wen and Mergen [80] presented a model for setting the optimum process mean in which they used a balanced step loss function for measuring the cost of nonconforming item. The selected optimum process mean was based on minimizing the costs of falling below the lower specification limit and exceeding the upper specification limit. The used a quality characteristic of nominal-is-best type. This quality characteristic ($-\infty < y < +\infty$) was assumed to be normally distributed with an unknown mean μ and a constant variance σ^2, and its probability density function was given by: $f(y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{y-\mu}{\sigma}\right)^2}$ and the target τ was assumed to be at the middle of the specifications $\tau = \frac{USL + LSL}{2}$.

The expected total loss per item as per Wen and Mergen's model was given by:

$$C_T = C_{RL} \int_0^{LSL} f(y)dy + C_{RU} \int_{USL}^{+\infty} f(y)dy \tag{3.6}$$

When the quality characteristic variable is normally distributed, C_T can be expressed in terms of the cumulative normal distribution function as follows:

$$C_T = C_{RU}\Phi\left(\frac{LSL-\mu}{\sigma}\right) + C_{RU}\left[1-\Phi\left(\frac{USL-\mu}{\sigma}\right)\right] \tag{3.7}$$

where $\Phi(z)$ is the cumulative distribution function for standard normal random variable, and $-\infty < z < +\infty$.

3.3.2 Modified Model for Setting Optimum Process Mean:

Wen and Mergen's [80] model is based on step loss function which assumes a zero cost for items falling between the specification limits and ignores the quality loss for the society. In our work, the model was improved by integrating it with the mixed quality loss function, which we developed in Section 3.2.4, to include the loss between the specification limits. Following is the expected total loss per item as per the modified model:

$$C_T = C_{RL}\int_0^{LSL} f(y)dy + \int_{LSL}^{USL} k\left(y-\tau\right)^2 f(y)dy + C_{RU}\int_{USL}^{+\infty} f(y)dy \tag{3.8}$$

This can be written in terms of the cumulative normal distribution function as follows:

$$\begin{aligned} C_T = {} & C_{RL}\Phi\left(\frac{LSL-\mu}{\sigma}\right) + C_{RU}\left[1-\Phi\left(\frac{USL-\mu}{\sigma}\right)\right] + k\left[\left(\mu-\tau\right)^2+\sigma^2\right]\left[\Phi\left(\frac{USL-\mu}{\sigma}\right)-\Phi\left(\frac{LSL-\mu}{\sigma}\right)\right] \\ & +k\sigma\left[\left(\mu-2\tau+LSL\right)\phi\left(\frac{LSL-\mu}{\sigma}\right)-\left(\mu-2\tau+USL\right)\phi\left(\frac{USL-\mu}{\sigma}\right)\right] \end{aligned} \tag{3.9}$$

3.3.3 Proposed Bi Model for Joint Determination of Optimum Process Mean and Production Run Length:

This model takes into consideration the process deterioration over time, and for including this effect, we split out the process mean into two periods, based on the process condition whether it is being in-control or out-of-control as follows:

$$\mu_t = \begin{cases} \mu_{t-1} & \text{for } t \le T_d \\ \mu_{t-1} + \delta\sigma & \text{for } t > T_d \end{cases} \tag{3.10}$$

where μ is the process mean, t is the current time, which is assumed to be exponentially distributed with mean 1/£ and probability density function: $f(t) = \lambda\, e^{-£t}$, T_d is the total time until the process starts to deteriorate, σ is the standard deviation, and δ is the shift parameter. Accordingly, the non-conformance cost is divided as:

$$C_S = \begin{cases} C_{S0} & \text{for } t \le T^* \\ C_{S1} & \text{for } t > T^* \end{cases} \tag{3.11}$$

where T^* is the optimal production run length, C_{S0} is the loss when the process is in-control and C_{S1} is the loss when the process is out-of-control.

When the process is in-control, the quality characteristic is $y \sim N(\mu,\sigma^2)$ and the expected total loss per item C_{S0} is expressed by Equation 3.8. As the process shifts to an out-of-control state, the quality characteristic becomes $y \sim N(\mu+\delta\sigma,\sigma^2)$ and cost of operating the out-of-control process C_{OP} is added. Accordingly, the expected total loss per item is expressed by the following model:

$$C_{S1} = C_{RL} \int_{0}^{LSL} f(y)dy + \int_{LSL}^{USL} k\left(y - \tau\right)^2 f(y)dy + C_{RU} \int_{USL}^{+\infty} f(y)dy + C_{OP} \tag{3.12}$$

Which is written in terms of cumulative normal distribution function as follows:

$$
\begin{aligned}
C_{S1} = {} & C_{RL}\Phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right) + C_{RU}\left[1-\Phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)\right] + C_{OP} \\
& + k\left[\left(\mu-\delta\sigma-\tau\right)^2+\sigma^2\right]\left[\Phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)-\Phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right)\right] \\
& + k\sigma\left[\left(\mu-\delta\sigma-2\tau+LSL\right)\phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right) - \left(\mu-\delta\sigma-2\tau+USL\right)\phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)\right]
\end{aligned}
\tag{3.13}
$$

The overall total cost is found by integrating the costs of the two process conditions as:

$$
\begin{aligned}
C_T &= C_{S0}\Pr(t \le T_d) + C_{S1}\Pr(t > T_d) \quad = C_{S0}\Pr(t \le T_d) + C_{S1}[1-\Pr(t \le T_d)] \\
&= [C_{S0} - C_{S1}]\Pr(t \le T_d) + C_{S1} \quad = [C_{S0} - C_{S1}]\int_0^{T_d} \lambda e^{-\lambda t}\,dt + C_{S1} \\
&= [C_{S0} - C_{S1}][1-e^{-\lambda T_d}] + C_{S1} \quad = [e^{-\lambda T_d}]\,C_{S1} + [1-e^{-\lambda T_d}]\,C_{S0}
\end{aligned}
\tag{3.14}
$$

By substituting the cost values, the Bi model results:

$$
\begin{aligned}
C_T(\mu, T_d) = {} & e^{-\lambda T_d}\left\{
\begin{aligned}
& C_{RL}\Phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right)+C_{RU}\left[1-\Phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)\right] \\
& +k\left[(\mu-\delta\sigma-\tau)^2+\sigma^2\right]\left[\Phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)-\Phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right)\right] \\
& +k\sigma\left[(\mu-\delta\sigma-2\tau+LSL)\phi\left(\frac{LSL-\mu-\delta\sigma}{\sigma}\right)-(\mu-\delta\sigma-2\tau+USL)\phi\left(\frac{USL-\mu-\delta\sigma}{\sigma}\right)\right]
\end{aligned}
\right\} \\
& +(1 - e^{-\lambda T_d})\left\{
\begin{aligned}
& C_{RL}\Phi\left(\frac{LSL-\mu}{\sigma}\right)+C_{RU}\left[1-\Phi\left(\frac{USL-\mu}{\sigma}\right)\right]+C_{OP} \\
& +k\left[(\mu-\tau)^2+\sigma^2\right]\left[\Phi\left(\frac{USL-\mu}{\sigma}\right)-\Phi\left(\frac{LSL-\mu}{\sigma}\right)\right] \\
& +k\sigma\left[(\mu-2\tau+LSL)\phi\left(\frac{LSL-\mu}{\sigma}\right)-(\mu-2\tau+USL)\phi\left(\frac{USL-\mu}{\sigma}\right)\right]
\end{aligned}
\right\}
\end{aligned}
\tag{3.15}
$$

3.3.4 Proposed Trine Model for Joint Determination of Optimum Process Mean, Production Run Length and Specification Limits:

The model resulted by extending the model presented by Equation 3.15, in which the quality loss coefficient was written in term of the specification limits as:

$$k = \frac{C_r}{\Delta^2} = \frac{C_r}{(USL\ -\ LSL)^2} \tag{3.16}$$

The specification limits were written in terms of the target and the tolerance as:

$$\begin{aligned} USL &= \tau + \frac{\Delta}{2} = \tau + \varsigma \\ LSL &= \tau - \frac{\Delta}{2} = \tau - \varsigma \end{aligned} \tag{3.17}$$

where τ is the target value, USL is the upper specification limit, LSL is the lower specification limit and ς is half the tolerance. Accordingly, the Trine model for the total cost is expressed as:

$$\begin{aligned} C_T(\mu, T_d, \varsigma) = e^{-\lambda T_d} &\left\{ \begin{array}{c} C_{RL}\Phi\left(\frac{\tau-\varsigma-\mu-\delta\sigma}{\sigma}\right)+C_{RU}\left[1-\Phi\left(\frac{\tau+\varsigma-\mu-\delta\sigma}{\sigma}\right)\right] \\ +\frac{C_r}{\Delta^2}\left[(\mu-\delta\sigma-\tau)^2+\sigma^2\right]\left[\Phi\left(\frac{\tau+\varsigma-\mu-\delta\sigma}{\sigma}\right)-\Phi\left(\frac{\tau-\varsigma-\mu-\delta\sigma}{\sigma}\right)\right] \\ +\frac{C_r}{\Delta^2}\sigma\left[(\mu-\delta\sigma-2\tau+\tau-\varsigma)\phi\left(\frac{\tau-\varsigma-\mu-\delta\sigma}{\sigma}\right)-(\mu-\delta\sigma-2\tau+\tau+\varsigma)\phi\left(\frac{\tau+\varsigma-\mu-\delta\sigma}{\sigma}\right)\right] \end{array} \right\} \\ +(1 - e^{-\lambda T_d}) &\left\{ \begin{array}{c} C_{RL}\Phi\left(\frac{\tau-\varsigma-\mu}{\sigma}\right)+C_{RU}\left[1-\Phi\left(\frac{\tau+\varsigma-\mu}{\sigma}\right)\right]+C_{OP} \\ +\frac{C_r}{\Delta^2}\left[(\mu-\tau)^2+\sigma^2\right]\left[\Phi\left(\frac{\tau+\varsigma-\mu}{\sigma}\right)-\Phi\left(\frac{\tau-\varsigma-\mu}{\sigma}\right)\right] \\ +\frac{C_r\sigma}{\Delta^2}\left[(\mu-2\tau+\tau-\varsigma)\phi\left(\frac{\tau-\varsigma-\mu}{\sigma}\right)-(\mu-2\tau+\varsigma+\rho)\phi\left(\frac{\tau+\varsigma-\mu}{\sigma}\right)\right] \end{array} \right\} \end{aligned} \tag{3.18}$$

3.4 Numerical Examples:

In this section, we will present examples on problems related to: determination of optimum process mean, joint determination of process mean and production run, joint determination of optimum process mean, production run and specification limits, and optimum process mean for satisfying manufacturing requirements. The solution for these problems will be based on using the developed models in this work.

3.4.1 Optimum Process Mean Problem:

Consider a beverage filling process in which the scrap cost (monetary loss for items below the lower specification limit) is \$65, the rework cost (monetary loss for items exceeding the upper specification) is \$25, and customer's loss for quality variation between the upper and the lower specification limits is \$10. The lower specification limit is 10 liters and the upper specification limit is 13 liters. The process standard deviation is 0.75. It is required to find the optimum process mean that will minimize the total loss.

This problem was solved by applying the use of the model represented by Equation 3.8, then formulating it by using Matlab (Appendix B.3.1). Accordingly, the optimum value for process mean was found to be 11.64 liters at which the total loss was \$6.0195, as shown in Figure 3.4.

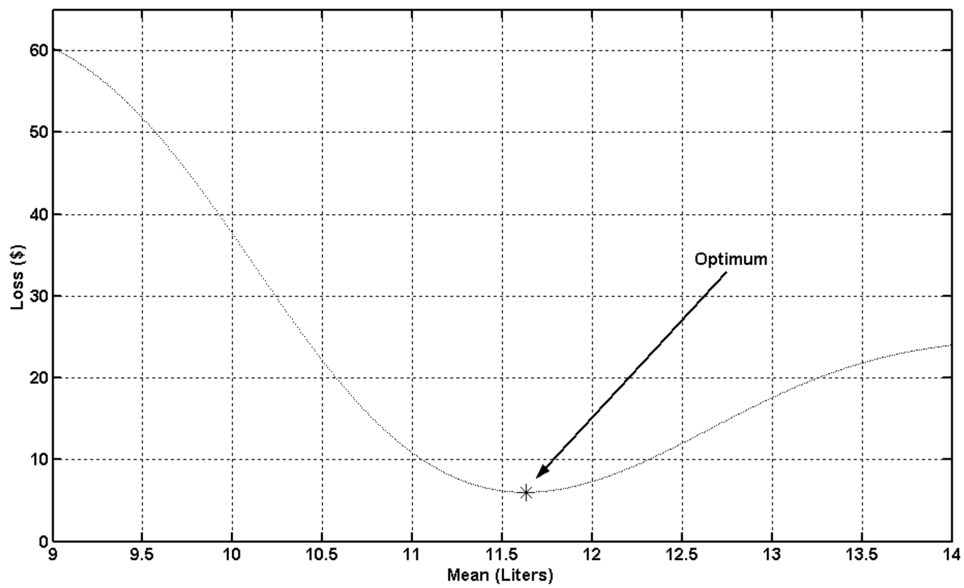


Figure 3.4: Total loss for different values of process mean

3.4.2 Optimum Process Mean and Production Run Length Problem:

Suppose that the scrap cost for previous process is estimated to be $35, the rework cost is reduced to $10, and customer's loss for quality variation between the upper and the lower specification limits at $5. The lower specification limit is 9 liters and the upper specification limit is 13 liters. The process standard deviation is 0.76, failure rate is 2 and shift parameter is 0.7. Cost of operating out of control is $3. It is required to find the optimum process mean and production run length for minimum the total loss per item.

Using the Bi model represented by Equation 3.15, and after coding the problem in Matlab (Appendix B.3.2), the optimum process mean was found to be 11.05 liters the optimum run length was 18.5 days, and the total loss was estimated to be $2.8559. The resulted graph was as shown in Figure 3.5.

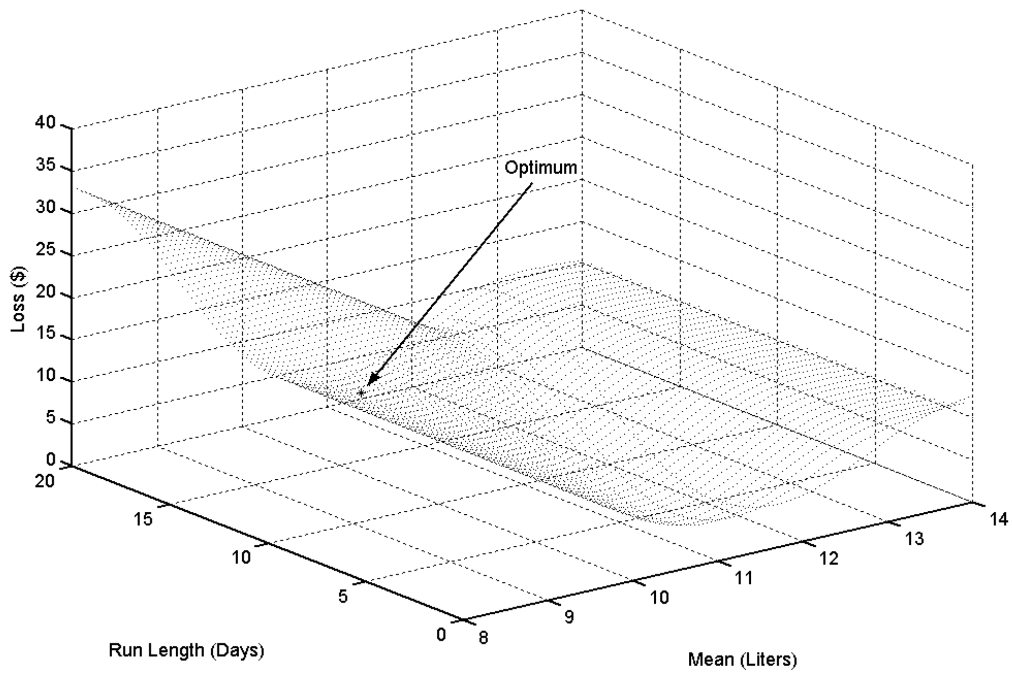


Figure 3.5: Total loss for different process means and production runs

3.4.3 Optimum Process Mean, Production Run Length and Specification Limits Problem:

Consider the case in which the scrap cost for the filling process is \$28, the rework cost is \$13, and the rejection cost is \$9. The process standard deviation is 0.75, failure rate is 3 and shift parameter is 0.8. If the process goes out of control, cost of \$5 is added. The management is interested in determining the optimum process mean, production run length, and specification limits that will minimize the total loss per item given that the required filling target value is 10 liters.

Using the Trine model represented by Equation 3.18 for joint determination of optimum process mean, production run length and specification limits, and programming the problem in Matlab (Appendix B.3.3), the resulted graph was as shown in Figure 3.6.

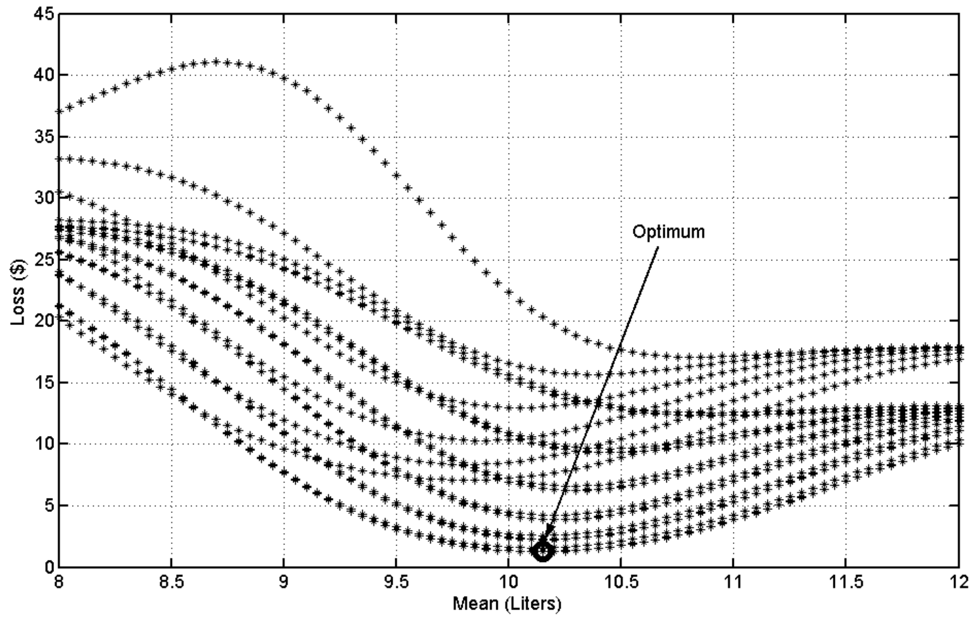


Figure 3.6: Total loss for different process means with different tolerances and runs

The optimum value for process mean was found to be 10.15 liters, the production run length was 13 days, the upper specification limit was at 11.5 liters, the lower specification limit was at 8.5 liters, the tolerance was 3, and the total loss was estimated to be $1.2786.

3.4.4 Optimum Process Mean Problem for Satisfying Manufacturing Requirements:

A cement packing system is composed of two processes: a filling process and an inspection process. Each cement bag processed by the filling machine is moved to the loading and dispatching stages on a conveyor belt. Based on previous data, the weight of the cement bag is normally distributed with standard deviation σ = 0.25. The desired target value for the cement bag fill is achieved when the filling machine is set to fill a quantity of τ = 40.75 kg. The quality loss coefficient is k = 25. The scrap cost per item is \$55. The rework cost per item is \$10. The inspection cost per item is \$4. The manufacturing cost per item is \$90. The selling price for each item is \$200. The lower specification limit is 40 kg and the upper specification limit is 41.5 kg. The management is interested in determining the optimum process target for minimizing the total cost for society that includes both the producer and the customer, and maximizing the expected gross profit per item.

If the weight of the processed cement bag falls above the *USL*, the processing cost will increase since the exceeding amount of cement will not be sold with a higher price. In such a case it will be recommended to rework the over weighted bags. On the other hand, if the weight of the bag falls below the *LSL*, it will result in facing penalty cost because of violating government's law. To avoid such kind of loss, the under weighted bags will be scrapped. Optimum process mean will be found by maximizing the expected total profit per item using the following relation:

$$P_r = SP - C_T - C_M - C_I \tag{3.19}$$

where SP is the selling price per item, C_T is the expected total loss per item, C_M is the manufacturing cost per item and C_I is the inspection cost per item.

The problem was formulated using Matlab (Appendix B.3.4), and the optimum process mean was found to be 40.7650 kg and the total expected profit was found to be \$104.4012 per bag. Resulted graph was as shown in Figure 3.7.

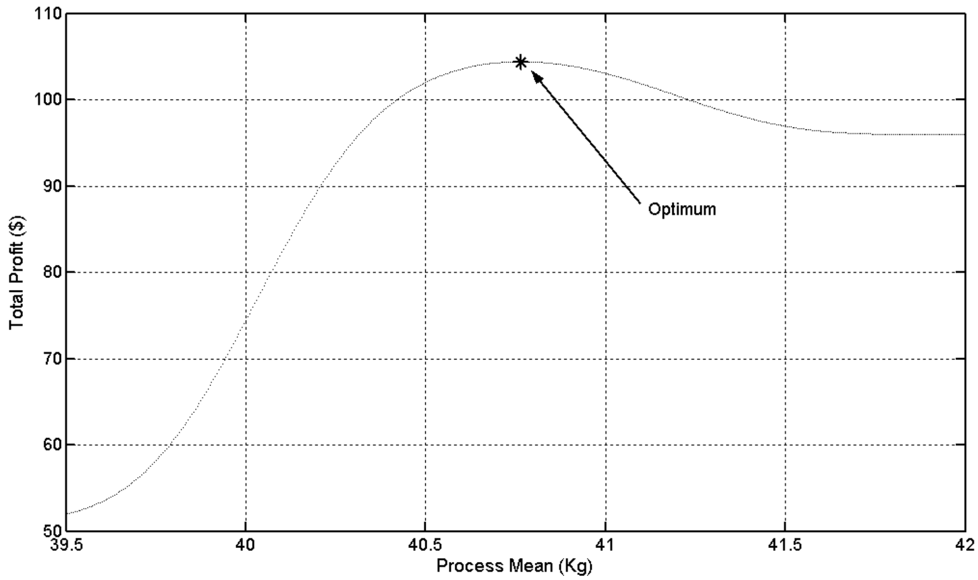


Figure 3.7: Total profit for different values of process means

3.4.5 Sensitivity Analysis:

Numerical Example 4.4 was extended to study the effect of different parameters on the overall profit as follows:

1. Effect of Quality Loss Coefficient (k)*:* For different values of quality loss coefficient, calculated results were listed in Table 3.1. These results indicated that the total expected profit and the process mean decrease as the quality loss coefficient (k) increases. This implies that using high quality level material increases the manufacturing cost, but on the other side, reduces the process mean since less effort is needed to process a fine material.

Table 3.1: Effect of quality loss coefficient

k	μ	*Profit*
0	40.8200	105.9388
5	40.7900	105.6239
15	40.7700	105.0104
25	40.7650	104.4012
35	40.7600	103.7932
45	40.7600	103.1856
55	40.7550	102.5781
65	40.7550	101.9712
75	40.7550	101.3643
85	40.7550	100.7574
95	40.7550	100.1505
105	40.7550	99.5436

2. Effect of Scrap Cost (C_{RL})*:* For different values of scrap cost, calculated results were listed in Table 3.2, from which it was concluded that the total expected profit decreases and the process mean increases as the scrap cost increases. This implies that processing on a material of low quality results into increased amount of scrapped items which reduces the profit and increases the effort needed for processing it.

Table 3.2: Effect of scrap cost

C_{RL}	μ	*Profit*
5	40.7500	104.4630
15	40.7500	104.4495
35	40.7600	104.4244
55	40.7650	104.4012
70	40.7700	104.3848
85	40.7700	104.3693
100	40.7750	104.3546
120	40.7800	104.3357
140	40.7850	104.3178
170	40.7900	104.2926

3. Effect of Standard Deviation (σ)*:* By applying different values for the standard deviation, calculated results were listed in Table 3.3, from which we noted that the total profit decrease and the process mean increase as the process standard deviation increase. This implies that processing under abnormal process conditions requires a large control action which incorporates large processing cost, and in turn, decreases the profit.

Table 3.3: Effect of standard deviation

σ	μ	*Profit*
0.000	40.7500	106.0000
0.100	40.7500	105.7500
0.15	40.7500	105.4375
0.25	40.7650	104.4012
0.35	40.8350	102.7360
0.45	40.9550	100.9371
0.55	41.1100	99.4410
0.65	41.2950	98.3303
0.75	41.5150	97.5475
0.85	41.7700	97.0113
0.95	42.0000	96.6459
1.00	42.0000	96.4542

4. Effect of Rework Cost (C_{RU})*:* Under different values of rework costs, obtained results were listed in Table 3.4. It was noted that the process mean decreases as the rework cost increases, since less effort is needed for re-processing finished product as compared to processing from raw material. But since processing will be done twice, the total profit will decrease as well.

Table 3.4: Effect of rework cost

Rework	μ	*Profit*
0	42.0000	105.7507
5	40.7650	104.4094
10	40.7650	104.4012
25	40.7600	104.3776
50	40.7500	104.3415
75	40.7450	104.3087
100	40.7400	104.2782
125	40.7350	104.2499
150	40.7300	104.2233
175	40.7250	104.1980
200	40.7200	104.1739
250	40.7150	104.1296

3.5 Conclusion:

In this chapter, different models for determining optimum values of process parameters were developed. The extension of these models ended up with development of a trine model that can be used for joint determination of optimum process mean, production run length and specification limits. We concluded that for maximizing the profit, it is recommended to minimize the process variability by maintaining the system, to conduct rework the over-specified items at low cost, try to reduce the amount of scrapped items as minimum as possible, and to minimize the total quality loss to the society through appropriate selection for process parameters.

CHAPTER 4

ROBUST TUNING AND GAIN SCHEDULING OF CONTROL PARAMETERS

4.1 Overview:

Proper selection of control parameters is critically important since it has a large impact on the end product and enables keeping the operation run within the specified limits. It also helps to maximize profitability, to ensure quality and safety. In this chapter, we will apply the use of robust design principle to determine the optimal value of process parameters so that the controller maintains the process on target with low variability while keeping the performance robust against the external factors, and apply the use of gain scheduling to modify the control parameters depending of the state of the system to maintain its stability. Our objective is to develop a Robust Gain-Scheduled (*RGS*) methodology that combines between the uses of these two techniques. An example for carbonated beverage filling process will also be presented on which we will apply our suggested methodology.

4.2 Background:

One common reason that affects the performance of controllers is the incorrect selection of gain parameters. In the case of dynamic systems, nominal parameters might change depending on what state the system is in. For example, many systems exhibit different characteristics during warm-up stages after being running for long time, or they might need to operate with different gain parameters once a certain set-point has been reached. Gain scheduling is the process of modifying the gain parameters depending on the states of the system which are defined by some time duration or by the expected quality level of the output. For systems that have predictable changes in dynamics, this method works best so that predetermined gains could be calculated and applied.

Despite the use of *PID* controllers for controlling most processes, their parameters are usually not well defined, and in many cases need to be modified or scheduled according to the change of the behavior of the process which in many cases depend also on external noise factors that affect the process. Robust design is a cost effective methodology to achieve robustness, which aims to make the performance less sensitive to these factors. Its purpose is to minimize variability of the system by finding the best setting of control variables. Most of the work found in literature has used robust design principles during the design stage of the product and no attention is made to apply it in the processing stage. Changing this philosophy is one of our objectives.

4.2.1 Common Methods for Controller Tuning:

By having the controller parameters tuned properly, it can provide the control action designed for specific process requirements. Despite the availability of hundreds of tools, methods and theories for finding proper control parameters, effective tuning is still remaining a difficult task. One reason is that these methods or tools may give the proper setting for reducing the variability within the process, but on the other hand, they ignore the effect of external factors that may affect the performance such as noises and disturbances. A study made by Bialkowski has shown that 30% of their control loops functioned poorly due to the incorrect *PID* controller setting. Up to date, no enough research has been done about the robustness of controllers under noisy conditions. Common methods for control loop tuning are as follows: [2, 79]

a. Trial and Error Method: Trial and Error is the easiest way of controller tuning since it requires a little or no knowledge about the controlled process. This method is also known as Zone-Based tuning because the low and high frequency parts of the controller parts are tuned separately. General procedure for this method is as follows: [84]

1. Eliminate integral action ($\tau_i \rightarrow \infty$) and the derivative action ($\tau_d \rightarrow 0$).
2. Find the controller gain (K_p) that causes sustained oscillations in the output, this value is known as the ultimate gain (K_U), set $K_p = 0.5\ K_U$.
3. Decrease τ_i until sustained oscillations are obtained, set τ_i to three times this value.
4. Increase τ_d until sustained oscillations are obtained, set τ_d to one-third this value.

Figure 4.1 shows a flow chart for this method. [25]

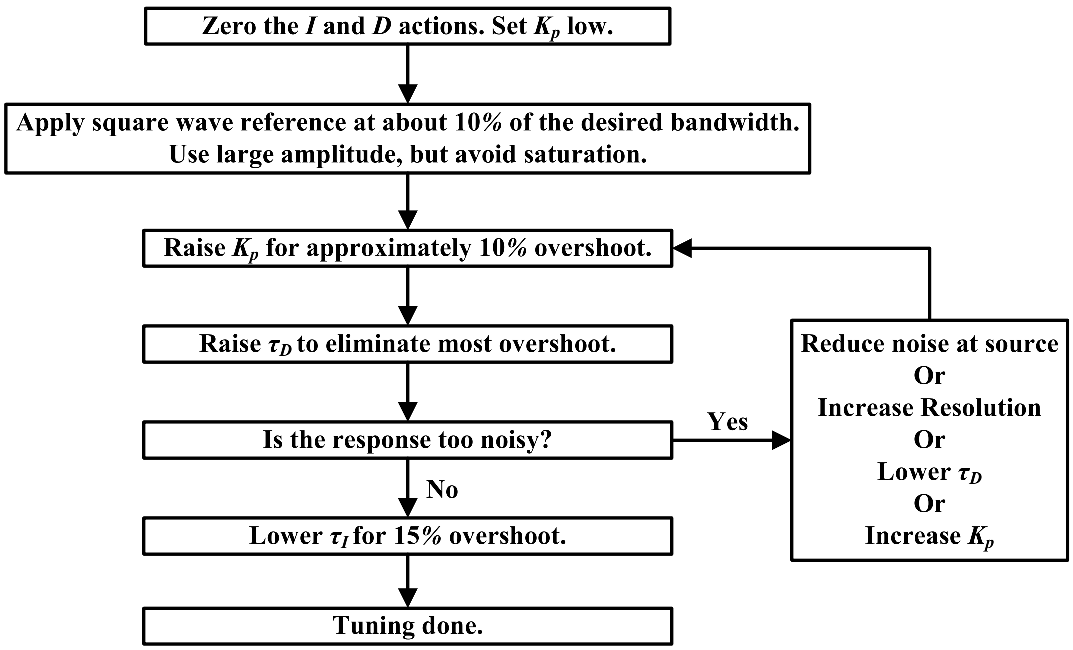


Figure 4.1: Tuning procedure by trial and error method

The disadvantages of this method are that its procedure is time consuming and potentially costly since it requires going through large number of iterations before obtaining the final result and the resulted sustained oscillations could lead to complete loss of stability. This method is not applicable to unstable processes and processes without an ultimate gain, such as first order system without a time delay. Moreover, it does not guarantee any robustness of the system.

b. Process Reaction Curve Method: The response of the output to a step change in the manipulated input is known as process reaction curve. It is based on the fact that many processes have a step response approximated by a first order plus dead time model. The advantage of this method is that it requires a single experiment test only. Parameters for the *PID* regulator by this method are obtained based on two parameters namely *a* and *l*, which are obtained from the reaction curve as the one shown in the Figure 4.2.

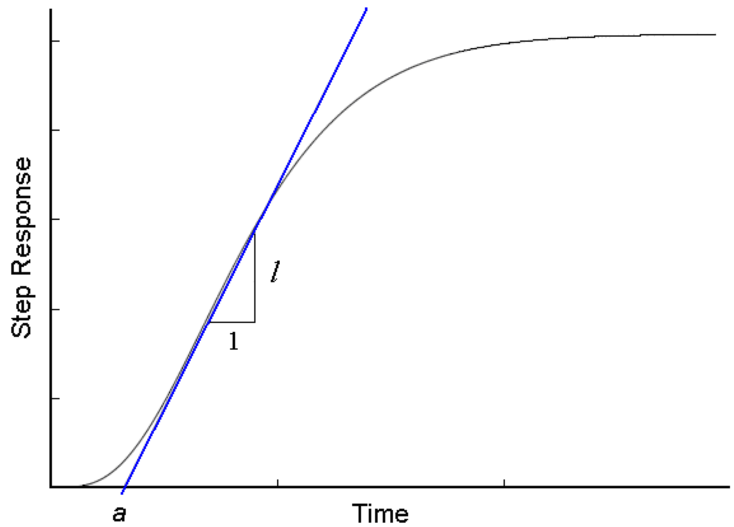


Figure 4.2: Process reaction curve

The parameter *l* is the slope of the tangent line through the inflection point, and *a* is the time at which the tangent intersects the time axis. Table 4.1 lists formulas used to obtain controller parameters by this method. [2, 63, 84]

Table 4.1: Parameters setting by reaction curve method

Controller	K_p	τ_i	τ_d
P	$1/a$	-	-
PI	$0.9\ a$	$3.33\ l$	-
PID	$1.2/a$	$2\ l$	$l/2$

The drawback in this method is that it gives a poorly damped closed-loop system for which tuning is usually needed. Another disadvantage of this method is its sensitivity to disturbance since it is based on open loop experiment.

c. Ultimate Cycle Method: This method is also known as the Ziegler-Nichols method and it is based on the ultimate gain K_U and the ultimate period T_U. For obtaining these parameters, the integral and derivative actions are set to zero, after which the proportional gain is increased gradually until an oscillation is obtained. The gain at this point is K_U and the oscillation period is T_U. The controller parameters are obtained using the formulas listed in Tables 4.2 and 4.3.

Table 4.2: Parameters setting by ultimate cycle method

Controller	K_p	τ_i	τ_d
P	0.5 K_U	-	-
PI	0.4 K_U	0.83 T_U	-
PID	0.6 K_U	0.5 T_U	0.125 T_U

Table 4.3: Modified parameters setting by ultimate cycle method

	K_p	τ_i	τ_d
Original (¼ Decay)	0.6 K_U	0.5 T_U	0.125 T_U
Some Overshoot	0.33 K_U	0.5 T_U	0.333 T_U
No Overshoot	0.2 K_U	0.5 T_U	0.333 T_U

The disadvantage of this method is that the procedure requires driving the system towards instability, which is dangerous for practical situations. In some cases, the resulted closed loop behavior can be different from the characteristics of the process. [2, 84]

d. Other Tuning Methods: Another famous method is Cohen-Coon's which depends upon the identification of a suitable process model. This method is practical if the process delay is small. The method is not suitable for systems where there is zero or virtually no time delay. Another disadvantage of the method is that *PID* controller setting may not be realized unless an appropriate model form is used to synthesize the control law. Beside the existence of these tuning methods, *PID* tuning and loop optimization softwares can also be used to ensure consistent results. These software packages work by gathering the data from which they develop the process models, and afterwards suggest optimal values for tuning parameters. Table 4.4 gives comparison between different tuning methods.

Table 4.4: Comparison between different tuning methods

Method	*Advantages*	*Disadvantages*
Trial & Error	Online method, no calculations required	Require experienced personnel
Ziegler-Nichols	Proven online method	Dangerous for practical situations, need some trial & error
Cohen-Coon	Provide good results	Require calculations, offline method, only suitable for 1st order processes
Software Tools	Result into consistent tuning, may include valve and sensor analysis, allow simulation before downloading	Adds purchase and training cost

4.2.2 Gain Scheduling Control:

As per the control theory, gain scheduling is an approach to control non-linear systems that apply the use of linear controllers to provide satisfactory control for different operating points of the system. In other words, gain scheduling is the process of modifying the gain parameters depending on the states of the system which are defined by some time duration or by the expected quality of the output. Gain Scheduling is one of the most popular approaches for controlling nonlinear systems that can be successfully applied in fields ranging from aerospace to process control. This approach enables well established linear design methods to be applied to nonlinear problems by decomposing them into a number of linear sub-problems. For systems that have predictable changes in dynamics, this method works best so that predetermined gains could be calculated and applied. The method works by dividing up the process into sections that approximate its expected characteristics, after which each section could then be tuned to a different set of parameters that optimally control the system. Gain scheduled controller has a constant control gain that varies with a single scheduling variable, which is the error signal e as shown in Figure 4.3 [66].

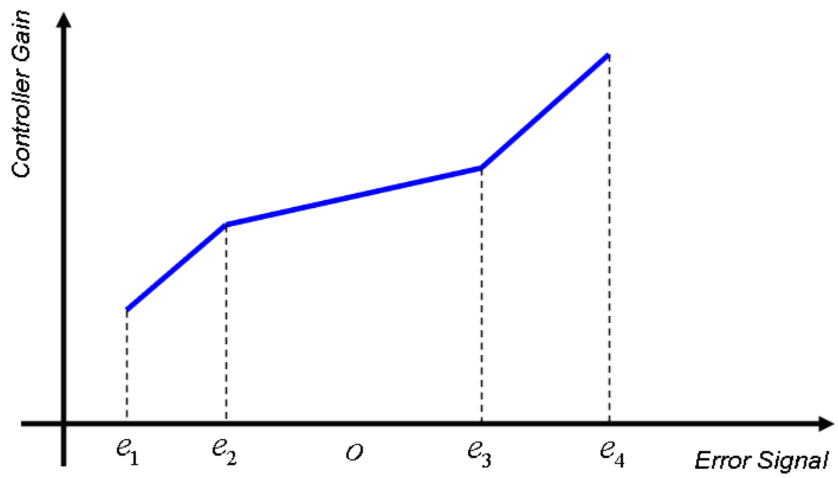


Figure 4.3: Gain scheduled controller gain

$$K = \begin{cases} K_1 & for \quad e_1 \le e \le e_2 \\ K_2 & for \quad e_2 \le e \le e_3 \\ K_3 & for \quad e_3 \le e \le e_4 \end{cases} \tag{4.1}$$

where K is the controller gain and e is the error.

Programmed adaptation is a strategy that develops relationship between the controller setting and the scheduling variables. Liptak applied the use of programmed adaptation to a boiler problem where the feed flow rate had significant effect on the steady state and dynamic behavior, and its value at 100% flow rate was twice large as compared at 50%

flow rate. Liptak's solution for handling this problem was by having the *PID* controller setting to be varied with the fraction of full-scale flow ($0 \le \upsilon \le 1$) in the following manner: [66]

$$K_p = \upsilon K_p^* \qquad \tau_i = \frac{\tau_i^*}{\upsilon} \qquad \tau_d = \frac{\tau_d^*}{\upsilon} \tag{4.2}$$

where K_p^*, τ_i^*, and τ_d^* are the optimal control settings for 100% flow.

4.2.3 Robust Design Method:

The performance or response of a process may vary from the targeted value due to several reasons that can influence the quality characteristic or response of the product. Deming stated that: "The central problem of management in all its aspects, including: planning, procurement, manufacturing, research, sales, personnel, accounting and law, is to understand better the meaning of variation and to extract the information contained in variation". Generally, there are three basic ways to control variation: [27]

1. Reduce the magnitude of the variation sources, which can be through using higher-grade material or by specifying a tighter tolerance.
2. Deal with the response by compensating for the variation, such as using a feedback control system.
3. Through robust design, by identifying and adjusting system variables to make the system less sensitive to the variation sources.

Robust design is a cost effective methodology to achieve robustness, which aims to make the performance less sensitive to variability factors. The fundamental definition of robust design is described as: a product or a process is said to be robust when it is insensitive to the effects of sources of variability, even through the sources themselves have not been eliminated. In the early 1980s, Japanese quality engineer Dr. Genichi Taguchi introduced the philosophy and some methods closely related to robust design. Taguchi showed the general public the importance of robust design and the expected benefits behind applying it. His major contributions to the quality society included systematic study of noise factors and the introduction of quadratic loss function. Taguchi applied his methods in the American telecommunications industry and since then his robust design method has been successfully applied to various industrial fields such as electronics, automotive products, photography, and telecommunications. As per Taguchi, robust design is mainly composed of three stages: system design, parameter design, and tolerance design [79, 85].

1. System Design: is the conceptual design stage where the system configuration is developed. It is based on using the experience and knowledge gained in a specific field to develop and select the most appropriate design concept.
2. Parameter Design: it conducts investigations to identify the setting that minimize or at least reduce the performance variation. Its objective is to find the optimum setting of control factors such that the system is at least sensitivity to noise factors.
3. Tolerance Design: it is a balancing process about finding the optimum tolerance setting for the control factors so that the total life cycle cost of the system is minimal subject to the condition that all process requirements (performance, durability and reliability) are satisfied. It specifies the allowable deviations in the parameter values by loosening tolerances if possible and tightening tolerances if necessary.

4.2.4 Taguchi's Method of Robust Parameter Design:

Taguchi's method for Robust Parameter Design is based on the design of experiments theory along with using orthogonal arrays (*OA*) to study large number of decision variables with a small number of experiments in order to reach a near optimum parameter combination. The method classifies the inputs to the system into two types:

- Control Factors: factors that can be controlled and manipulated
- Noise Factors: factors those are difficult or expensive to be controlled

The basic idea is to exploit the interactions between control and noise variables and then identify the appropriate settings of control parameters for which the system's performance is robust against variation in noise factors. The aim is to make the system response close to the target with low variation in performance as illustrated in P-diagram of Figure 4.4 in which the large circle denote the target and the response distribution is indicated by the dots for the associated probability density function.

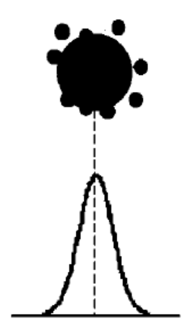


Figure 4.4: Performance variation with robust design

The objective functions arise from quality measures using quadratic loss functions. Taguchi suggested the Signal to Noise Ratio (*SNR*) as a measure of the Mean Squared Deviation (*MSD*) in the performance. The larger the *SNR*, the more robust the performance becomes. *SNR* is different for different types of quality characteristics. *SNR* for the prominent types of quality characteristics are given below: [53, 79, 84, 85]

a. Nominal the Best: Its Quality characteristic has a finite target value and the quality loss is symmetric on either side of the target (Figure: 4.5 A).

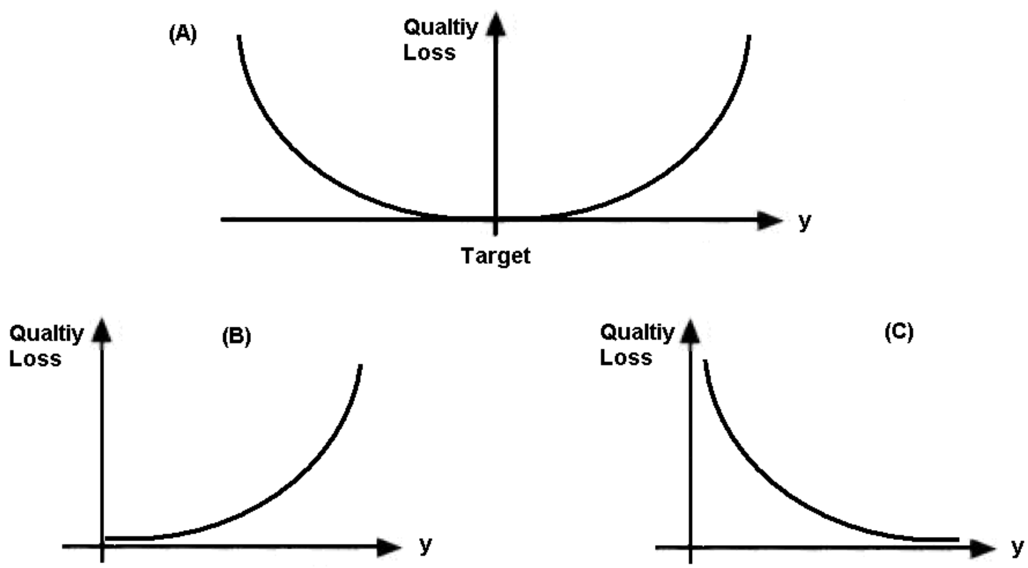


Figure 4.5: Quality loss functions: (A) Nominal the best type (B) Smaller the better type (C) Larger the better type.

This *SNR* quantifies the deviation of the response from the target τ, and it is given as:

$$SNR = -10\log_{10}\left(MSD\right) = -10\log_{10}\left[\frac{1}{n}\sum_{i}\left(y_i - \tau\right)^2\right] = -10\log_{10}\left[\sigma^2 + \left(\overline{y} - \tau\right)^2\right] \qquad (4.3)$$

where y_1, y_2, ..., y_n represent a random sample of n observations with mean $\overline{y}$ and variance σ^2. If the control parameters are chosen such that $\overline{y} = \tau$ (the population mean is the target value), then the *MSD* is equivalent to the variance. If the standard deviation is related to the mean, then the *MSD* may also be scaled by the mean to give:

$$SNR = -10\log_{10}\left(MSD\right) = -10\log_{10}\left[\frac{\sigma^2}{\overline{y}^2}\right] = 10\log_{10}\left[\frac{\overline{y}^2}{\sigma^2}\right] \tag{4.4}$$

2. Smaller the Better: Its quality characteristic never takes negative values, its ideal value is zero, and as it increases, the performance becomes progressively worse (Figure: 4.5 B). This *SNR* considers the deviation from zero and, as the name suggests, it penalizes large responses.

$$SNR = -10\log_{10}\left[\frac{1}{m}\sum_{i=1}^{m} y_i^2\right] \tag{4.5}$$

3. Larger the Better: Its quality characteristic does not take negative values and zero is its worst value, and as its value becomes larger the performance becomes progressively smaller. Its ideal value is infinity and at that point the quality loss is zero (Figure: 4.5 C). The *SNR* is given by:

$$SNR = -10\log_{10}\left[\frac{1}{m}\sum_{i=1}^{m}\frac{1}{y_i^2}\right] \tag{4.6}$$

4.3 Methodology:

In our work, the procedure of *RGS* methodology will be based on using two approaches. First, using Taguchi's method of robust parameter design to obtain a robust controller gain. Next, applying gain scheduling on the results obtained by using the Robust Design method to modify the use of control parameters based on the process condition to maintain the stability of the process and to compensate against its nonlinearity.

The *APC* controller tuning will be based on applying the use Taguchi's method of robust parameter design by dividing independent variables into controllable factors and noise factors and then conducting fractional factorial experiments on them. The objective is to obtain gain parameters those result into having a robust controller that maintains a high level of performance with low variation while remaining insensitive to changes in noise factors. Our solution procedure up to this point will follow these steps:

1. Description of the process model and the existing control scheme
2. Determination of the quality characteristic
3. Selection of control factors with their alternative levels
4. Identification of the noise factors with their alternative levels
5. Design of the experiment
6. Experimental runs and data analysis
7. Decision about the optimum setting for controller gain parameters

Further explanation for the previous steps is given below:

1. Description of the process model and the existing control scheme: In this work, we will illustrate our scheme by describing the process model with a First Order Plus a Time Delay (*FOPTD*) function. The *APC* control scheme is of a *PID* controller type.

2. Determination of the quality characteristic: Since the performance of the system increases depending on the decrease in output error, the quality characteristic will be selected to be of a smaller the better type (Figure 4.5 B).

3. Control factors selection: The control factors are selected from the *PID* control rule described by Equation 2.5 to be: K_p, τ_i, and τ_d. These factors could be changed under the objective of minimizing the *MSD*. For each control factor, three levels will be selected.

4. Noise factors identification: The noise factors are identified from the process model accounting the fact for the impossibility of their control. The *FOPTD* function is described by:

$$G(s) = \frac{K_c \, e^{-ds}}{Ts + 1} \tag{4.7}$$

where K_c is the gain of the process model, d is the time delay, and T is the time constant. Accordingly, the noise factors are selected to be: K_c, d, and T. For each factor, two levels will be selected.

5. Design of experiment: For the control factors, the degree of freedom (*DOF*) is calculated to be: 3×(3–1)+1=7. Correspondingly, the nearest *OA* to 7 *DOF* was selected to be $OA(L_9)$ which contains 3 levels with 9 experimental runs (Appendix: C.4.2). For the noise factors, *DOF* is: 3×(2–1)+1=4, therefore, an *OA* of level 2 with 4 experimental runs $OA(L_4)$ is selected (Appendix: C.4.1).

6. Experiment Run: Starting from the inner array of noise factors, all combinations of the three factors each with two levels will be evaluated against different combinations for the three control factors each with three levels at the outer array for control factors. After studying the statistics for the mean, variance, *MSD*, and *SNR*, optimum values for the robust controller gain will be chosen at the maximum value for *SNR*.

4.4 Case Study: Carbonated Beverage Filling Process:

To illustrate the use of our suggested *RGS* methodology and examine its effectiveness, we will present a case study for carbonated beverage filling process in this section.

4.4.1 Problem Description:

Carbonated beverage is a soft drink into which carbon dioxide gas has been dissolved. This beverage was originally intended as a patent medicine when it was invented in the late 19th century by John Pemberton, but later led its dominance of the world soft-drink market throughout the 20th century. Nowadays, carbonated beverage is internationally found in stores, restaurants, and even vending machines, and it is claimed that it is sold in more than 200 countries. The production of carbonated beverage integrates water and syrup component deaerating, dosing, mixing and subsequent carbonating. The first step in the production process involves two-stage water deaeration using the vacuum spray process. The dosing unit is designed for proportional flow metering. Syrup is continuously added to the water inline and controlled by mass flow of the media. The carbonating process involves dissolving carbon dioxide gas under constant pressure and results in the formation of carbonic acid which has the chemical formula H_2CO_3. The filling process should result into the exact fill level target with high level of accuracy under appropriate filling speed to neutralize the effects of splashing while keeping the production quantity on target [65]. Sudden filling of the beverage through the narrow bottle top could produce a dramatic foaming fountain that can reach a height of several meters as shown in Figure 4.6 [7].

Figure 4.6: Carbonated beverage splash

The height of this fountain depends upon several parameters, such as:

- *Temperature:* The height of the fountain increases as the temperature increase.
- *Presence of other solutes:* Diet sodas generally produce higher fountains than sodas sweetened with sugars.
- *Aqueous CO_2 concentration:* A beverage that has been opened for a period of time produce smaller fountain than a freshly opened beverage.
- *Surface tension and partial pressure:* mainly increase the height as their corresponding values are raised.

Table 4.5 lists fountain height obtained with containers of different carbonated beverages, from which maximum effect is found with Diet Coke at room temperature [7].

Table 4.5: Fountain heights for various carbonated beverages

Beverage	*Bottle Size* (*mL*)	*Temperature* (^oC)	*Fountain Height* (*m*)
Harp Beer	350	5	< 1.0
Coca Cola	470	5	2.3
	470	21	3.7
Diet Coke	470	5	3.9
	470	21	> 4.5
Mountain Dew	710	5	0.9
	710	21	2.5
Diet Mountain Dew	710	5	1.5
	710	21	3.3
Diet Pepsi	710	5	3.0
	710	21	3.9

It is shown that fountain height increases with temperature and that diet beverages produce higher fountains than the sugar-sweetened ones. Numbers of effects combine to give these results, but ultimately a higher fountain is produced when the rate of bubble formation increases relative to the rate of bubble collapse. Temperature change during the filling could result either from the internal factors of the filling system itself (such as overheating), or could be result of outside environmental factors. An effective solution to deal with these problems is by making the system insensitive to these factors by applying the techniques of robust design. Other factors that affect the rate of bubble formation are surface tension and vapor pressure. The speed of liquid flow is the main variant to those two. Setting the filling speed to a low level could avoid splashing, but will reduce the overall profit. On the other hand, setting the filling speed to a high level will achieve the desired production target, but will result into having more scrapped product. One solution is to schedule the gain of the filling process, by starting with a high filling speed then begin decreasing it near the point where it is near the fill target [7, 65].

4.4.2 Illustrative Example:

An optimization study is conducted on a carbonated beverage filling process, which is used to fill soft drink bottles having volume of 1 liter. The beverage level inside the bottle is measure by means of a level sensor. This value is sent to a transducer which compares its value with the corresponding value of filling level that corresponds to the desired amount of filling volume and then calculates the difference as an error signal. The error signal is further transmitted to a flow controller, which is of a *PID* control type, which accordingly calculates the output signal to be fed to a flow control valve to adjust the amount of beverage flow. The followed control strategy is shown in Figure 4.7.

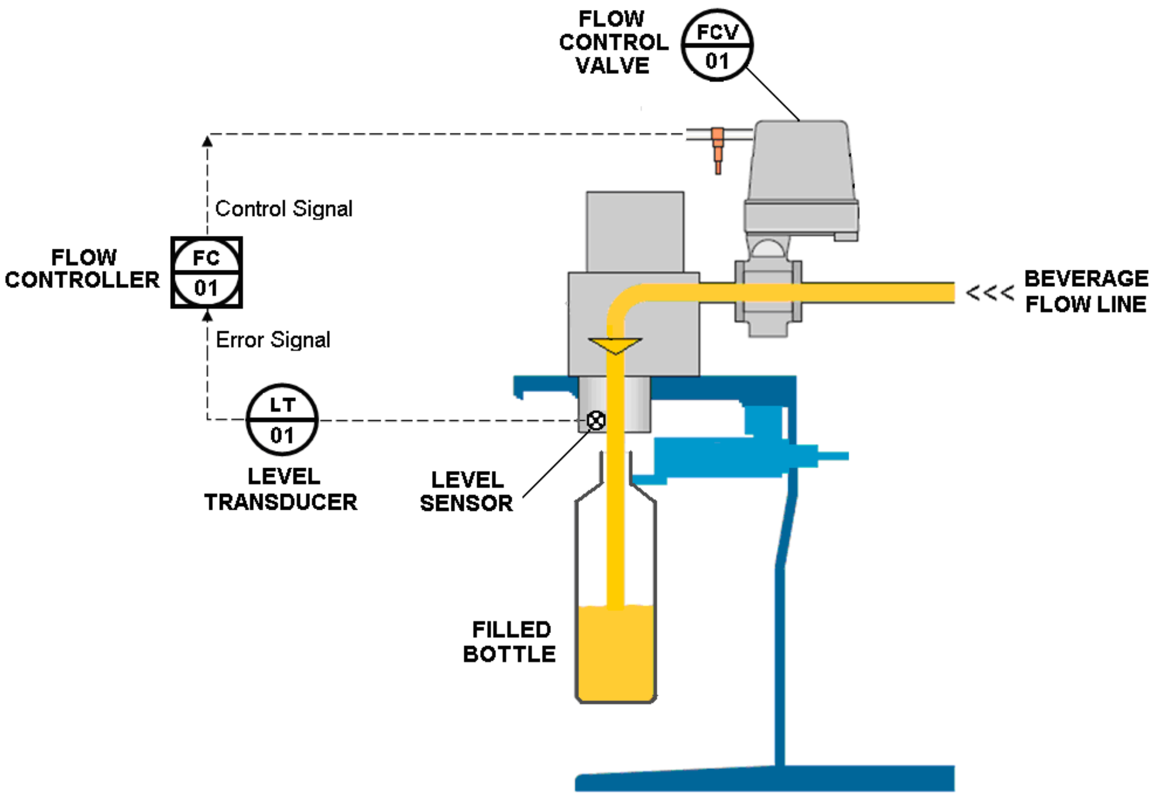


Figure 4.7: Control strategy for beverage filling process

At the beginning of the process, the beverage volume *v*, inside the bottle varies linearly with the input flow rate as per the following differential equation:

$$A\frac{dh_1}{dt} = F_{in} \tag{4.8}$$

where *A* is the cross sectional area of the bottle, h_1 is the beverage level inside the bottle at the beginning of the process, F_{in} is the beverage flow rate. As the beverage level approaches its targeted value, the input flow starts to decrease after level h^*. The corresponding beverage volume after h^* varies as per the following differential equation:

$$A\frac{dh_2}{dt} = F_{in} - \Re\sqrt{h_2} \tag{4.9}$$

where h_2 is the beverage level inside the bottle at the end of the filling process, and $\Re$ is the flow resistance factor. Note that the system is nonlinear, since the flow rate decreases depending on the square root of the beverage level. The steady-state operating conditions are given in Table 4.6.

Table 4.6: Steady-state operating conditions

V	F_{in}	A	h	$\Re$
10048 cm^3 (~1 lt)	15.0 cm^3/sec	314.0 cm^2	32.0 cm	2.6

Using values of Table 4.6, equations (4.8) and (4.9) can be written as follows:

$$\dot{h}_1 = \frac{F_{in}}{A} = \frac{F_{in}}{314} \tag{4.10}$$

$$\dot{h}_2 = \frac{1}{A}\left(F_{in} - \Re\sqrt{h_2}\right) = \frac{1}{314}\left(F_{in} - 2.6\sqrt{h_2}\right) \tag{4.11}$$

where $\dot{h}$ is rate of change of beverage level inside the bottle. The corresponding transient response is plotted in Figure 4.8. To approximate the overall process and model it by a *FOPTD* function, model parameters were identified by applying the Two-Points-Based Method [66]. This method is based on the estimation of two time instants from the reaction curve. It consists of determining the time instants t_1 and t_2 when the process output attains 35.3% and 85.3% of its final steady-state values respectively. Afterwards, the time delay (dead time) and the time constant are calculated by the following formulas:

$$T = 0.67\ (t_2 - t_1) \tag{4.12}$$

$$d = 1.3t_1 - 0.29t_2 \tag{4.13}$$

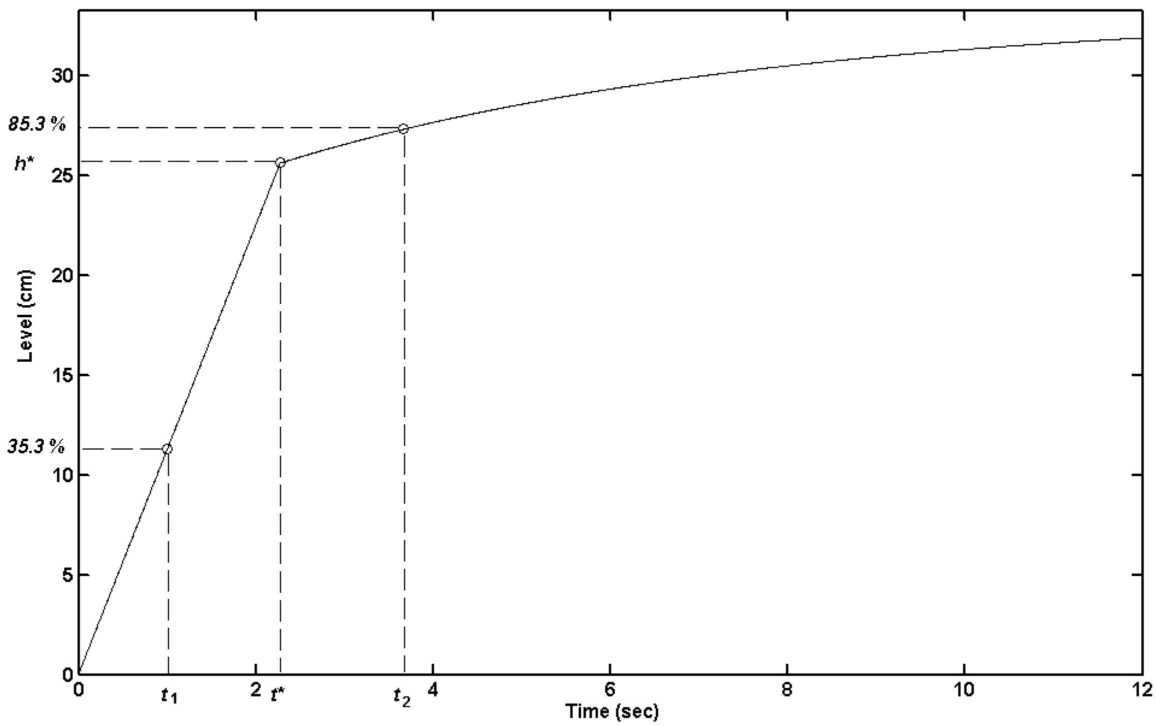


Figure 4.8: Transient response for the filling process

By applying this method on the transient response obtained by the process (Figure 4.8), the two time instants were found to be:

t_1 = 0.9988 seconds (corresponds to 35.3% for level h = 11.3 cm)

t_2 = 3.6678 seconds (corresponds to 85.3% for level h = 27.3 cm)

After performing the calculations using equations (4.12) and (4.13), parameters of the *FOPTD* model were found to be:

$K_c = 1.0000$ $\qquad$ $d = 0.2347$ $\qquad$ $T = 1.7882$

The resulted *FOPTD* process model was written as:

$$G(s) = \frac{K_c\ e^{-d.s}}{Ts+1} = \frac{e^{-0.2347s}}{1.7882\ s+1} \tag{4.14}$$

It is required to find the optimum setting for the *PID* controller parameters and schedule their usage by the controller to reach the desired filling target smoothly while keeping the system insensitive to environmental changes. First, we attempted to solve the problem by using a standard tuning method, the ultimate cycle method, and afterwards re-solved it by applying our suggested *RGS* methodology.

Solution (1): Ultimate Cycle Method:

The block diagram was generated using Simulink tool (Appendix A.4.1). From the closed loop step response, the ultimate gain and the ultimate period were found to be:

$K_u = 13.5000$ $\qquad$ $T_u = 0.9000$

The corresponding values by the ultimate cycle method (Table: 4.3) for the proportional gain, the integral and derivative time constants were found to be:

$K_p = 2.7000$ $\qquad$ $\tau_i = 0.4500$ $\qquad$ $\tau_d = 0.3000$

The integral gain K_i and the derivative gain K_d were calculated using below equations:

$$K_i = \frac{T}{\tau_i} K_p \tag{4.15}$$

$$K_d = \frac{\tau_d}{T} K_p \tag{4.16}$$

From which their corresponding values were found to be:

$K_i = 6.0000$ $\qquad$ $K_d = 0.8100$

The resulted response was as shown in Figure 4.9. The plot clearly indicated that this setting is not applicable to this type of problem, which is for a filling process.

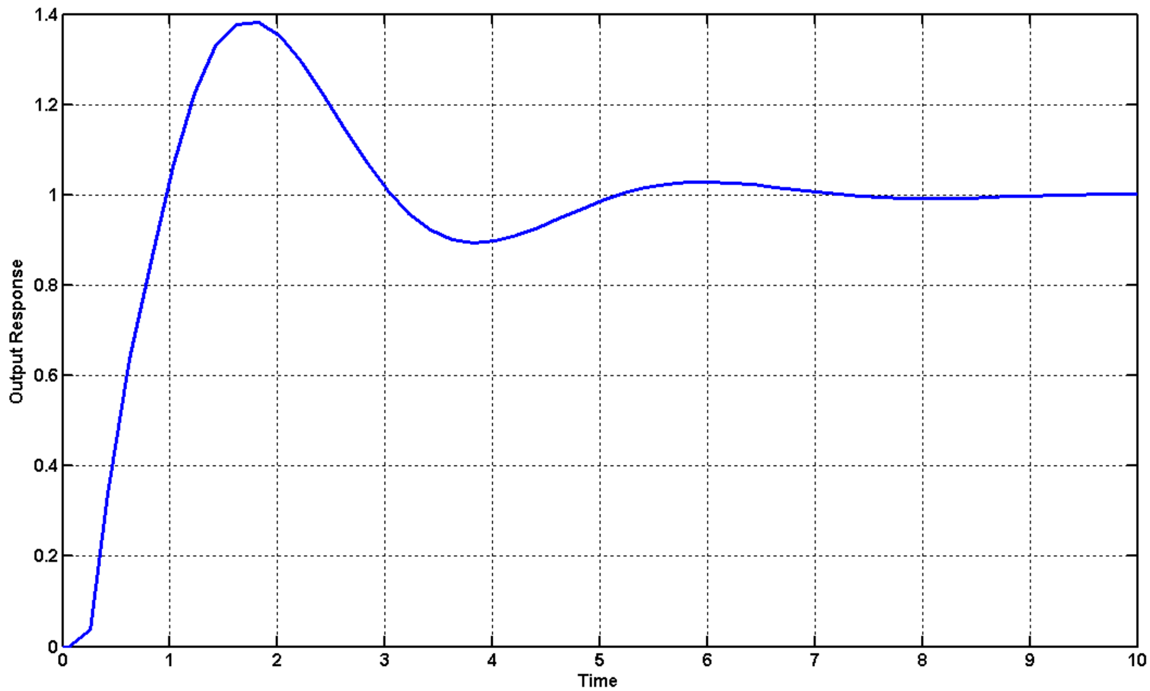


Figure 4.9: Output response by ultimate cycle method

Moreover, the output indicated the *MSD* to be 0.1635, at which the *SNR* was found to be 7.8648 and the variance of the output was 0.1502, and all of them were high.

Solution (2): Robust Gain Scheduled Methodology:

First, we will conduct robust tuning on the controller obtained from Solution 1 by following the methodology steps illustrated in Section 4.3. The control factors were selected to be: K_p, τ_i, and τ_d. Using the control parameter obtained in Solution 1 as a reference, three levels for each control factor were selected by taking different deviation from them as shown in Table 4.7. These factors were changed under the objective of minimizing the *MSD* and maximizing the *SNR* during experimental run.

Table 4.7: Control factors

Factor	*Parameter*	*Levels*		
		1	*2*	*3*
A	K_p	2.7000	4.0000	4.5000
B	τ_i	1.8000	1.0800	0.4500
C	τ_d	0.3000	0.2222	0.1481

The integral gain K_i and the derivative gain K_d were calculated from (4.15) and (4.16). The noise factors were identified from the process model described by Equation 4.12 accounting the fact for the impossibility of their control. These factors included: K_C, d, and T, and for each factor, two levels were selected as shown in Table 4.8.

Table 4.8: Noise factors

Factor	*Parameter*	*Levels*	
		1	*2*
NF1	K_C	1.0000	1.2500
NF2	d	0.2347	0.2934
NF3	T	1.7882	2.2353

For the control factors, the *DOF* is 7. Therefore, an outer *OA* of level 3 with 9 experimental runs *OA*(L_9) was selected (Appendix C.4.2). For the noise factors, the degree of freedom *DOF* is 3. Therefore, an inner *OA* of level 2 with 4 experimental runs *OA*(L_4) was selected (Appendix C.4.1).

Experimental runs were conducted by evaluating the effect for different combination of the three noise factors each with two levels resulted from the inner array against different combinations for the three control factors each with three levels using the outer array. The *MSD* error was evaluated for each of the nine trials against four different combinations of noise factors. The process model was built using the Simulink tool and the computations were done using the Matlab and Microsoft XL softwares. The results were summarized in Table 4.9.

Table 4.9: Experiment results

Noise Factors	*Levels*			
	1	*2*	*3*	*4*
NF1	1.0000	1.0000	1.2500	1.2500
NF2	0.2347	0.2934	0.2347	0.2934
NF3	1.7882	2.2353	2.2353	1.7882

Trial	*Control Factors*			*MSD*				$\overline{MSD}$	$\overline{\sigma^2}$	*SNR*
	K_p	τ_i	τ_d	*1*	*2*	*3*	*4*			
1	2.7000	1.8000	0.3000	0.1584	0.1666	0.1579	0.1551	0.1595	0.1355	7.9724
2	2.7000	1.0800	0.2222	0.1376	0.1649	0.1574	0.1537	0.1534	0.1405	8.1417
3	2.7000	0.4500	0.1481	0.1612	0.1799	0.1647	0.1661	0.1680	0.1556	7.7476
4	4.0000	1.8000	0.2222	0.1478	0.1549	0.1241	0.1478	0.1437	0.1246	8.4269
5	4.0000	1.0800	0.3000	0.1483	0.1559	0.1484	0.1485	0.1503	0.1320	8.2311
6	4.0000	0.4500	0.1481	0.1502	0.1618	0.1515	0.1534	0.1542	0.1409	8.1185
7	4.5000	1.8000	0.1481	0.1476	0.1550	0.1469	0.1488	0.1496	0.1243	8.2514
8	4.5000	1.0800	0.2222	0.1461	0.1542	0.1462	0.1491	0.1489	0.1301	8.2711
9	4.5000	0.4500	0.3000	0.1490	0.1456	0.1499	0.1528	0.1493	0.1391	8.2587

Next, Gain Scheduling was applied, in which we splitted the process into two stages:

- *The first stage:* This stage represents the process where the filling varies between 0% → 75% of the total amount, in which we will apply the use of *PID* controller setting resulted from the first approach for maximizing the performance and obtaining insensitivity to environmental changes.
- *The second stage:* This stage represents the process where filling varies between 75% → 100% of the total amount, for which we will select the control parameters those maintain the stability to avoid beverage splash and over/under filling errors.

More illustration for the two stages is given in Figure 4.10.

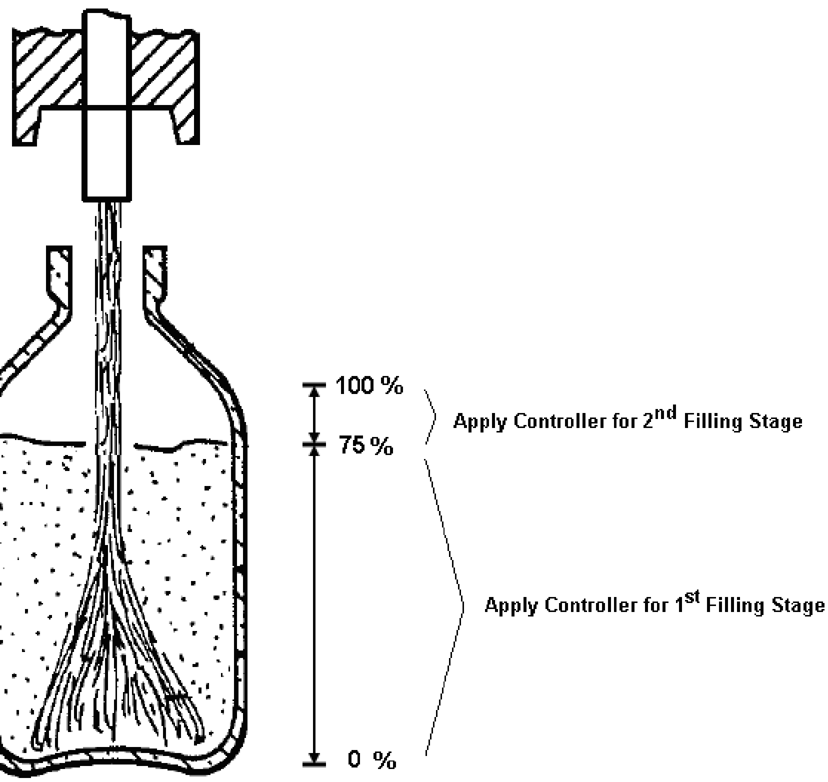


Figure 4.10: Splitted stages for the filling process

1. Controller setting for 1st filling stage: Based on previous results, the maximum value for the *SNR* was found to be 8.2997 at parameters of trial 8. Accordingly, the optimum values for the *PID* controller parameters were set to be:

$K_p = 4.5000 \qquad K_i = 2.5000 \qquad K_d = 0.4000$

2. Controller setting for 2nd filling stage: The system was subjected to operate under assignable causes by including white noise and shift of 0.2 in the process mean at time t = 10 sec. After testing the control parameters of trials 4, 7 and 8, the obtained results were summarized in Table 4.10.

Table 4.10: Output statistics for operating under assignable causes

Trial	K_p	τ_i	τ_d	σ^2	*MSD*	*SNR*
4	4.0000	1.8000	0.2222	0.0347	0.0376	14.2463
7	4.5000	1.8000	0.1481	0.0336	0.0366	14.3667
8	4.5000	1.0800	0.2222	0.0340	0.0352	14.5324

The minimum value of variance was found to be at trial 7, and accordingly, the *PID* controller parameters were set as:

$K_p = 4.5000 \qquad K_i = 1.5000 \qquad K_d = 0.6000$

Using the controller setting obtained by the *RGS* method, the simulation model was generated using Simulink tool for the overall process (Appendix A.4.2). The resulted response was plotted as shown in Figure 4.11. The *MSD* was found to be 0.1241, at which the *SNR* was 9.0617 and the variance of the output was found to be 0.0910. Note the time delay near time $t = 1$ sec which results due to controllers switching.

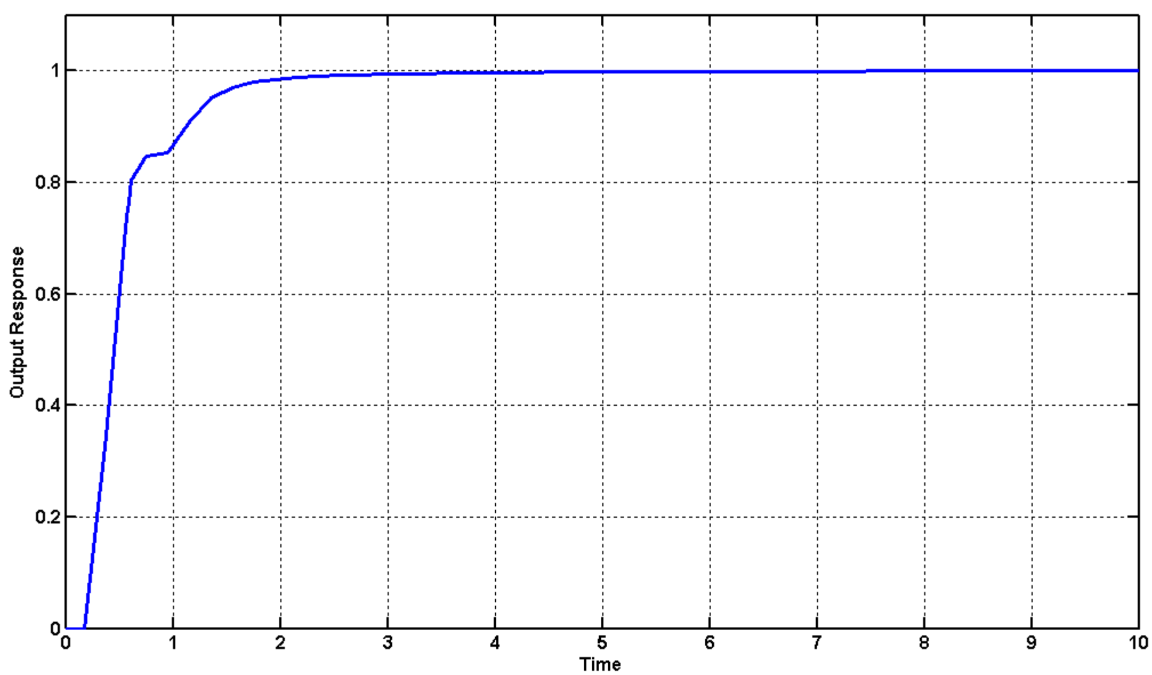


Figure 4.11: Output response by *RGS* method

4.4.3 Results Summary:

The overall statistics for both control actions were as entered in Table 4.11.

Table 4.11: Overall statistics for both control actions

	MSD	*SNR*	σ^2
RGS Control	0.1241	9.0617	0.0910
PID Control	0.1635	7.8648	0.1502

By comparing with results found using the ultimate cycle method, it was found that by applying the *RGS* Method, the *SNR* was increased by 15.22%, the variance of the process output was reduced by 39.41% and the *MSD* was reduced by 24.10%. This is due to the combined effects of: robust tuning (which raised the performance and took care of external factors), and gain scheduling (which reduced the variability of the process).

4.5 Conclusion:

In this chapter, we applied the use of robust design as well as gain scheduling for proper setting of control parameters. By combining these techniques together, we developed a *RGS* methodology. We also presented a case study on carbonated beverage filling process in which we applied the use of this methodology. Results have shown the successfulness of our suggested methodology in terms of increasing the performance and the *SNR*, and reducing the *MSD* as well as the variability of the process.

CHAPTER 5

PROCESS MONITORING AND PERFORMANCE EVALUATION

5.1 Overview:

The objective of this chapter is to develop a unified scheme that combines between the use of *SPC* and *APC* techniques of process monitoring and performance evaluation from which thorough assessment could be resulted. Among *SPC* tools, the Exponentially Weighted Moving Average (*EWMA*) control chart with *ARL* calculation will be used, while Signal to Noise Ratio and efficiency measures will be selected from *APC* techniques. Furthermore, an *SPC* controller based on the constrained principle and incorporated with quadratic quality loss function will be constructed and applied as a benchmark for performance evaluation. Indication for out of control signal will also be included within the monitoring part. By combining all these statistics together, an effective integrated *SPC/APC* monitoring and evaluation scheme is expected to result out.

An illustrative example for concentration control process is also presented on which we applied our proposed scheme to illustrate its effectiveness

5.2 Background:

Having the knowledge about plant performance, decision could be made about whether the facility is performing well and how effective is it in satisfying the required tasks. The objective of performance evaluation is to enable tracking and fixing problems before they cause production of poor quality products and result into financial loses. Although the human side of performance assessment can be accounted for use, real industrial process running at fast production rate result into high dimensionality data which makes it difficult for a human operator to monitor them, analyze their output data, evaluate the performance, and find causes of degradation. All of this calls the need for having a well defined systematic monitoring and evaluation strategy which provides concise information for effective decision making use. Eriksson and Isaksson envisioned that: "In the short term, such a tool probably has to be a stand-alone unit with its own software that hooks on to and collects data straight from the input of the process computer; in the long term, such a function will be an integral part of any commercial control system". Many possible factors can result into having poor performance, such as: incorrect controller tuning, incipient faults within the system, and poor operating practices. Generally, process monitoring and assessment of performance should not disturb routine operation of the processes or at least should be carried out under closed-loop conditions [6, 34].

5.2.1 SPC and Process Monitoring:

Since the time Shewhart illustrated the technique of the control charts, it has played a major role in controlling the product quality by applying statistical concepts for manufacturing processes. Shewhart's vision for a control chart was: "The control chart may serve: first, to define the goal or standard for a process that management strives to attain; second, it may be used as an instrument for attaining that goal and third, it may be serve as a means of judging whether the goal has been reached". As per Duncan, the control chart was viewed as: "… a statistical device principal used for the study and control of repetitive processes". Furthermore, Feigenbaum defined control chart as: "A graphical comparison of the actual product-characteristics with limits reflecting the ability to produce as shown by past experience on the product characteristics".

The applications of *SPC* control charts could be classified into four categories: process monitoring, planning, evaluating customer satisfaction, and forecasting. Among these categories, process monitoring is considered the traditional use of *SPC* control chart in order to stabilize and improve the process capability. Traditional control charts (i.e. Shewhart control charts, Section 2.2.2) could be successfully used in the steady-state manufacturing processes, but for unstable processes with dynamic behavior, the use of *SPC* methodologies to address the process shifts needs to be addressed [32, 45].

Exponentially Weighted Moving Average Control Chart: A major disadvantage of the Shewhart control chart is that it extracts process information from the last observations and ignores other information from the entire process run, which makes it insensitive to process shifts and less useful for process monitoring. An effective alternative to the Shewhart control chart for detecting process shifts and changes in quality characteristics is the *EWMA* control chart. Box and Luceño [12] suggested the use of the *EWMA* approach to forecast and keep track of the process mean, since it has been proven to be successful in estimating various time series. *EWMA* is viewed as a weighted average of all past and current observations, and it is defined as [55]:

$$z_i = \lambda x_i + (1-\lambda) z_{i-1} \tag{5.1}$$

where λ is the weight, $0 < \lambda \leq 1$, and z_0 is the starting value, which is usually set to be: $z_0 = Target$. The control limits and the centerline for *EWMA* control chart are as follows:

$$\begin{aligned} UCL &= \mu_0 + L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \\ CL &= \mu_0 \\ LCL &= \mu_0 - L\sigma\sqrt{\frac{\lambda}{(2-\lambda)}\left[1-(1-\lambda)^{2i}\right]} \end{aligned} \tag{5.2}$$

where L is the width of the control limits. Montgomery suggested that the optimal range of λ should lie between 0.05 and 0.25, so the values of λ are always set at 0.05, 0.1, or 0.2. The rule of thumb in selecting λ is that a small value of λ should be used to detect small shifts, and this value is varied as per the size of the shift. For the width of the control limit, Montgomery recommended setting L at 3, since it works well in detecting shifts in many situations [45, 55].

For illustration, consider the data [55] in Table 5.1. The first 20 observation were drawn at random from a normal distribution with mean μ = 10 and standard deviation σ = 1. To represent the process when it is out of control (experienced a shift in the mean of 1σ), the last 10 observations were drawn at mean μ = 11 and standard deviation σ = 1.

Table 5.1: Input data for the control chart

i	x_i	i	x_i	i	x_i
1	9.45	11	9.03	21	10.90
2	7.99	12	11.47	22	9.33
3	9.29	13	10.51	23	12.29
4	11.66	14	9.40	24	11.50
5	12.16	15	10.08	25	10.60
6	10.18	16	9.37	26	11.08
7	8.04	17	10.62	27	10.38
8	11.46	18	10.31	28	11.62
9	9.20	19	8.52	29	11.31
10	10.34	20	10.84	30	10.52

First, we will consider a Shewhart control chart, for which the centre line and the 3σ control limits are set as: LCL = 7, CL = 10, and UCL = 13. The plot for Shewhart control chart is shown in Figure 5.1.

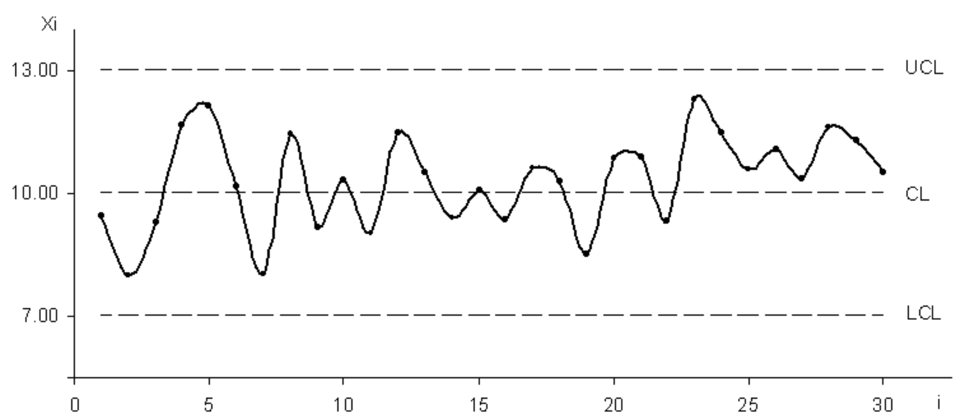


Figure 5.1: Shewhart control chart

The plot indicates a shift in the process level for the last 10 points, because all plots are above the centerline, except one. However, there is no strong evidence that the process is out of control because none of the points plot outside the control limits. Next, consider an *EWMA* control chart with λ = 0.1 and L = 2.7 for the same data points (Table 5.1) as shown in Figure 5.2.

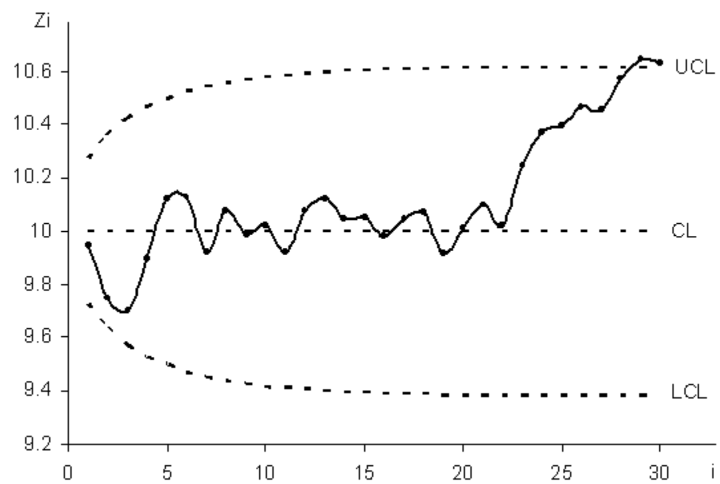


Figure 5.2: EWMA control chart

The *EWMA* signals at observation 28 to indicate that the process is out of control, which indicates its effectiveness over the Shewhart control chart in detecting process shifts.

Performance Evaluation from Control Charts: General practice during process monitoring through a control chart is as follows: If the sample point falls within the control limits, the process is deemed to be in control, or free from any assignable causes. Points beyond the control limits indicate an out-of-control process (i.e. assignable causes are likely to present), which calls the need for corrective action, in order to find and remove the assignable causes. The assignable causes (also known as special causes), are the portion of the variability in a set of observations that can be traced to specific causes, such as operators, materials, or equipment. On the other hand, chance causes (also known as common causes), are the portion of the variability in a set of observations resulted from random forces that cannot be traced to specific sources.

In order to evaluate the performance from control charts, the probabilities associated with Type-I and Type-II errors are used as performance measures. When the process is in control, we define the probability of Type-I error *by* α (also known as the probability of false alarm) as:

$$\alpha \;=\; P[Type\text{ - }I\ Error] = P[point\ \ falls\ outside\ control\ limits\ \ |\ process\ is\ in\ control] \tag{5.3}$$

For an out of control process, we define the probability of Type-II error by β (also known as the probability of not detecting a shift) as:

$$\beta \;=\; P[Type\text{ - }II\ Error] = P[point\ \ falls\ inside\ control\ limits\ |\ process\ is\ out\ of\ \ control] \tag{5.4}$$

Figure 5.3 shows the probability plots for: Type-I error when the process is in control (process mean is μ_0), and Type-II error when the process is out of control (process mean shifts to μ_1).

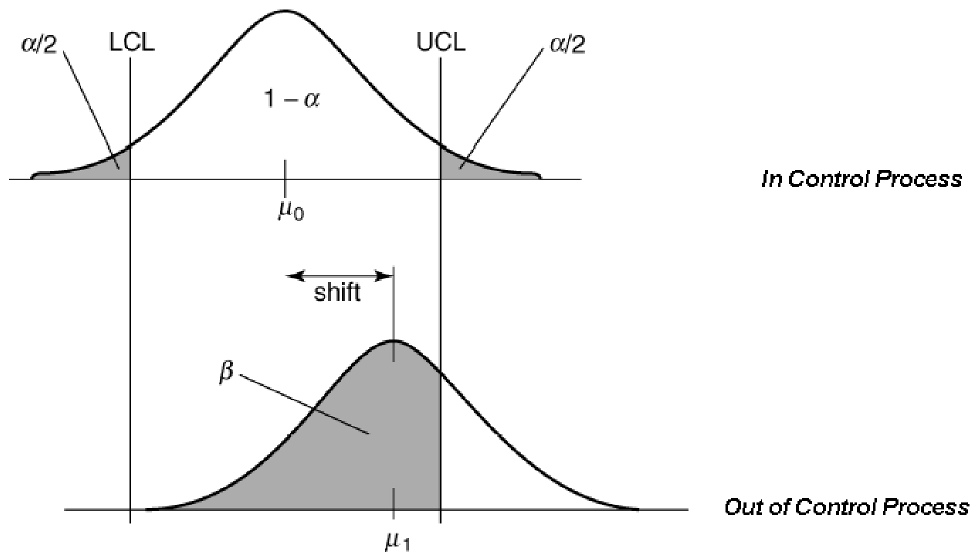


Figure 5.3: Probability plots for type-I and type-II errors

By defining the power of a control chart to be 1- β, it can be said that it is desired to have a high power and a low α. However, for a process engineer or an operator, discussing the probability of false alarms or α's and β's may sound to be esoteric. Which leads to an obvious question: Is α = 0.005 low enough? To avoid such issues, a better way for describing the performance is through *ARL* calculation, which is defined as the average number of points that must be plotted before a point indicates an out of control signal. For an in control process, it is calculated from: [45]

$$ARL_0 = \frac{1}{\alpha} \tag{5.5}$$

For an out of control process, it is calculated from:

$$ARL_1 = \frac{1}{1-\beta} \tag{5.6}$$

5.2.2 APC and Performance Evaluation:

Control loop performance is the key for manufacturing high quality product that aims to improve product quality by reducing process variation. In the past, statistical techniques, such as Shewhart control charts were used, but recently, focus has been placed for the development of more effective techniques. Modern research in the field of control performance assessment began with Harris [33] who presented the Minimum Variance (*MV*) benchmark which was derived from the theoretical background of *MV* controller. Since then, number of methods for measuring the performance of control loops have been developed. There are many different measures of control performances, such as: offset from set-point, overshoot, rise-time, and variance. Most commonly used measure of performance is the variance of key process variables in which the performance of the control loop might be deemed unacceptable if the variance of the process output exceeds some critical value. Generally, the performance of an existing control loop is often measured against some kind of benchmark (such as: *MV*) from which performance of the system is assessed by computing it ratio to that of the process output. Unfortunately, implementing *MV* controllers requires high level of accuracy and incorporates high cost for control action. For these reasons and due to some other practical issues, controllers in process plants are almost never implemented with *MV* objectives. In stead, they are implemented to minimize some integral indices (e.g. integrals of error) or to achieve the desired dynamic properties in time domain or frequency domain, such as: rise time, overshoot, or settling time [22, 26, 34, 35]. Below are some of the techniques used for evaluating control loop performance:

a. Step Response Evaluation Criteria: This approach is about perturbing the process in steady state with a step change in the input signal then observing the output of the process. Some quantitative criteria for evaluating control system performance are as follows: [33]

- Dead Time: is the time taken from injecting the input until its effect is seen.
- Rise Time: is the time taken by the output to rise from 10% → 90%.
- Settling Time: is the time taken by the output to remain within 5% of the set-point.
- Overshoot: is the maximum amount raised by the output signal above set-point.
- Steady State Error: is the difference between the output signal and the set-point when the time tends to infinity.

These criteria are illustrated in Figure 5.4.

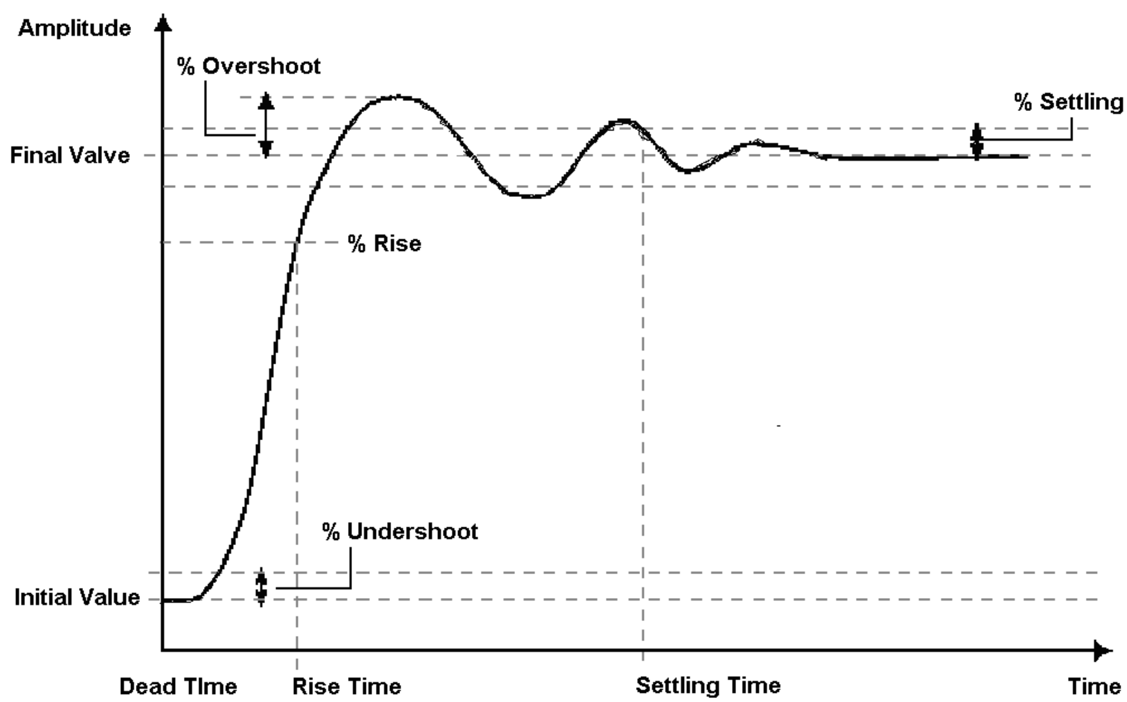


Figure 5.4: Step response evaluation criteria

b. Integral Error Evaluation Criteria: This criterion is based on evaluating the performance of the controlled system in the event of a step change to the input. It is practically done by introducing a step change to process input at $t = 0$, then computing the integral until the error becomes close enough to zero. Common integral performance indices are derived from the control error (difference between the input signal and the actual output of the process) as illustrated below: [34]

Integral of Squared Error (ISE): It is very aggressive, since squaring the error term provides a greater punishment for large errors, its formula is given as:

$$I_{ISE} = \int_0^\infty \left(e(t)\right)^2 dt = \int_0^\infty \left(y(t) - \tau(t)\right)^2 dt \tag{5.7}$$

where $e(t)$ is the control error, $y(t)$ is the measured output, and $\tau(t)$ is the target.

Integral of Time Weighted Squared Error (ITSE): It is the most conservative between other error indexes. The squared error is multiplied with time t, which emphasizes the steady state error and gives less weight to the invertible error that occurs immediately after the change in the input, and it is formulated as:

$$I_{ITSE} = \int_0^\infty t\left(e(t)\right)^2 dt = \int_0^\infty t\left(y(t) - \tau(t)\right)^2 dt \tag{5.8}$$

Integral of Weighted Squared Error (IWSE): Takes into account the monetary cost of the control action by distributing weights between the control signal and the error, and it is formulated as:

$$I_W = \int_0^\infty \left(w_e \left(e(t)\right)^2 + w_c \left(u(t)\right)^2 \right) dt \tag{5.9}$$

where $u(t)$ is the input signal, w_e is the weight for the error, and w_c is the weight for the control signal.

All of the above criteria enable monitoring of transient behavior of control loop by considering the rise time, overshoot, settling time and steady state error [34].

c. Minimum Variance Benchmarking Criteria: The unique feature of this technique is that it conducts performance monitoring without disturbing the process. It views *MV* as the smallest theoretical achievable variance and applies it as a standard benchmark, from which the variance of the process is compared. Harris [33] showed that a lower bound of process variance under feedback control could be estimated from routine operating data. This lower bound (or *MV*) can be used as a reference point to assess current control loop performance. Harris defined the controller performance index as: [6, 40]

$$\eta_{MV} = \frac{\sigma_{MV}^2}{\sigma_y^2} \tag{5.10}$$

where σ_y^2 is the variance of the process output, σ_{MV}^2 is the minimum achievable variance by the *MV* controller, and η_{MV} is the performance index, $0 \le \eta_{MV} \le 1$. This technique has attracted significant interest and has been further developed by many researchers [6, 40].

Despite that this technique has been proved to be very useful in many applications, it requires expertise and experience for appropriate data preprocessing, performance index calculation, and interpretation of results. Other factors that limit its application in plant environment are: [26]

- It is only valid for linear minimum phase systems.
- Only extreme situations are well defined, good if close to 1 and poor if minimum.
- It does not achieve all desirable attributes.
- It may result into slow tracking of set-point changes.

5.3 Methodology:

In this scheme, both the statistical, as well as the automatic process control techniques will be combined within one frame work for effective analysis and decision support. *SPC* techniques will be mainly used for process monitoring, while *APC* techniques will be applied for performance analysis. The overall procedure is illustrated below.

5.3.1 Process Model Development:

The process is described by a linear transfer function incorporated with an error term. It is derived by extracting the information from the closed loop process input and output data, then deriving the process model by using linear regression as follows:

$$y(t) = b_0 + b_1 u(t) + e(t) \tag{5.11}$$

where $u(t)$ is the input (control action), $y(t)$ is the output (measured quality characteristic), $e(t)$ is the error (deviation of the process output from the target), and b_0, b_1 are model parameters which are estimated as:

$$b_1 = \frac{\sum u\,y - n\,\overline{u}\,\overline{y}}{\sum u^2 - n(\overline{u})^2} \tag{5.12}$$

$$b_0 = \overline{y} - b_1\,\overline{u} \tag{5.13}$$

5.3.2 Benchmark Controller Design:

In our work, the benchmark is considered to be a Constrained Input Output Controller (*CIOC*). This controller is derived by applying the constrained principle in which the objective is to find the control action that minimizes the constrained index. Our constrained index accounts both of:

- the deviation of the output (measured quality characteristic) from its target value, which we express in terms of quadratic quality loss function
- the deviation of the input (control action) from its steady state value, which is set to be zero

The *CIOC* optimizes the expected value of resulted index which is expressed as follows:

$$Min: \quad I = E\left\{\left[y(t) - \tau(t)\right]^2 + \phi\, u(t)^2\right\} = \left[y(t) - \tau(t)\right]^2 + \sigma^2 + \phi\, u(t)^2 \tag{5.14}$$

where ϕ is an adjustment factor. By substituting the process model presented by Equation (5.8) within the index, it is written as follows:

$$I = \left[b_0 + b_1 u(t) + e(t) - \tau(t)\right]^2 + \sigma^2 + \phi\, u(t)^2 \tag{5.15}$$

After differentiating the resulted index with respect to the control action and equating it to zero, the resulted control action is expressed as follows:

$$u(t) = \frac{b_1\left[\tau(t) - e(t) - b_0\right]}{{b_1}^2 + \phi} \tag{5.16}$$

The advantage behind our method is that it combines between disturbance rejection and the reduction of quality loss of the product, which in turn optimizes the level of quality as well as the performance.

5.3.3 Performance Index Derivation:

The performance index is based on using the variance of the *CIOC* controller's output as a reference to the best achievable value that could result from applying the best control action. By combining the information of the closed loop process variance, the index is calculated as:

$$\eta_{CC} = 1 - \frac{\sigma_{yc}^2}{\sigma_y^2} \tag{5.17}$$

where η_{CC} is bounded between 0 and 1, σ_{yc}^2 is the variance of the process when it is controlled by the constrained controller, and σ_y^2 is its variance when it is controlled by the existing control scheme. This benchmark controlled output may or may not be achievable in practice due to the incorporated high control cost. However, it provides useful information such as how well the current controller is tuned as compared to the constrained controller and how much potential is there to improve its performance.

5.3.4 Process Monitoring:

The main objective behind process monitoring is to detect the variability within the process, and for achieving that, the use of an *SPC* control chart will be implemented. In this work, *EWMA* control chart is used for process monitoring, and it is selected due to its effectiveness in detecting process shifts.

5.3.5 Performance Assessment:

Final decision will be based of combining the statistics from the previous techniques which are: the performance index, the *MSD*, *SNR*, *ARL*, and the variance of the process output. If these statistics indicate process normality, and if the performance index is satisfactory, further tuning or redesigning of the control algorithm will be neither necessary nor helpful. On the other hand otherwise, if the process is turned to be out of control or the performance index indicates a poor performance measure, further action such as: identification of assignable causes, process shutdown and maintenance, controller tuning, or at the worse case, controller redesign may be necessary.

5.4 Illustrative Example: Concentration Control:

To examine the effectiveness of out proposed scheme, an illustrative example for concentration control process is presented in this section.

5.4.1 Process Description:

The reactant conversion in a chemical reactor is a function of the resident time or its inverse which is the space velocity. In this example, product concentration within an Isothermal Continuous Stirred Tank Reactor (*CSTR*) is controlled by manipulating the feed flow rate. The followed control strategy is shown by the schematic diagram of Figure 5.5 which was generated by Yokogawa's Centum CS3000 and Microsoft softwares.

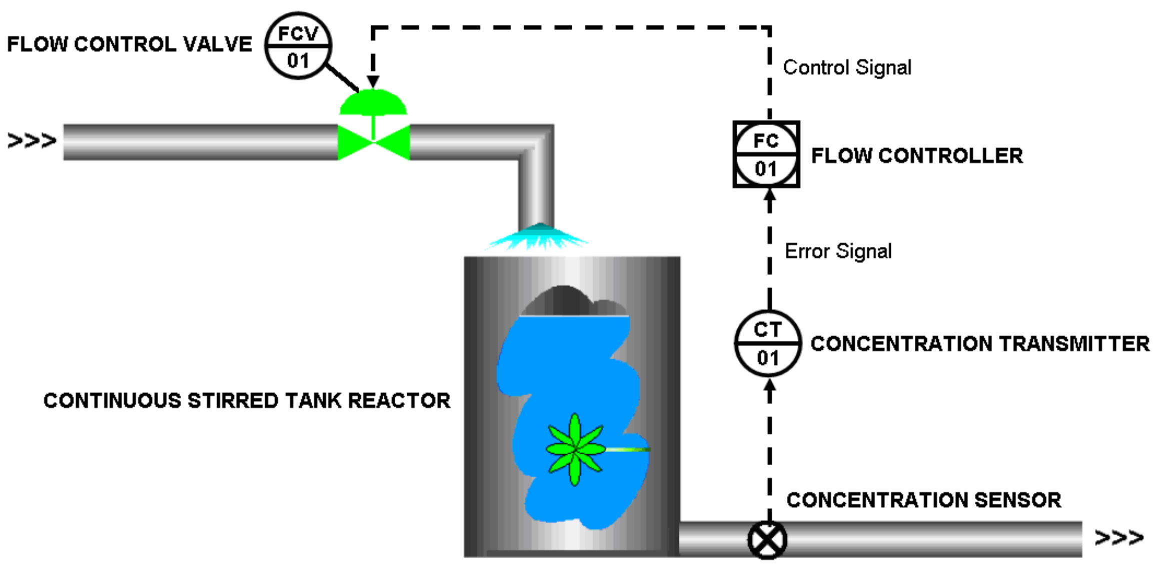


Figure 5.5: Control strategy for concentration control process

In this process, the concentration of the output is measured by a concentration sensor and sent to concentration transmitter. By comparing the measured concentration with its targeted value, the difference is calculated as an error signal and further transmitted to concentration controller. This controller is of a *PID* control type, which accordingly calculates the output signal to be fed to the flow control valve to adjust the feed flow rate to the reactor. The overall process is described by the following first order plus a time delay function:

$$G(s) = \frac{K_C \, e^{-d.s}}{Ts+1} = \frac{1.26 \, e^{-0.85s}}{2 \, s+1} \tag{5.18}$$

where K_C is the gain of the process model, d is the time delay, and T is the time constant.

5.4.2 Controller Gain Setting by Ultimate Cycle Method:

The initial setting for controller gain was set as per the ultimate cycle method (Section 4.2.1). For deriving the control parameters, the process model was generated using Simulink (Appendix A.5.1) and from closed loop step response, the ultimate gain and ultimate period were found to be:

$K_U = 3.590 \qquad T_U = 3.000$

The corresponding values by the ultimate cycle method (Table 4.3) for the proportional gain, integral and derivative time constants were found to be:

$K_p = 0.718 \qquad \tau_i = 1.500 \qquad \tau_d = 0.999$

Afterwards, the integral gain and the derivative gain were calculated from equations (4.15) and (4.16) and their corresponding values were found to be:

$K_i = 0.9573 \qquad K_d = 0.3586$

The resulting response was as shown in Figure 5.6. The *MSD* was found to be 0.1733, at which the *SNR* was 7.6120 and the variance of the output was found to be 0.1572.

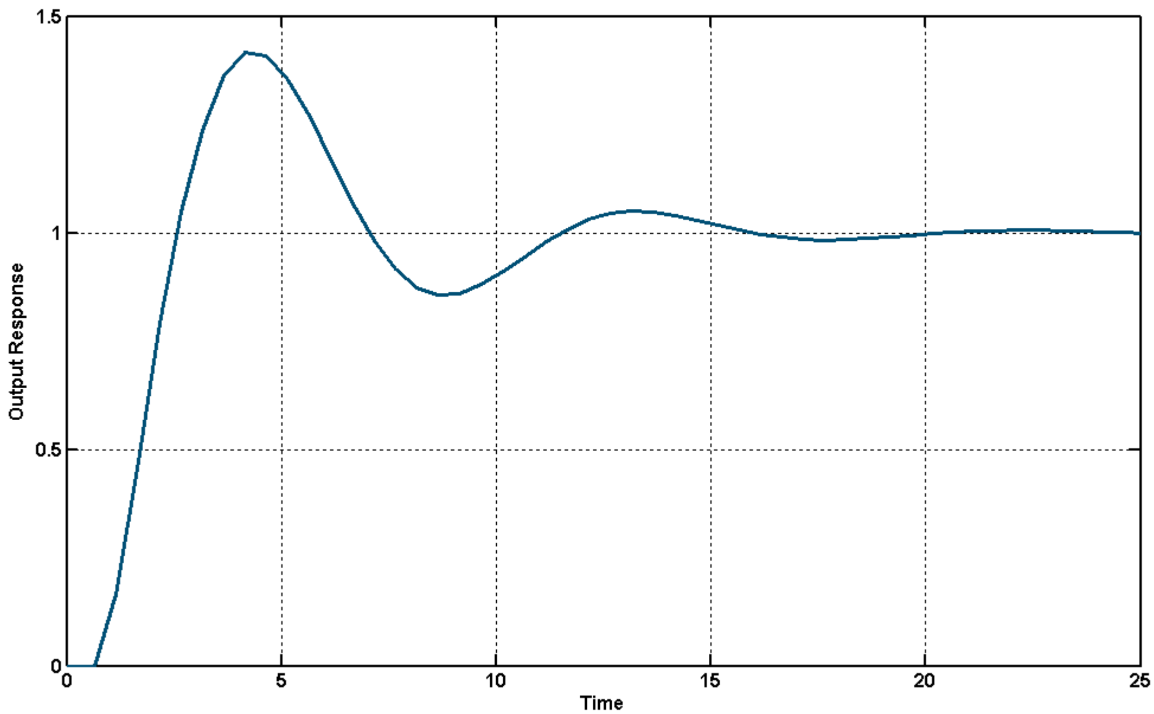


Figure 5.6: Output response by ultimate cycle method

5.4.3 Controller Tuning by Robust Design Method:

The tuning was obtained by following the Robust Design methodology described in Section 4.3. The control factors were selected to be: K_p, τ_i, and τ_d. The nominal values for these parameters were set to the ones resulted using the ultimate cycle method, and for each control factor, three levels are selected as shown in Table 5.2.

Table 5.2: Control factors

Factor	*Parameter*	*Levels*		
		1	*2*	*3*
A	K_p	0.5744	0.7180	0.8616
B	τ_i	1.0345	1.5000	2.7274
C	τ_d	0.5995	0.9990	1.3986

The integral gain K_i and the derivative gain K_d were calculated from (4.15) and (4.16). The noise factors were identified from the process model described by Equation 5.18 to be: K_c, d, and T, and for each noise factor, two levels were selected as shown in Table 5.3.

Table 5.3: Noise factors

Factor	*Parameter*	*Levels*	
		1	*2*
NF1	K_C	1.260	1.512
NF2	d	0.850	1.020
NF3	T	2.000	2.400

For the control factors, $OA(L_9)$ was selected (Appendix C.4.2). While for the noise factors, $OA(L_4)$ was selected (Appendix C.4.1). After conducting the experiments, their results were summarized in Table 5.4.

Table 5.4: Experimental results for robust tuning

Noise Factors	*Levels*			
	1	*2*	*3*	*4*
NF1	1.2600	1.2600	1.5120	1.5120
NF2	0.8500	1.0200	0.8500	1.0200
NF3	2.0000	2.4000	2.4000	2.0000

Trial	*Control Factors*			*MSD*				$\overline{MSD}$	$\overline{\sigma}$	*SNR*
	K_p	τ_i	τ_d	*1*	*2*	*3*	*4*			
1	0.5744	1.0345	0.5995	0.3279	0.5269	0.4234	0.7953	0.5184	0.6995	2.8536
2	0.5744	1.5000	0.9990	0.2305	0.2837	0.2491	0.2738	0.2593	0.4923	5.8624
3	0.5744	2.7274	1.3986	0.2119	0.2343	0.2151	0.2176	0.2197	0.4340	6.5812
4	0.7180	1.0345	1.3986	0.2525	0.3519	0.2840	0.3546	0.3108	0.5448	5.0759
5	0.7180	1.5000	0.5995	0.2167	0.2774	0.2316	0.2607	0.2466	0.4792	6.0801
6	0.7180	2.7274	0.9990	0.2003	0.2205	0.2021	0.2056	0.2071	0.4189	6.8377
7	0.8616	1.0345	0.9990	0.2397	0.3344	0.2679	0.3519	0.2985	0.5310	5.2509
8	0.8616	1.5000	1.3986	0.2027	0.2360	0.2105	0.2224	0.2179	0.4463	6.6174
9	0.8616	2.7274	0.5995	0.1919	0.2106	0.1929	0.1983	0.1984	0.4083	7.0240

The maximum value for the *SNR* was found to be 7.0240, at which the average *MSD* was found to be 0.1984. Accordingly, the optimum values for the *PID* controller parameters were found to be:

$K_p = 0.8616 \qquad \tau_{\mathrm{i}} = 2.7274 \qquad \tau_{\mathrm{d}} = 0.5995 \qquad K_i = 0.5265 \qquad K_d = 0.2152$

The resulted response was as shown in Figure 5.7.

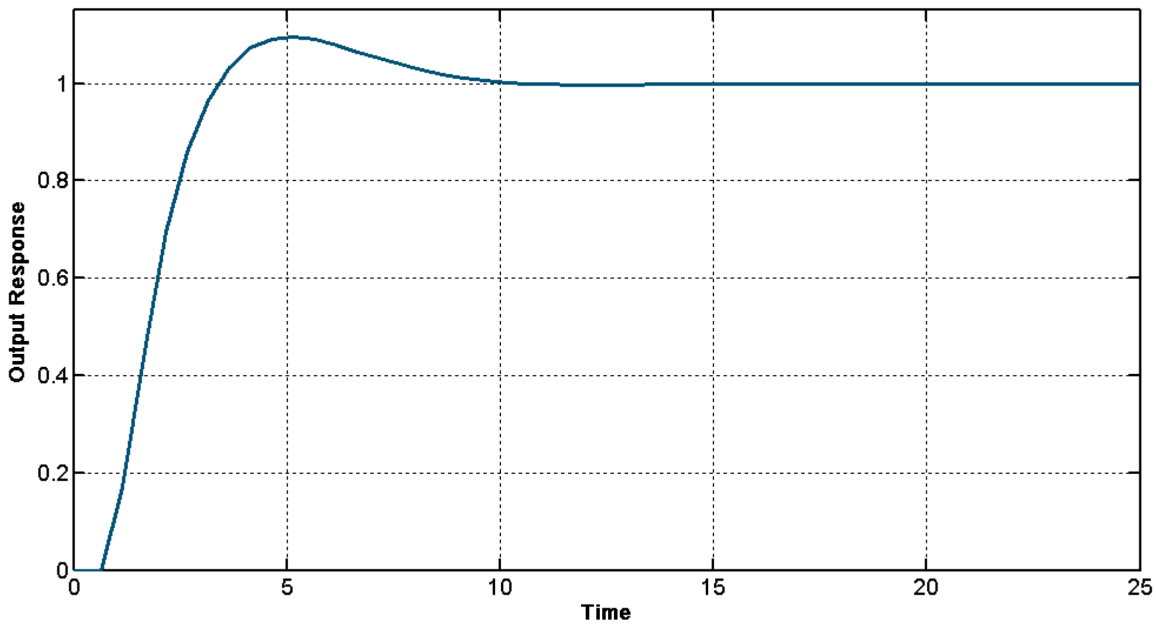


Figure 5.7: Output response by robust tuned controller

The *MSD* was found to be 0.1606, at which the *SNR* was found to be 7.9425 and the variance of the output was found to be 0.1370.

5.4.4 Bench-Mark Controller Design:

The bench-mark controller was selected to be of a constrained controller type. Extracted data from closed loop step response was analyzed and the corresponding values for b_0 and b_1 were calculated from equations (5.9) and (5.10) and found to be: b_0=2.2036 and

b_1=-1.4872 (Appendix C.5.1). Accordingly, the process model by using Linear Regression as per equation (5.11) was as follows:

$$y(t) = 2.2036 - 1.4872\, u(t) + e(t) \tag{5.19}$$

Following the constrained controller principle, the resulted control action as per equation (5.16) was as follows:

$$u(t) = \frac{-1.4872\left[\tau(t) - e(t) - 2.2036\right]}{2.2117 + \phi} \tag{5.20}$$

5.4.5 Monitoring and Assessment of Control Schemes:

The process was set to operate under assignable causes by introducing white noise and a shift of 0.1 units in process mean at time 16 sec which was also included. The block diagram for the process was built in Simulink which included both of: the *PID* controller which was set by the ultimate cycle method, and the benchmark *CIOC* controller; and the process was set to operate under assignable causes (Appendix A.5.2). For the conventional *PID* controlled output, the resulted *EWMA* control chart (Appendix B.5.1) using $\lambda = 0.1$ was as shown in Figure 5.8, and the calculated statistics for both controllers were as shown in Table 5.5.

Table 5.5: Calculated statistics for both controllers

Control Scheme	*MSD*	*SNR*	*VAR*	*ARL*
Conventional PID Control	0.0856	10.6753	0.0840	4.3102
Benchmark CIOC Control	0.0601	12.2113	0.0551	9.1591

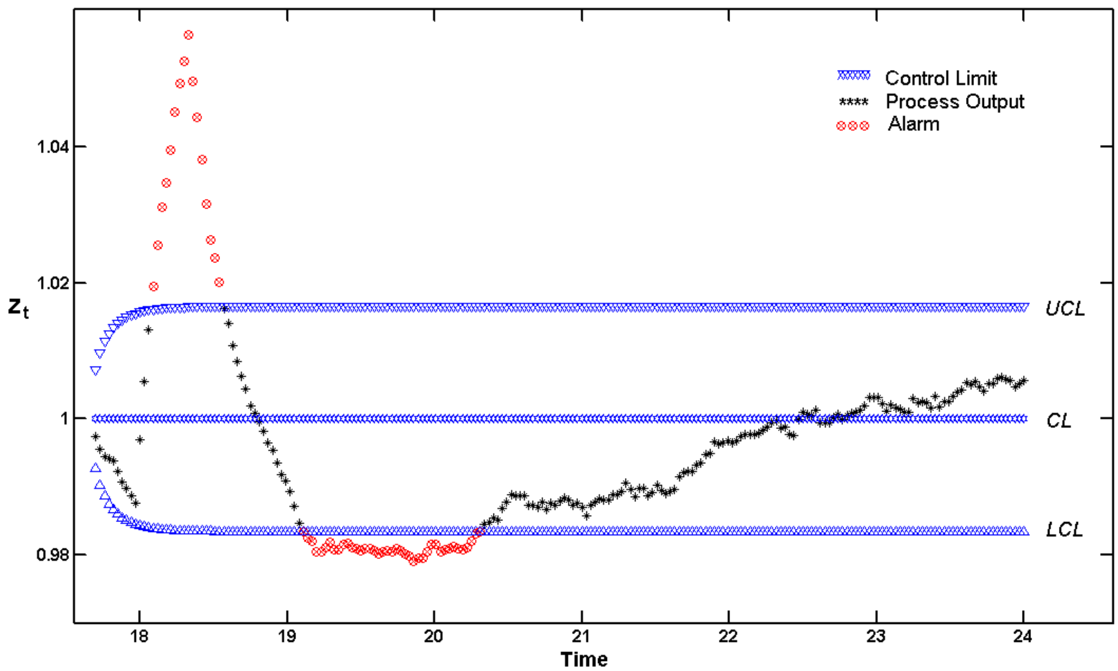


Figure 5.8: *EWMA* control chart for conventional *PID* controlled process

The *SNR* was found to be 12.57% less than its maximum achievable value. The performance index with respect to the constrained controller was calculated as follows:

$$\eta_{CC} = 1 - \frac{\sigma_{yc}^2}{\sigma_{yu}^2} = 0.3440$$

This implied that the performance was 34.40% less than its maximum achievable amount. Moreover, the ARL turned out to be low and the variability in the process output was high. After considering these statistics, tuning for control parameters was recommended.

Next, the process was set to operate under robust *PID* control scheme under same assignable causes. The *EWMA* control chart (Appendix B.5.1) using $\lambda = 0.1$ was with out of control indication was as shown in Figure 5.9.

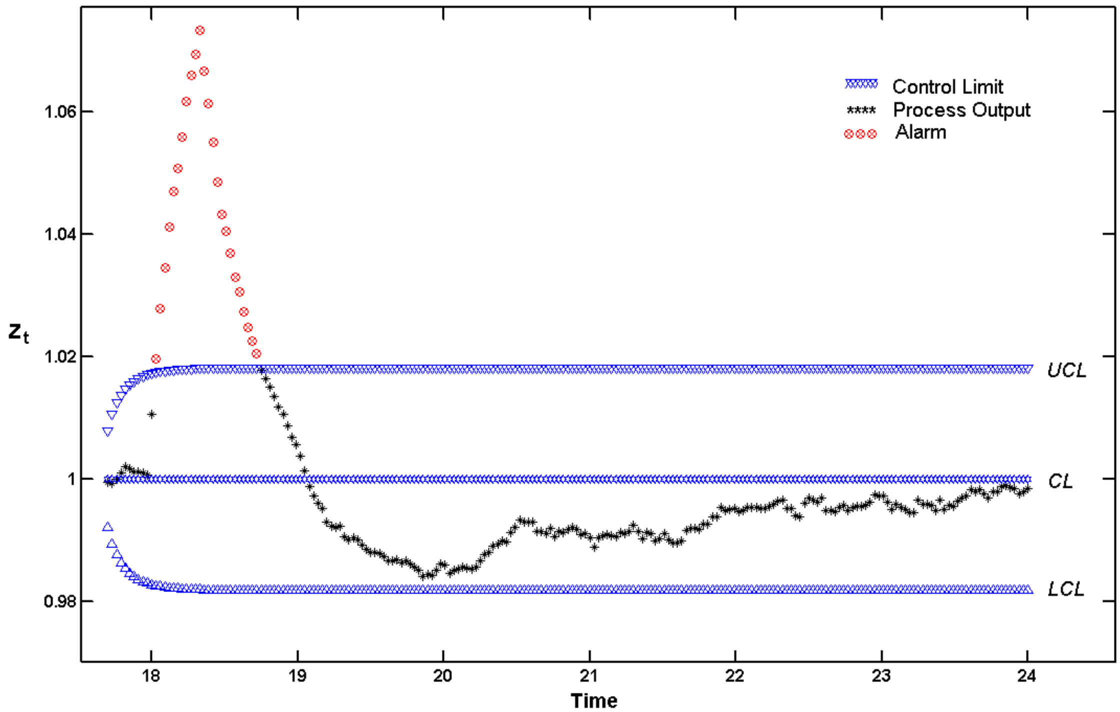


Figure 5.9: *EWMA* control chart for robust *PID* controlled process

The relative efficiency between the conventional *PID* controller and the robust *PID* controller was found to be 0.1391 which indicated an improvement of 20.49% in the performance.

5.4.6 Results Summary:

Under the presence of same assignable causes and overall statistics for the three controllers were summarized in Table 5.6 and the output responses for the three controllers were as shown in Figure 5.10.

Table 5.6: Calculated statistics for all control schemes

Control Scheme	*MSD*	*SNR*	σ^2	*ARL*	η_{cc}
Convtional PID Control	0.0856	10.6753	0.0840	4.3102	0.3440
Robust PID Control	0.0687	11.6304	0.0640	7.9802	0.1391
CIOC Control	0.0601	12.2113	0.0551	9.1591	0.0000

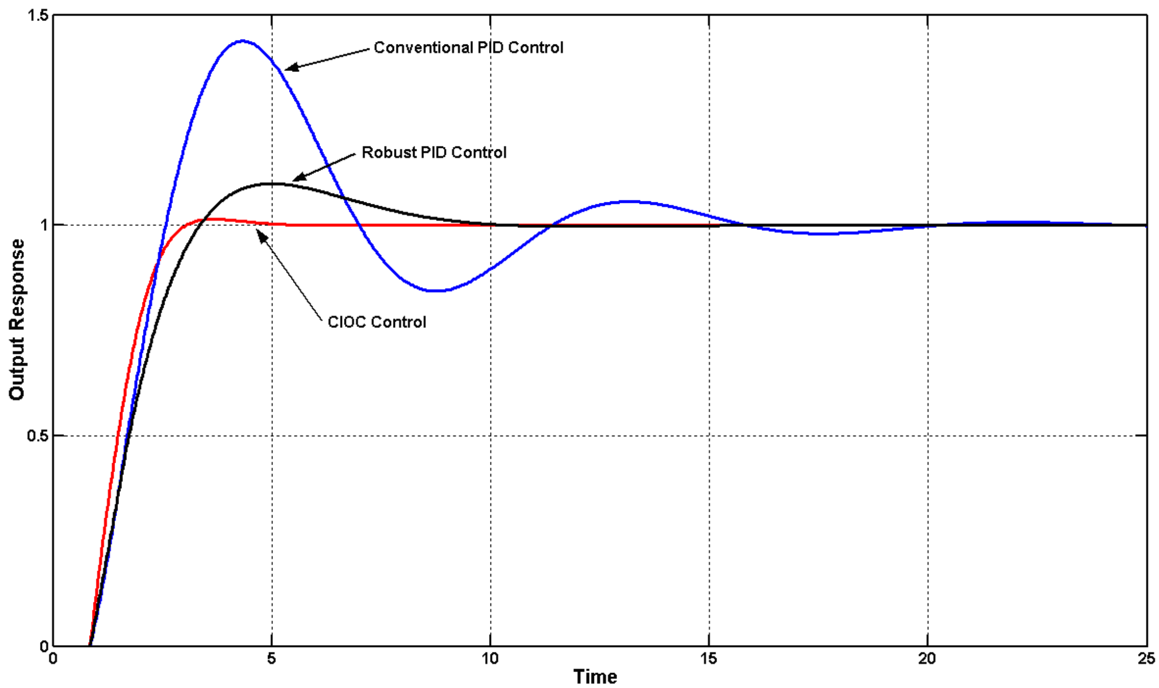


Figure 5.10: Process output plots under all control schemes

Results have shown that the *MSD* was reduced by 19.74% while the variance was reduced by 23.81%. The *SNR* was increased by 8.95% with an increase of 85.15% in the *ARL*. The performance indexes have indicated an improvement of 20.49% in the controller performance. This reflects the process enhancement gained by conducting robust tuning on the existing control scheme which was suggested to be done from our unified *SPC/APC* monitoring and evaluation scheme.

5.5 Conclusion:

In this chapter, we developed a unified scheme that combines between the use of *SPC* and *APC* techniques of process monitoring and performance evaluation. Among *SPC* tools, we applied the use *EWMA* control chart with *ARL*. From the other side, we considered *SNR* and efficiency measures among *APC* techniques. Furthermore, we developed an *SPC* controller which was based on the constrained principle and was incorporated with quadratic quality loss function and used it as a benchmark to evaluate the performance. We also included indication for out of control signals within the monitoring part. By combining all these statistics together, we ended up by developing an integrated *SPC/APC* monitoring and evaluation scheme. An illustrative example for concentration control process was presented in which process monitoring and performance evaluations were illustrated. Results were satisfactory in terms of reducing the process variability, minimizing the *MSD*, improving the performance and increasing the *ARL*. This indicated the effectiveness of the unified scheme in taking the correct decision about operating the process.

CHAPTER 6

A FUZZY INTEGRATED SPC/APC SCHEME

6.1 Overview:

Due to the knowledge gap between the advocates of *SPC* and *APC*, they were initially thought to be in conflict with each other, and their integration was out of question, until their advocates realized the fact about the techniques applied by their methods being complementary rather than contradictory. Since then, some work about integrating *SPC* and *APC* techniques appeared in literature. Most of integration strategies found in literature have applied the use of *SPC* techniques for monitoring and *APC* techniques for process regulation, while others derived *SPC* controllers and applied their use alone, which does not result into real integrated schemes. The objective of this chapter is to develop an integrated scheme that combines between the utilization of *SPC* and *APC* techniques for process monitoring and control under *FZL* interaction. We envision that that driving any system under our proposed strategy will result into obtaining optimum level of quality, performance as well as robustness. A case study for a pH control process is also presented on which we applied the use of our proposed strategy.

6.2 Background:

In order to reduce the variation in a manufacturing process, traditional *SPC* techniques are the most frequently used tools in monitoring *APC*-controlled processes for detecting assignable cause process variation. Many studies have been conducted about the integrated use of *SPC* and *APC*, because using them individually cannot optimally control the manufacturing process. The majority of these studies have reported that the integrated approach results into better performance than using only *SPC* or *APC*, details can be seen in Lu et al [50]. Although the application of *SPC* controller is effective in terms of minimizing the variability and maintaining the quality, its application incorporates high control cost and required large amount of memory use and calculation time which limits its practical application. Despite the effectiveness of traditional *APC* control schemes; there is no guarantee about their performance to be maintained under abnormal process conditions. Although the human utilization may be useful in trading off between the utilization of *SPC* and *APC* techniques, it cannot handle all tasks properly for real industrial processes. All of this calls the need for having a systematic strategy which can translate the human way of decision making and its knowledge about the process into machine language. A suggested solution is apply the use of Fuzzy Logic (*FZL*), which is close to the human way of thinking and reasoning and provides means for modeling and dealing with the approximate and inexact nature of the real world. *FZL* captures experience and intuition in the form of IF-THEN rules from which conclusions are drawn using fuzzy inference. This type of logic is convenient for describing systems which are too complex or have uncertainty to be successfully described with mathematical models.

6.2.1 Integrated SPC/APC Systems:

Generally, it is aimed that integration yields a process that effectively regulates the process to its target using *APC* while providing effective process monitoring and removal of assignable causes using *SPC*. Palm [59] provided a review on *APC* and *SPC* and the approaches taken in pursuit of both. He presented an example to outline how much each method of process control may improve the process. He concluded that neither approach alone can perform well without the help of the other. Vender Weil et al. [78] viewed *SPC* as a collection of techniques useful in improving product quality by helping the analyst to locate and remove root causes of quality variation. They thought of *APC* as a collection of algorithms for manipulating the adjustable variables of a process to achieve the desired process behavior (output close to a target value). Montgomery et al. [56] described and illustrated a simple method of integrating *SPC* and *APC* and supported the claim that *SPC* can be applied to detect assignable causes from the output rapidly, while *APC* can effectively keep the process on target. Jiang and Tsui [43] developed an economic model for *SPC* monitoring of *APC* controlled processes. They also developed an economic loss-based criterion to evaluate the performance of *SPC* charting methods. Capilla et al. [14]

described a case study of integrating *SPC* and *APC* approaches in a polymerization process and showed that the use of both *SPC* and *APC* techniques can outperform the use of either of them alone.

6.2.2 Fuzzy Logic Control:

Fuzzy logic is a formal methodology for representing, manipulating, and implementing human's heuristic knowledge about how to best control a process. It is defined as a mathematical system that analyzes analog input values in terms of logical variables that take on continuous values between 0 and 1, in contrast to classical or digital logic, which operates on discrete values of either 0 or 1 (true or false). Its basic idea is to mimic the fuzzy feature of human thinking for the effective control of uncertain systems through fuzzy logic reasoning. *FZL* was first proposed by Zadeh [83] who further introduced the concept of linguistic variables (equates to a variable defined as a fuzzy set). Afterwards, the first industrial application based on this concept came on line in 1975 which was a cement kiln built in Denmark. *FZL* has the advantage that the solution to the problem can be cast in terms that human operators can understand, so that their experience can be used in the design of the controller. This makes it easier to mechanize tasks those are already successfully performed by humans. Furthermore, *FZL* is well suited to low-cost implementations based on cheap sensors, low-resolution converters, and microcontroller chips. Such systems could be easily upgraded by adding new rules to improve the performance or by adding new features [49].

A fuzzy logic control (*FZLC*) system is a control system based on *FZL*. Fuzzy controllers are being used in various control schemes, and in many cases, they can be used to improve existing traditional controller systems by adding an extra layer of intelligence to the current control method. The most obvious type of *FZLC* is direct control, where the fuzzy controller is kept in the forward within the feedback control system. Usually the process output is compared with a reference, and if there is any deviation, the controller takes action as per the designed control strategy. Basic architecture of a *FZLC* is shown in Figure 6.1 which consists of four modules including:

- *Fuzzification:* it involves the conversion of the crisp input and output signals into a number of fuzzy represented values (fuzzy sets).
- *Rule Base:* its basic function is to represent expert's knowledge in form of IF-THEN rule structure.
- *Fuzzy Inference:* it provides the mechanism for referring to the rule base such that appropriate rules are fired.
- *Defuzzification:* it produces a non fuzzy control action that represents the membership function of an inferred fuzzy control action.

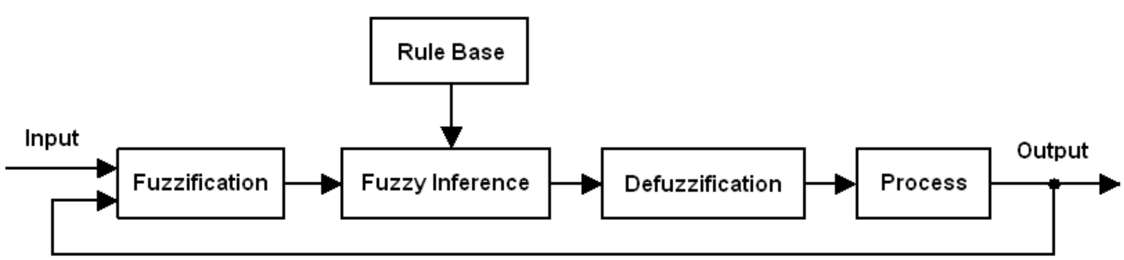


Figure 6.1: Architecture of a fuzzy logic controller

The input variables in a fuzzy control system are generally mapped by sets of membership functions known as fuzzy sets. Given mappings of input variables into membership functions along with their truth values, the controller can make decisions about what action to be taken based on a set of rules, which are usually expressed in the form: (IF *variable* IS *property* THEN *action*). The AND, OR, and NOT operators of Boolean logic can also exist in *FZL*, which are usually defined as the minimum, maximum, and complement. This combination of fuzzy operations and rule-based inference describes a fuzzy expert system [39, 49, 82].

6.3 Methodology:

Our intention in this chapter is to develop a unified strategy that combines between the utilization of *SPC* and *APC* techniques for process monitoring as well as control under fuzzy logic interaction. For achieving that, we will follow a solution procedure based on below eight steps:

1) Study the Existing System
2) Tune the existing *APC* Controller by using robust design method
3) Develop the *SPC* controller by applying constrained principle
4) Construct the *FZL* controller and set it for control utilization scheme
5) Set the *SPC* monitoring scheme including indication for out of control signals
6) Set the performance evaluation index

7) Construct the integrated *SPC/APC* system

8) Conduct experimental runs and evaluate the results

By following the previous steps, we expect to have an integrated *SPC/APC* system as shown in Figure 6.2.

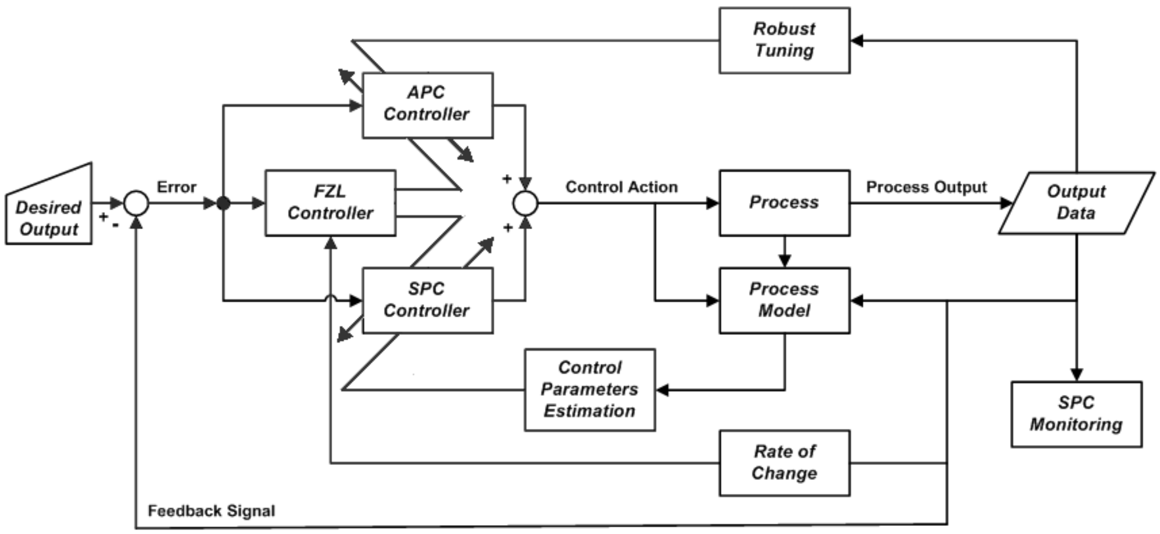


Figure 6.2: Block diagram for the integrated *SPC/APC* system

6.3.1 Fuzzy Logic Controller Development:

We will construct the *FZLC* by setting its four basic modules (Section 6.2.2) as explained below:

Fuzzification: Our *FZLC* will have two inputs which are the: output error er_t and the rate of change of the output quality characteristic dy_t, and will have one output which is the controller utilization factor w_t. The first input, which is er_t, is divided into five membership functions, namely: Negative High (*NHI*), Negative Low (*NLO*), Zero (*ZERO*), Positive Low (*PLO*), and Positive High (*PHI*); as shown in Figure 6.3.

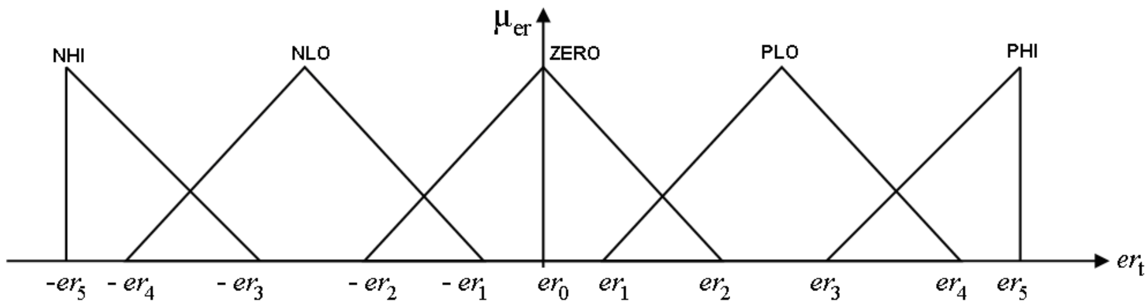


Figure 6.3: Membership functions for the first input (output error)

Five membership functions are developed for the second input which is dy_t, namely: Negative Maximum (*NMAX*), Negative Minimum (*NMIN*), Normal (*NORM*), Positive Minimum (*PMIN*), and Positive Maximum (*PMAX*); as shown in Figure 6.4.

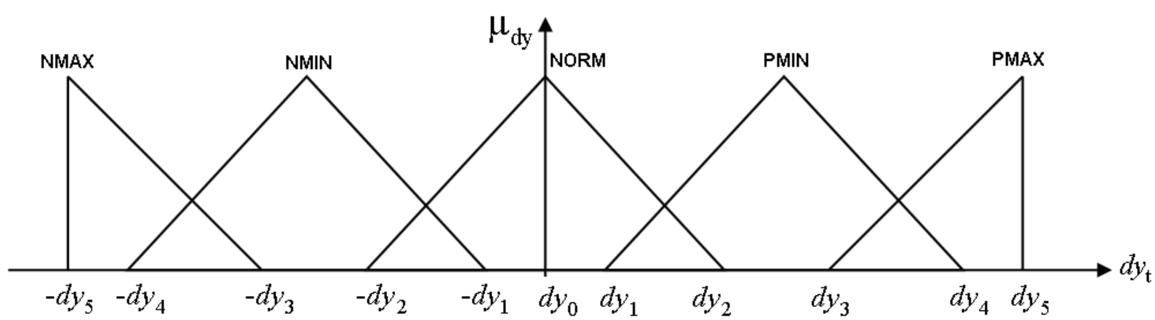


Figure 6.4: Membership functions for the second input (rate of change of output)

For the *FZLC* output w_t, five membership functions are created, namely: Statistical Process Control (*SPC*), Larger Statistical Control (*SAC*), Both Control Schemes (*BIC*), Larger Automatic Control (*ASC*), and Automatic Process Control (*APC*); as shown in Figure 6.5.

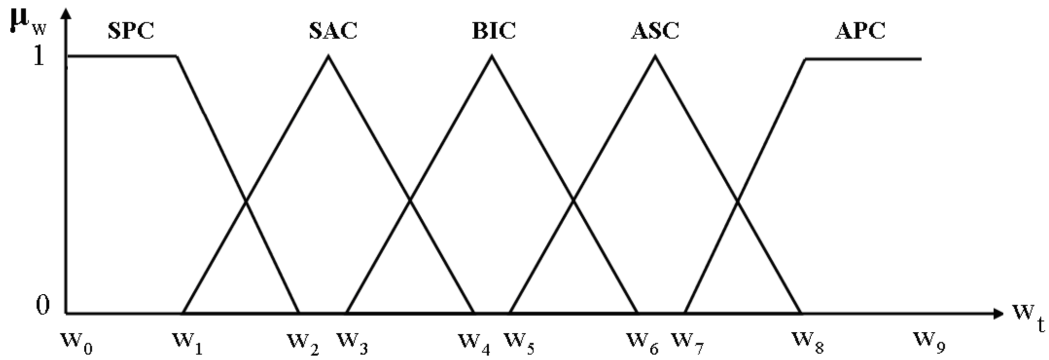


Figure 6.5: Membership functions for the controller output

Rule Based Inference: In order to relate the inputs to the output, fuzzy inference rules are developed. Our philosophy in setting these rules was based on applying the use of the *APC* controller during normal situations, and deviate to *SPC* as soon as abnormalities begin to occur. For example, when the output error is negligible and the change in the output quality characteristic is almost zero, the *FZLC* will provide an utilization factor parallel for applying an *APC* controller. However, when er_t is large and dy_t is high, the w_t will utilize the application of *SPC* controller. In our work, following 25 rules are used:

1. If (*er* is *NMAX*) And (*dy* is *NHI*) Then (*w* is *BIC*)
2. If (*er* is *NMAX*) And (*dy* is *NLO*) Then (*w* is *SAC*)
3. If (*er* is *NMAX*) And (*dy* is *ZERO*) Then (*w* is *SPC*)
4. If (*er* is *NMAX*) And (*dy* is *PLO*) Then (*w* is *SPC*)
5. If (*er* is *NMAX*) And (*dy* is *PHI*) Then (*w* is *SPC*)
6. If (*er* is *NMIN*) And (*dy* is *NHI*) Then (*w* is *BIC*)
7. If (*er* is *NMIN*) And (*dy* is *NLO*) Then (*w* is *SAC*)
8. If (*er* is *NMIN*) And (*dy* is *ZERO*) Then (*w* is *SAC*)
9. If (*er* is *NMIN*) And (*dy* is *PLO*) Then (*w* is *SAC*)

10. If (*er* is *NMIN*) And (*dy* is *PHI*) Then (*w* is *SPC*)

11. If (*er* is *ZERO*) And (*dy* is *NHI*) Then (*w* is *SPC*)

12. If (*er* is *ZERO*) And (*dy* is *NLO*) Then (*w* is *SAC*)

13. If (*er* is *ZERO*) And (*dy* is *ZERO*) Then (*w* is *APC*)

14. If (*er* is *ZERO*) And (*dy* is *PLO*) Then (*w* is *SAC*)

15. If (*er* is *ZERO*) And (*dy* is *PHI*) Then (*w* is *SPC*)

16. If (*er* is *PMIN*) And (*dy* is *NHI*) Then (*w* is *SPC*)

17. If (*er* is *PMIN*) And (*dy* is *NLO*) Then (*w* is *SAC*)

18. If (*er* is *PMIN*) And (*dy* is *ZERO*) Then (*w* is *SAC*)

19. If (*er* is *PMIN*) And (*dy* is *PLO*) Then (*w* is *SAC*)

20. If (*er* is *PMIN*) And (*dy* is *PHI*) Then (*w* is *BIC*)

21. If (*er* is *PMAX*) And (*dy* is *NHI*) Then (*w* is *SPC*)

22. If (*er* is *PMAX*) And (*dy* is *NLO*) Then (*w* is *SPC*)

23. If (*er* is *PMAX*) And (*dy* is *ZERO*) Then (*w* is *SPC*)

24. If (*er* is *PMAX*) And (*dy* is *PLO*) Then (*w* is *SAC*)

25. If (*er* is *PMAX*) And (*dy* is *PHI*) Then (*w* is *BIC*)

Table 6.1 provides a summery for these results.

Table 6.1: Fuzzy inference rules

		Rate of Change of Output Quality Characteristic (dy)				
		NHI	*NLO*	*ZERO*	*PLO*	*PHI*
Output Error (er)	*NMAX*	BIC	SAC	SPC	SPC	SPC
	NMIN	BIC	SAC	SAC	SAC	SPC
	NORM	SPC	SAC	APC	SAC	SPC
	PMIN	SPC	SAC	SAC	SAC	BIC
	PMAX	SPC	SPC	SPC	SAC	BIC

Defuzzification: In our work, the center of area (*COA*) method is used for defuzzification. This method calculates the center of gravity of the distribution for the control action, and mathematically it is expressed as: [82]

$$Z^* = \frac{\sum_{j=1}^{q} z_j \ \mu_C(z_j)}{\sum_{j=1}^{q} \mu_C(z_j)} \tag{6.1}$$

where Z^* is the number of quantization levels of the output, z_j is the amount of control output at the quantization level j and $\mu_c(z_j)$ represents its membership value in C.

6.3.2 Performance Index Derivation:

We will use the Absolute Efficiency (*AE*) as a performance index. This index measures the absolute efficiency of variation reduction, which is expressed as:

$$AE = \frac{\sigma_D}{\sigma_e} \tag{6.2}$$

where σ_D is the standard deviation of the disturbance, and σ_e is the standard deviation of the controlled output.

6.3.3 Integrated SPC/APC Scheme Settlement:

The integrated *SPC/APC* system (Figure 6.2) results by combining all previous contents which include: the robust tuned *APC* controller, the *CIOC SPC* controller, the *FZL* controller, the monitoring scheme. The *FZLC* acts as supervisory controller that provides an output w to utilize the use of both *SPC* and *APC* controllers. The final control action is given by:

$$u(t) = w(t) \cdot u_{APC}(t) + \left[1 - w(t)\right] \cdot u_{SPC}(t) \tag{6.3}$$

where $u(t)$ is final control action, $u_{SPC}(t)$ is control action from the *SPC* controller, $u_{APC}(t)$ is the control action from the *APC* controller, and $0 \leq w(t) \leq 1$ is the controller utilization factor.

6.4 Case Study: pH Control Process:

To examine the effectiveness of our proposed scheme and illustrate its use, we conducted an optimization study on a pH control process which is presented in this section.

6.4.1 Process Description:

The control of pH is very important in many processes, such as: wastewater treatment, chemical, and biochemical processes. From the process side, pH neutralization is a very fast and simple reaction. But on the other hand, and in terms of control, it has been recognized as a very difficult control problem. The difficulties arise from strong process nonlinearity resulted from the process gain that can change from tens to hundreds of times over a small pH range. Moreover, the load changes frequently as the influent component varies [14]. The process can also be affected by noises, disturbances and environmental changes such as outside temperature change. To overcome the previous factors, it is required to have a workable pH control methodology that combines between keeping the product quality on target, maintaining the controller performance, and keeping the system robust against external factors.

The pH control system consists of: a continuously stirred tank reactor (*CSTR*), two inlet streams, one outlet stream, two flow control valves, two controllers, a pH sensor, a level sensor, and an agitator, as show in Figure 6.6 which was generated using Yokogawa's Centum CS3000 and Microsoft softwares.

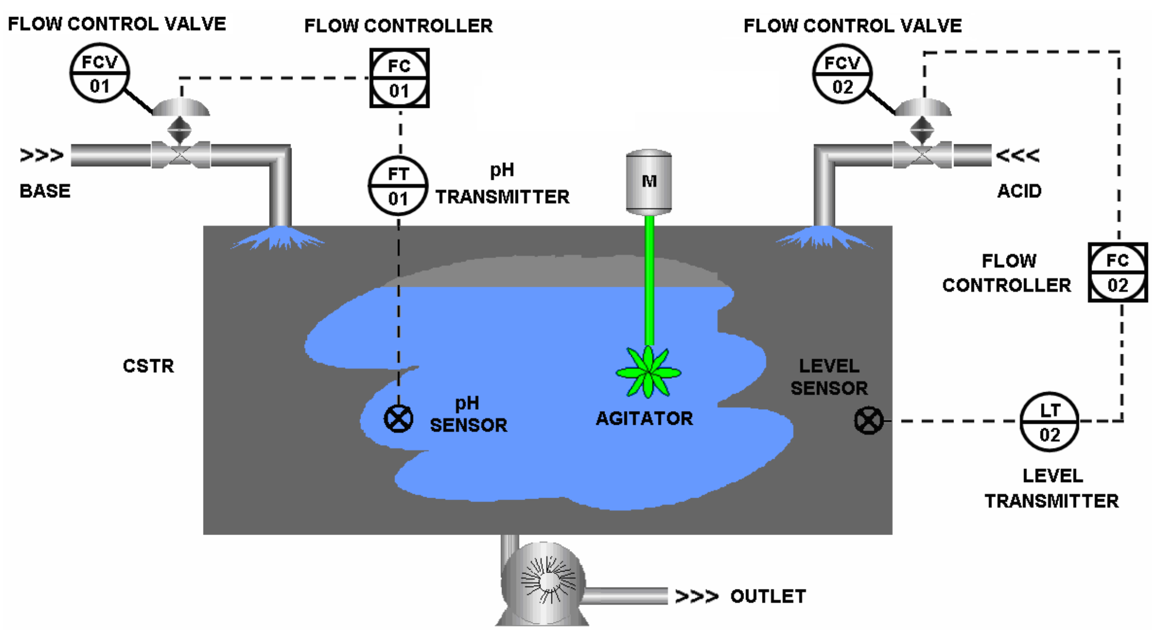


Figure 6.6: Process flow diagram for a pH control process

The process stream contains Hydrochloric Acid (*HCL*) with flow rate F_a and concentration κ_a, while the titrating stream contains Nitrogen Hydroxide (*NaOH*) with flow rate F_b and concentration κ_b. Since the outlet stream overflows from the *CSTR*, the outlet flow rate is equal to the sum of the inlet flow rates. The reaction equation for the neutralization of acid-base reaction is as below:

$$HCL + NaOH \rightarrow NaCL + H_2O \tag{6.4}$$

The differential equations for describing the pH neutralization are expressed as:

$$\frac{dy}{dt} = \frac{1}{V}\left[\kappa_a\, F_a - \kappa_{oa}\left(F_a - F_b\right)\right] \tag{6.5}$$

$$\frac{dx}{dt} = \frac{1}{V}\left[\kappa_b\, F_b - \kappa_{ob}\left(F_a + F_b\right)\right] \tag{6.6}$$

where κ_{oa} is overall concentration containing the anion of the acid, κ_{ob} is the overall concentration containing the cation of the base, and *V* is the volume of the reactor. The steady-state operating conditions are given in Table 6.2 [49].

Table 6.2: Steady-state operating conditions

V	F_a	F_b	κ_a	κ_b
20,000 Lt	500 Lt/min	7.027 Lt/min	0.02 N	2.0 N

The pH value in the *CSTR* is measured by a pH sensor and further transmitted to a pH controller which is of a *PID* type in which the control output is calculated then sent to a flow control valve that adjusts the base flow rate. The control objective is to maintain the pH value at the set point (pH_{set} = 1). An agitator is also included to ensure proper mixing, and baffles are added to prevent the formation of vortex [14]. The overall process is described by the following *FOPTD* model: [9]

$$pH(s) = \frac{K_c\, e^{-d\,s}}{Ts+1} = \frac{e^{-0.75s}}{3.6\,s+1} \tag{6.7}$$

where K_C is the gain of the process model, *d* is the time delay, and *T* is the time constant.

The reactor tank level is kept constant by an overflow control system. This is achieved by applying a level transmitter that sends the feedback signal to a flow controller which further calculates the output according to the *PID* control law then sends it to a flow control valve which adjusts the acid flow rate.

6.4.2 Evaluation of the Existing Control Scheme:

The existing pH controller is of a *PID* type and its control parameters are as follows: [9]

$K_p = 1.7667$ $\tau_i = 3.9750$ $\tau_d = 0.3396$ $K_i = 1.6000$ $K_d = 0.1667$

By combining the information from the *FOPTD* model and the existing *PID* controller setting, the block diagram for the existing process was built and simulated using Simulink (Appendix A.6.1). The resulted response was as shown in the following Figure 6.7.

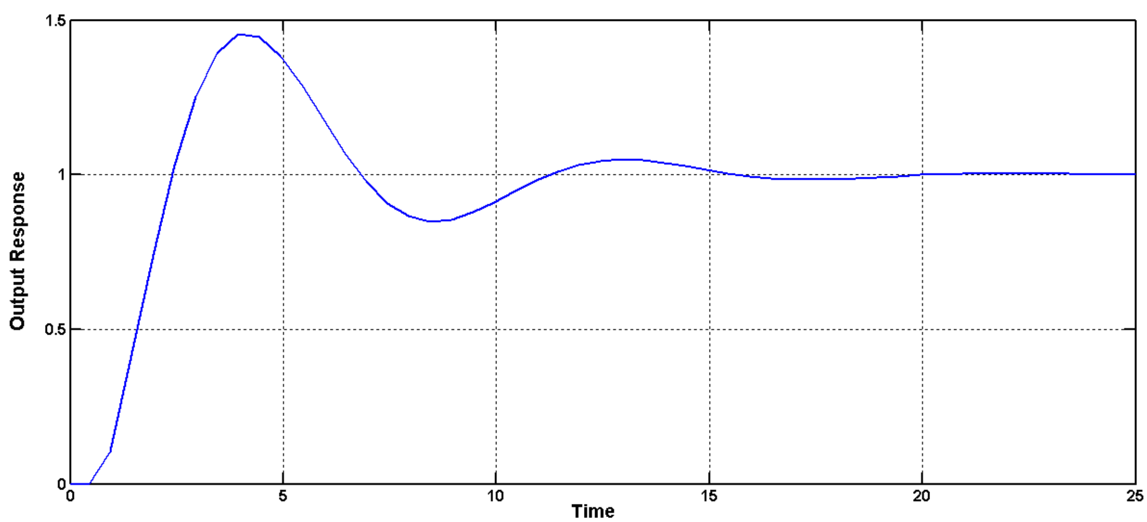


Figure 6.7: Output response by applying the existing *PID* controller

The MSD was found to be 0.1760 at which the SNR was found to be 7.5449 and the variance of the output was found to be 0.1604.

6.4.3 APC Controller Tuning:

The tuning was obtained by following the methodology described in Section 4.3. The control factors were selected to be: K_p, τ_i, and τ_d. The nominal values for these parameters were set to the ones used in the existing system, and for each control factor, three levels were selected as shown in Table 6.3.

Table 6.3: Control factors

Factor	*Parameter*	*Levels*		
		1	*2*	*3*
NF_1	K_p	1.5900	1.7667	1.9434
NF_2	τ_i	3.5775	3.9750	4.3725
NF_3	τ_d	0.3056	0.3396	0.3736

The noise factors were identified from the process model described by Equation 6.7 to be: K_C, d, and T. For each factor, two levels were selected as shown in Table 6.4.

Table 6.4: Noise factors

Factor	*Parameter*	*Levels*	
		1	*2*
CF_1	K_C	1.0000	1.2500
CF_2	d	0.7500	0.9375
CF_3	T	3.600	4.5000

After selecting the *OA*s as per the procedure described in Section 4.3, and conducting the experiments, the results were summarized in Table 6.5.

Table 6.5: Experimental results

Noise Factors	*Trials*			
	1	*2*	*3*	*4*
NF_1	1.0000	1.0000	1.2250	1.2250
NF_2	0.7500	0.8625	0.7500	0.8625
NF_3	3.600	4.3200	4.3200	3.600

Trials	*Control Factors*			*MSD*				$\overline{MSD}$	$\overline{\sigma}$	*SNR*
	CF_1	CF_2	CF_3	*1*	*2*	*3*	*4*			
1	1.5900	3.5775	0.3056	0.1857	0.2154	0.1953	0.2123	0.2022	0.0141	6.9427
2	1.5900	3.9750	0.3396	0.1795	0.2029	0.1865	0.1963	0.1913	0.0104	7.1829
3	1.5900	4.3725	0.3736	0.1755	0.1952	0.1809	0.1870	0.1847	0.0085	7.3365
4	1.7667	3.5775	0.3736	0.1807	0.2057	0.1879	0.2013	0.1939	0.0116	7.1242
5	1.7667	3.9750	0.3056	0.1761	0.1967	0.1817	0.1909	0.1864	0.0092	7.2967
6	1.7667	4.3725	0.3396	0.1761	0.1904	0.1771	0.1833	0.1817	0.0066	7.4059
7	1.9434	3.5775	0.3396	0.1775	0.1994	0.1833	0.1958	0.1890	0.0103	7.2354
8	1.9434	3.9750	0.3736	0.1733	0.1915	0.1777	0.1860	0.1821	0.0082	7.3963
9	1.9434	4.3725	0.3056	0.1707	0.1867	0.1743	0.1807	0.1781	0.0071	7.4934

From Table 6.5, The maximum value for the *SNR* was found to be 7.4934, at which the average *MSD* was found to be 0.1781. Accordingly, the optimum values for the robust *PID* controller parameters were found to be:

$K_p = 1.9434$ $\tau_{\mathrm{i}} = 4.3725$ $\tau_{\mathrm{d}} = 0.3056$ $K_i = 1.4546$ $K_d = 0.1500$

The output response for the process under this setting was as shown in Figure 6.8. The *MSD* was found to be 0.1707, at which the *SNR* was found to be 7.6777 and the variance of the output was found to be 0.1540. By comparing with results obtained under the exiting control scheme, the *SNR* was increased by 10.02% and the variability was reduced by 3.99%. These results will show more improvement when the process subjects to operate under assignable causes as we will see in the coming sections, which further indicates the effectives of robust tuning methodology.

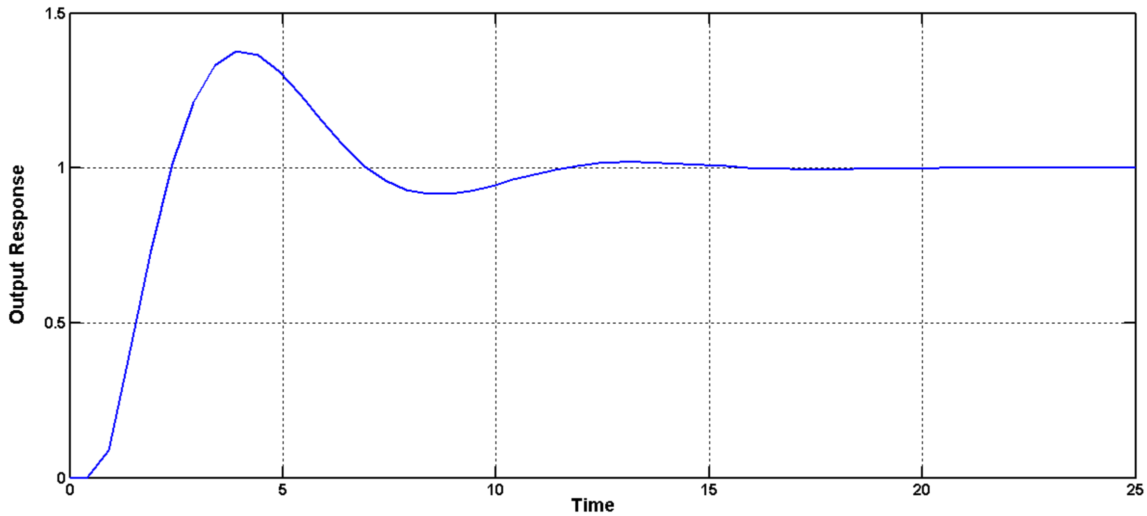


Figure 6.8: Output response by applying the robust PID controller

6.4.4 SPC Controller Development:

The *SPC* controller was developed by following the methodology described in section 3.3. The extracted data from closed loop step response was analyzed and the corresponding values for b_0 and b_1 were calculated from Equations 5.13 and 5.12 as shown in Appendix C.6.1. Accordingly, the process model described by Equation 5.11 was expressed as follows:

$$y(t) \ = \ 1.2775 \text{ - } 0.2467 \ x(t) \ + e(t) \tag{6.8}$$

The control action described by Equation 5.16 was expressed as follows:

$$u(t) = \frac{-0.2467\left[\tau(t) - e(t) - 1.2775\right]}{0.07386} \tag{6.9}$$

6.4.5 Fuzzy Logic Controller Setting:

The *FZLC* was constructed by following the procedure described in Section 6.3.1. For fuzzification, the membership functions for er_t, dy_t, and w_t were set as per the values found in Table 6.6. The 25 fuzzy inference rules were applied for fuzzy inference, and the *COA* method was used for defuzzification.

Table 6.6: Fuzzy logic controller setting

er_i	er_0	er_1	er_2	er_3	er_4	er_5
Velue	0.000	0.007	0.010	0.035	0.040	0.500
dy_i	dy_0	dy_1	dy_2	dy_3	dy_4	dy_5
Velue	0.000	0.007	0.010	0.035	0.040	0.500
w_i	w_0	w_1	w_2	w_3	w_4	w_5
Velue	0.000	0.030	0.050	0.300	0.400	0.600
w_i	w_6	w_7	w_8	w_9	-	-
Velue	0.700	0.950	0.970	1.000	-	-

6.4.6 Construction of the Integrated SPC/APC System:

For simulating the process, its block diagram was built using Simulink (Appendix A.6.2).

6.4.7 Experiment Run and Data Analysis:

The process was simulated to operate by all three control schemes separately, including: the existing *PID* control, the *SPC* control, and the fuzzy integrated *SPC/APC* control. The output responses for the three control schemes were compared in Figure 6.9 and the output statistics were summarized in Table 6.7.

Table 6.7: Results summary

Control Scheme	*MSD*	*SNR*	*AE*
Existing PID Control	0.0798	10.9800	0.7187
SPC Control	0.0547	12.6201	0.8841
Fuzzy Integrated SPC/APC Control	0.0552	12.5806	0.9123

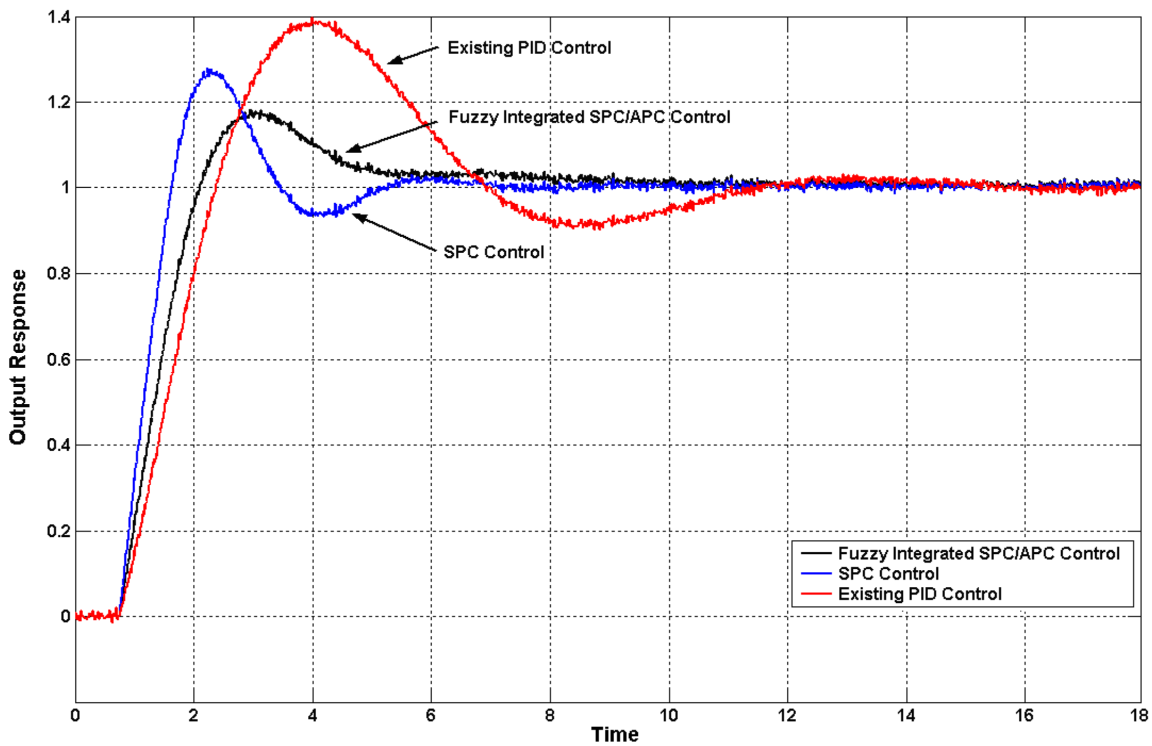


Figure 6.9: Output responses under the three control schemes

By comparing the output under our fuzzy integrated *SPC/APC* scheme to the output under the existing control scheme, results indicated a decrease of 30.83% in *MSD*, an increase of 14.58% in the *SNR*, and increase of 12.69% in the *AE*. These results turned out to be better even for the case when the process was derived under *SPC* control action.

Next, the process controlled by all three control schemes was set to operate under assignable causes by introducing white noise and including a shift of 0.04 units in the process mean at t = 26 sec. *EWMA* control charts (Appendix B.5.1) for λ = 0.1 and L = 6 were generated using Matlab, their plots were as shown in Figures: 6.10, 6.11, and 6.12.

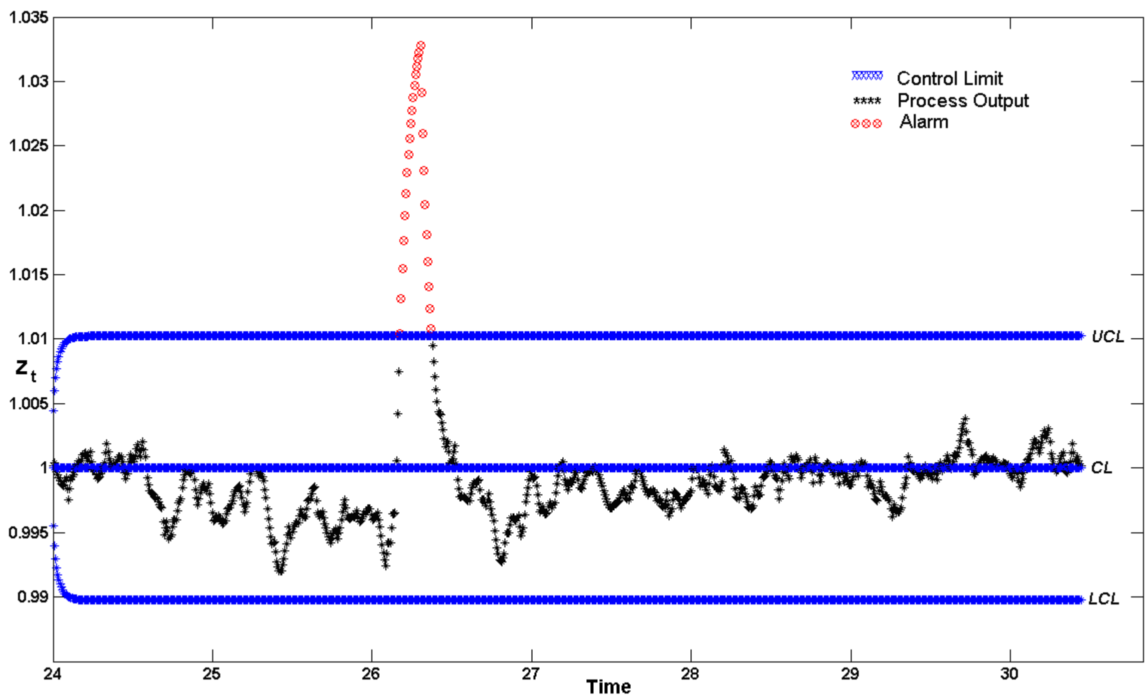


Figure 6.10: *EWMA* control chart for *PID* controlled output

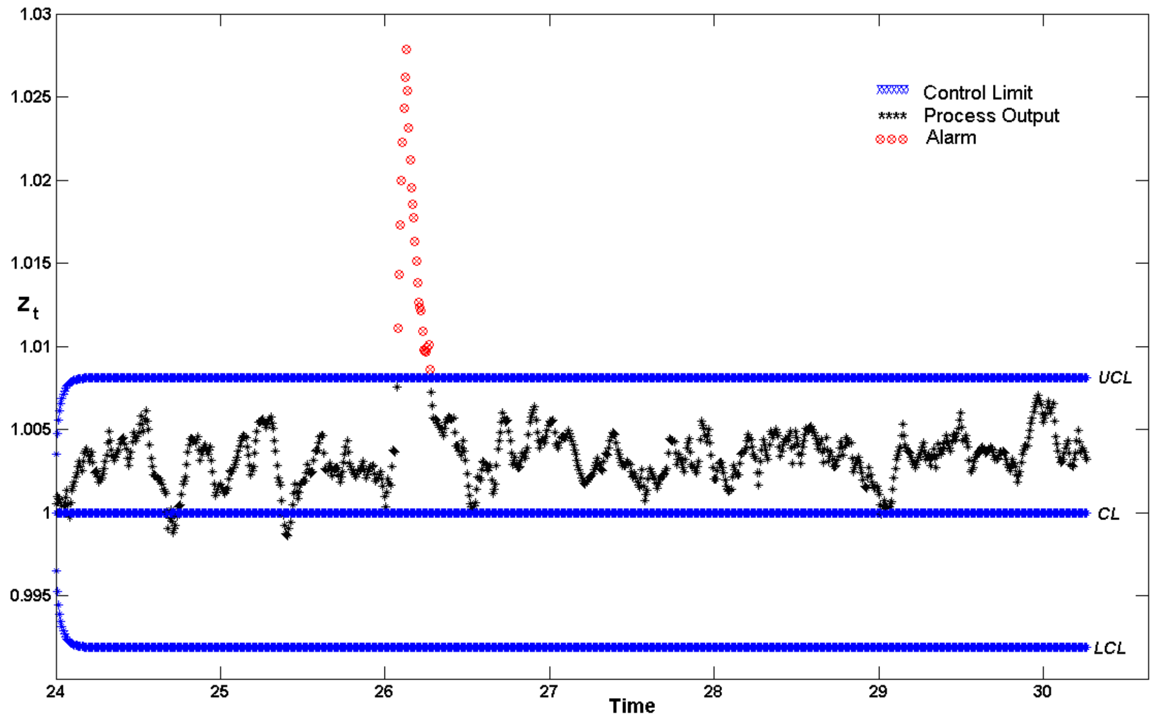


Figure 6.11: *EWMA* control chart for *SPC* controlled output

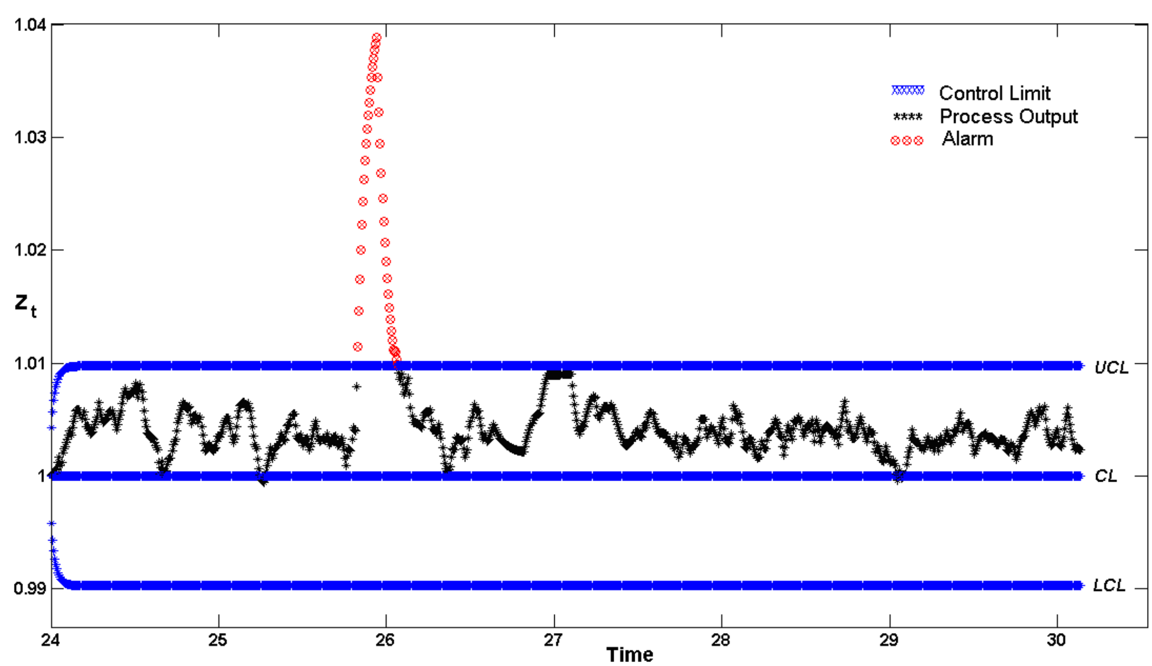


Figure 6.12: *EWMA* control chart for integrated *SPC*/*APC* controlled output

The output statistics were summarized in Table 6.8.

Table 6.8: Results summary

Control Scheme	*MSD*	*SNR*	*ARL*	*AE*
Existing PID Control	0.0537	12.7003	8.4350	0.7294
SPC Control	0.0338	14.7108	17.9920	0.9235
Fuzzy Integrated SPC/APC Scheme	0.0358	14.4612	19.6810	0.9641

Results indicated a decrease of 66.67% in *MSD*, an increase of 13.86% in the *SNR*, and increase of 32.18% in the *AE* and twice increase in *ARL*. This indicates the effectiveness of our proposed scheme over the existing scheme in terms of optimizing the level of quality, performance and robustness.

6.5 Conclusion:

In this chapter, we developed a fuzzy integrated *SPC/APC* scheme that combines between the utilization of *SPC* and *APC* techniques for process monitoring and control under *FZL* interaction. We envision that driving any system under the resulted strategy will result into obtaining optimum level of quality, performance, and robustness. We also presented a case study for a pH control process to demonstrate the application of this scheme and illustrate its effectiveness. Results have shown the successfulness of our proposed scheme in terms of maintaining the output quality on target, improving the performance and maintaining the robustness.

CHAPTER 7

SUMMARY AND CONCLUSIONS

7.1 Summary:

In this thesis, we considered different *SPC* and *APC* techniques for process enhancement and utilized their dual usage by proposing different integrated schemes. We started our work by presenting a review on *SPC* and *APC* techniques, discussing major issues facing their integration, and outlining the recent strategies followed to bridge the gap between them. We resumed our work by presenting different models for process parameters setting from which the Trine model for joint determination of process parameters was resulted. It followed the development of a robust gain-scheduled methodology for control parameters tuning. An integrated frame that combines between the use of *SPC* and *APC* techniques for process monitoring and performance evaluation was also presented. We also developed an *SPC* controller which was based on the constrained controller principle incorporated with quadratic quality loss function and applied its use for process control as well as a standard benchmark for performance evaluation. Our work ended up by the development of a unified scheme that combined between the utilization of *SPC* and *APC* techniques under *FZL* interaction. Throughout the thesis, we presented several examples and case studies to support our suggestions. We envision that applying these schemes to any process will result into enhanced level of product quality, better performance, and maintained robustness.

7.2 Future Research and Extensions:

Throughout the thesis, we focused to achieve an effective integration between *SPC* and *APC* techniques and to cover the gaps left in recent related work. Among this gap, we successfully covered areas related to: dual *SPC/APC* monitoring and control, application of robust design principles, account for performance deterioration, and application of intelligent techniques. Furthermore, there are areas for future research and extension in which research is proposed, such as:

a. Search for Assignable Causes for Process Variations:

The detection capabilities of many of the *SPC* charts are satisfactory in terms of generating alarms for process shifts. However, adaptation of a scientific method for identifying the location of assignable causes is still not developed, and currently it is based on judgment. This can be handled by reducing the degrees of freedom associated with search by monitoring the important process inputs only while implementing control.

b. Development of Software Tools for Integrated SPC/APC Techniques:

It is recommended to develop integration software that has the capability to link between process control, simulation, statistical analysis tools and optimization tools to mimic an integrated *SPC/APC* system. Although there are some existing simulation software packages as well as statistical analysis tools, most of them are designed to be stand alone. It is required to have an integrated software tool that applies both *SPC* as well as *APC* tools and reflects the true power of integrated *SPC/APC* techniques.

c. Extension to MIMO Systems:

Most researchers have limited their scope of combining *SPC/APC* control schemes for single-input single-output (*SISO*) systems. An extension to multiple-input multiple-output (*MIMO*) systems is recommended. The major challenge behind the development of such strategies is the complexity of these problems that arises from the large number of parameters needed to be examined, which results in statistical problems such as: existence of a large number of highly correlated input variables (multi-co-linearity) and information dispersion among many output variables. These problems could be handled by employing techniques such as: principal component analysis (*PCA*) for resolving the correlation problem, and partial least squares (*PLS*), which resolves the dispersion.

NOMENCLATURE

τ	target value
y	output quality characteristic
dy	rate of change of the output quality characteristic
u	control action
u_{SPC}	control action from the *SPC* controller
u_{APC}	control action from the *APC* controller
w	controller utilization factor
e	deviation of the process output from the target
k	quality loss coefficient
n	number of observations
t	time
T	time constant
T_d	total time until the process starts to deteriorate
T^*	optimal production run length
T_U	ultimate period
τ_i	integral time constant
τ_d	derivative time constant
d	time delay
μ	process mean
μ_0	process mean when the process is in control
μ_1	process mean when the process is out of control
σ	standard deviation
σ_D	standard deviation of the disturbance

σ_e	standard deviation of the controlled output
σ_{yc}^2	variance of the process by applying the constrained controller
σ_y^2	variance of the process by applying the existing controller
Δ	tolerance
L	width of the control limits
z	*EWMA* parameter
λ	weight for *EWMA* parameter
α	probability of Type-I error
β	probability of Type-II error
δ	shift parameter
ς	half value of the tolerance
K	controller gain
K_U	ultimate gain
K_p	proportional gain
K_i	integral gain
K_d	derivative gain
K_c	process model gain
ϕ	adjustment factor
$\Re$	flow resistance factor
η_{CC}	performance index
C_r	rejection cost per unit
C_{RL}	rejection cost for falling below the *LSL*
C_{RU}	rejection cost for exceeding the *USL*
C_S	nonconformance cost
C_{S0}	loss when the process is in-control
C_{S1}	loss when the process is out-of-control
C_{OP}	cost of operating the out-of-control process
b_0	regression function parameter

b_1	regression function parameter
v	beverage volume inside the bottle
V	reactor volume
h	beverage level
$\dot{h}$	rate of change of beverage level
h^*	beverage level near the target
A	cross sectional area
F_a	acid flow rate
F_b	base flow rate
F_{in}	beverage input flow rate
κ_a	acid concentration
κ_b	base concentration
κ_{oa}	overall concentration containing the anion of the acid
κ_{ob}	overall concentration containing the cation of the base

Note: Nomenclature provided in this list does not apply for the literature part covered in Section 2.5; all terms in this section are kept as written by their authors. Brief explanation for each nomenclature within this section is provided parallel to its occurrence.

BIBLIOGRAPHY

[1] Al-Fawzan, M.A. and Rahim, M.A., "Optimal Control of a Deteriorating Process with a Quadratic Loss Function", *International Journal of Quality and Reliability Engineering*, vol.17, no.1, pp.459–466, 2001.

[2] Al-Nemar, T.M. *"Fuzzy Logic-Based PID Self-Tuning"*, M.Sc. Thesis, Systems Engineering Department, King Fahd University of Petroleum & Minerals, 157 pages, 1996.

[3] Arcelus, F.J. and Banerjee, P.K., "Optimal Production Plan in a Tool Wear Process with Rewards for Acceptable, Undersized and Oversized Parts", *Engineering Costs Production Economics*, vol.11, no.1, pp.13–19, 1987.

[4] Arcelus, F.J., Banerjee, P.K. and Chandra, R., "The Optimal Production Run for a Normally Distributed Quality Characteristic Exhibiting Nonnegative Shifts in the Process Mean and Variance", *IEEE Transactions*, vol.14, no.1, pp.90–98, 1982.

[5] Badiru, A.B. and Ayeni, B.J., *Practitioner's Guide to Quality and Process Improvement*, Chapman & Hall, 1993.

[6] Badmus, O., Banks, D., Vishnubhotla, A., Huang, B., and Shah, S.L., *"Performance Assessment: A Requisite for Maintaining Your APC Assets"*, Dynamic Modeling Control Applications for Industry Workshop, IEEE Industry Applications, (1998).

[7] Baur, J.E. and Baur, M.B., "The Ultrasonic Soda Fountain: A Dramatic Demonstration of Gas Solubility in Aqueous Solutions", *Journal of Chemical Education*, vol.83, no.4, pp.577-580, 2006.

[8] Bettes, D.C., "Finding an Optimum Target Value in Relation to a Fixed Lower Limit and Arbitrary Upper Limit". *Appl. Stat.*, vol.11, no.1, pp.202–210, 1962.

[9] Boling, J.M., Seborg, D.E. and Hespanha, J.P., "Multi-Model Adaptive Control of a Simulated pH Neutralization Process", *Control Engineering Practice*, vol.15, no. 6, pp.663-669, 2007.

[10] Box, G.E.P. and Jenkins, G.M., *Time Series Analysis, Forecasting, and Control*, Holden-Day, San Francisco, CA, 1976.

[11] Box, G.E.P. and Kramer, T., "Statistical Process Monitoring and Feedback Adjustment: A Discussion", *Technometrics*, vol. 34, no. 3, pp. 251-267, 1992.

[12] Box, G.E.P. and Luceño, A., *Statistical Control by Monitoring and Feedback Adjustment*, John Wiley & Sons, New York, 1997.

[13] Box, G.E.P., Jenkins, G.M. and Reinsel, G., *Time Series Analysis, Forecasting, and Control*, 3rd Edition, Englewood Cliffs, Prentice Hall, 1994.

[14] Capilla, C., Ferrer, A. and Romero, R., "Integration of Statistical and Engineering Process Control in a Continuous Polymerization Process", *Technometrics*, vol.41, no.1, pp.14-28, 1999.

[15] Chan, C.H. and Chou, C.Y., "Determining the Optimum Process Mean under a Log-normal Distribution", *Quality & Quantity*, vol.39, no.1, pp.119-124, 2005.

[16] Chan, W.M. and Ibrahim, R.N., "Designing the Optimal Process Means and the Optimal Production Run for Deteriorating Process", *International Journal of Advance Manufacturing Technology*, vol.31, no.1, pp.367-373, 2006.

[17] Chan, W.M. and Ibrahim, R.N., "Evaluating the Quality Level of a Product with Multiple Quality Characteristics", *International Journal of Advance Manufacturing Technology*, vol.24, no.1, pp.738-373, 2004.

[18] Chen, C.H., "Determining the Optimum Process Mean for a Mixed Quality Loss Function", *International Journal of Advanced Manufacturing Technology*, vol.28, no.1, pp.571–576, 2005.

[19] Chen, C.H. and Chou, C.Y., "Determining the Optimum Process Mean of a One-Sided Specification Limit", *International Journal of Advance Manufacturing technology*, vol.20, no.1, pp.439-441, 2002.

[20] Cho, B.R. and Leonard, M.S., "Identification and Extension of Quasi Convex Quality Loss Functions", *International Journal of Reliability, Quality and Safety Engineering*, vol.4, no.1, pp.191-204, 1997.

[21] Deming, W.E., *Out of the Crisis*, MIT Center for Advanced Engineering Study, Cambridge, MA, 1989.

[22] Desborough, L. and Harris, T.J., "Performance Assessment Measures for Univariate Feedback Control", *The Canadian Journal of Chemical Engineering*, vol.70, no.1, pp.1186-1197, 1992.

[23] Dorf, R.C. and Bishop, R.H., *Modern Control Systems*, 9th Edition, Prentice Hall Inc., Upper Saddle River, New Jersey, 2001.

[24] Duffuaa, S.O., Khursheed, S.N., and Noman, S.M., "Integrating Statistical Process Control, Engineering Process Control, and Taguchi's Quality Engineering", *International Journal of Product Research*, vol. 42, no. 19, pp. 4109-4118, 2004.

[25] Ellis, G., *Control Systems Design Guide*, Academic Press, London, 1991.

[26] Ettaleb, L. *"Control Loop Performance Assessment and Ascillation Detection"*, Ph.D. Thesis, Department of Electrical and Computer Engineering, the University of British Columbia, 122 pages, 1999.

[27] English, J.R. and Case, K.E., "Control Charts Applied as Filtering Devices within a Feedback Loop". *IIE Transactions*, vol.22, no.1, pp.255-269, 1990.

[28] Gibra, I.N., "Optimal Production Run of a Process Subject to Systematic Trends", *International Journal of Production Research*, vol.12, no.1, pp.511–517, 1974.

[29] Golhar, D.Y., "Determination of the Best Means Contents for a Canning Problem", *Journal of Quality Technology*, vol.19, no.1, pp.82–84, 1987.

[30] Golhar, D.Y. and Pollock, S.M., "Determination of the Best Mean and the Upper Limit for a Canning Problem", *Journal of Quality Technology*, vol.20, no.1, pp.188–192, 1988.

[31] Hall, R.I. and Eilon, S., "Controlling Production Processes which are Subject to Linear Trends", *Operations Research Quart*, vol.14, no.3, pp.179–189, 1963.

[32] Haridy, S. and Wu, Z., "Univariate and Multivariate Control Charts for Monitoring Dynamic-Behavior Processes: a Case Study", *Journal of Industrial Engineering and Management,* vol.2, no.3, pp.464-498, 2009.

[33] Harris, T.J., "Assessment of Control Loop Performance", *The Canadian Journal of Chemical Engineering*, vol.67, no.10, pp.856-861, 1989.

[34] Holtta, Vesa. *"Plant Performance Evaluation in Complex Industrial Applications"*, Ph.D. Thesis, Department of Automation and Systems Technology, Helsinki University of Technology, 108 pages, 2009.

[35] Huang, H.P. and Jeng, J.C., "Monitoring and Assessment of Control Performance for Single Loop Systems", *Industrial & Engineering Chemistry Research*, vol.41, no.5, pp.1297-1309, 2002.

[36] Hunter, R.P., *Automated Process Control Systems: Concepts And Hardware*, Prentice-Hall, Inc., 1987.

[37] Hunter, W.C. and Kartha, C.P., "Determining the Most Profitable Target Value for a Production Process", *Journal of Quality Technology*, vol.9, no.1, pp.176–181, 1977.

[38] Janakiram, M. and Keats, J. B., "Combining SPC and EPC in a Hybrid Industry", *Journal of Quality Technology*, vol. 30, no. 3, pp. 189-200, 1988.

[39] Jantzen, J., <u>*Design of Fuzzy Controllers*</u>, Technical Report, 98-E-864, Technical University of Denmark, 1998.

[40] Jasma-Jounela, S.L., Poikonen, R., Georgiev, Z., Zuehlke, U. and Halmevaara, K., *"Evaluation of Control Performance: Methods and Applications"*, Proceedings of the IEEE International Conference on Control Applications, Glasgow, Scotland, U.K, 2002.

[41] Jeang, A. and Yang, K., "Optimal Tool Replacement with Nondecreasing Tool Wear", *International Journal of Production Research*, vol.30, no.2, pp.299–314, 1992.

[42] Jiang, W. and Farr, J.V., "Integrating SPC and EPC Methods for Quality Improvement", *Quality Technology and Quantitative Management*, vol. 4, no. 3, pp. 345-363, 2007.

[43] Jiang, W. and Tsui, K.L, "SPC Monitoring of MMSE and PI Controlled Processes", *Journal of Quality Technology*, vol.34, no.4, pp.384-398, 2002

[44] Jiang, W. and Tsui, K.L., "An Economic Model for Integrated APC and Control Charts", *IEEE Transactions*, vol.32, no.1, pp.505-513, 2000.

[45] Kandananond, K. *"Performance Characterization of Integrated Process Control Systems"*, Ph.D. Dissertation, Department of Industrial and Manufacturing Engineering, Wichita State University, 96 pages, 2007.

[46] Kapur, K.C. and Cho, B.R., "Economic Design and Development of Specifications", *Quality Engineering*, vol.6, no.1, pp.401-417, 1994.

[47] Kapur, K.C. and Wang, C.J., "Economic Design of Specifications Based on Taguchi's Concept of Quality Loss Function", *Quality, Design, planning and Control*, vol.1, no.1, pp.23-36, 1987.

[48] Ladany, S.P., "Optimal Set Up of a Manufacturing Process with Unequal Revenue from Oversized and Undersized Items", *Front Statistical Quality Control*, vol.6, no.1, pp.93–101, 2001.

[49] Lin, J.Y. and Yu, C.C., "Automatic Tuning and Gain Scheduling for pH Control", *Chemical Engineering Science*, vol.48, no.18, pp.3159-3171, 1993.

[50] Lu, C.J., Wu, C.M., Keng, C.J. and Chiu, C.C., "Integrated application of SPC/EPC/ICA and neural networks", *International Journal of Production Research*, vol. 46, no. 4, pp. 873-893, 2008.

[51] MacGregor, J.F., "A Different View of the Funnel Experiment", *Journal of Quality Technology*, vol. 22, no. 4, pp. 255-259, 1999.

[52] MacGregor, J.F., "On-Line Statistical Process Control", *Chemical Engineering Process*, vol. 84, no. 1, pp. 21-31, 1988.

[53] Meng, J. *"Integrated Robust Design using Computer Experiments and Optimization of a Diesel HPCR Injector"*, Ph.D. Dissertation, Department of Industrial and Manufacturing Engineering, College of Engineering, The Florida State University, 152 pages, 2006.

[54] Messina, W.S. *"Strategies for the Integration of Statistical and Engineering Process Control"*, Ph.D. Dissertation, Department of Industrial Engineering, Arizona State University, 207 pages, 1992.

[55] Montgomery, D.C., *Statistical Quality Control*, 6th Edition, John Wliey & Sons, Inc., 2009.

[56] Montgomery, D.C., Keats, J.B., Runger, G.C., and Messina, W.S., "Integrating Statistical Process Control and Engineering Process Control", *Journal of Quality Technology*, vol.26, no.2, pp.79-87, 1994.

[57] Musheng, Y. and Yu, Z., *"Intelligent Integrated Control Method in Manufacturing Process"*, IEEE International Conference on Automation and Logistics, Jinan, China, pp.1320-1324, August, 18-21, 2007.

[58] Nembhard, H.B., and Mastrangelo, C.M., "Integrated Process Control for Startup operations", *Journal of Quality Technology*, vol.30, no.3, pp.201-211, 1988.

[59] Palm, A.C., "SPC versus Automatic Process Control", *Annual Quality Congress Transactions, ASQC, Milwaukee*, WI, vol.44, pp.694-699.

[60] Park, C., "Linear Filter Model Representation for Integrated Process Control with Repeated Adjustments and Monitoring", *Journal of the Korean Statistical Society,* vol.39, no.2, pp.177-187, 2010.

[61] Rahim, M.A. and Khan, M., "Optimal Determination of Production Run and Initial Settings of Process Parameters for a Deteriorating Process", *International Journal of Advanced Manufacturing Technology*, vol.32, no.1, pp.747-756.

[62] Rahim, M.A. and Tuffaha, F., "Integrated Model for Determining the Optimal Initial Setting for the Process Mean and the Optimal Production Run Assuming Quadratic Loss Function", *International Journal of Production Research*, vol.24, no.16, pp.3281-3300, 2004.

[63] Rasmussen, H., Automatic Tuning of PID-Regulators, Department of Control Engineering, Aalborg University, U93-4019, 2002.

[64] Ross, P.J., Taguchi Techniques for Quality Engineering, 2nd Edition, McGraw-Hill, New York, 1996.

[65] Scharsig, Thomas, "KHS and Coca-Cola in China: A Story of Success, Many Times Over", *Food & Beverage Asia*, pp.24-29, 2007.

[66] Seborg, D.E., Edgar, T.F. and Mellichamp, D.A., Process Dynamics and Control, 2nd Edition, John Wiley & Sons, Inc., 2003.

[67] Shewhart, W.A., *The Economic Control of Quality of Manufactured Product*, D.Van Nostand and Co., New York, 1931.

[68] Slocomb, R.A.W. *"The Integration of Statistical and Automatic Process Control in the Continuous Processing Industries"*, M.Sc. Thesis, Department of Chemical Engineering, University of Ottawa, Canada, 150 pages, 1994.

[69] Smith, C.A. and Corripio, A., *Principles and Practice of Automatic Process Control*, 3rd Edition, John Wiley & Sons, Inc., Hoboken, New Jersey, 2006.

[70] Springer, C.H., "A Method for Determining the Most Economic Position of a Process Mean", *Ind. Qual. Control*, vol.8, no.1, pp.36–39, 1951.

[71] Taguchi, G., *Quality Evaluation for Quality Assurance*, American Supplier Institute, Romulus, MI, 1984.

[72] Taha, H.A., "A Policy for Determining the Optimal Run Length for a Cutting Tool". *Journal of Industrial Engineering*, vol.7, no.33, pp.157–162, 1966.

[73] Tahera, K., Chen, W.M. and Ibrahim, R.N., "Joint Determination of Process Mean and Production Run: A Review", *International Journal of Advanced Manufacturing Technology*, vol.39, no.1, pp.388-400, 2008.

[74] Teeravaraprug, J. *"Economic Designs of the Process Target for Multiple Quality Characteristics"*, Ph.D. Dissertation, Clemson University, 103 pages, 2000.

[75] Teeravaraprug, J. and Cho, B.R., "Designing the Optimal Process Target Levels for Multiple Quality Characteristics", *International Journal of Production Research*, vol.40, no.1, pp.37–54, 2002.

[76] Tsung, F. and Shi, J., "Integrated Design of Run-to-Run PID Controller and SPC Monitoring for Process Disturbance Rejection", *IEE Transactions*, vol.31, no.6, pp.517-527, 1999.

[77] Vander Weil, S.A. and Tucker, W.T., Algorithmic Statistical Process Control Concepts and an Application, Management Science and Statistics Program, Corporate Research and Development, General Electric Company, 1991.

[78] Vander Weil, S.A. Tucker, W.T., Faltin, F.W. and Doganaksoy, N., "Algorithmic Statistical Process Control: Concepts and an Application", *Technometrics*, vol.34, no.3, pp.286-297, 1992.

[79] Vlachogiannis, J.G. and Roy, R.K., "Robust PID Controllers by Taguchi's Method", *The TQM Magazine*, vol.17, no.5, pp.456-466, 2005.

[80] Wen, D. and Mergen, A.E., "Running a Process with Poor Capability", *Quality Engineering*, vol.11, no.1, pp.505–509, 1999.

[81] Wiklund, S.J., "Adjustment Strategies When Using Shewhart Charts", *Economic Quality Control*, vol.8, no.1, pp.3-21, 1993.

[82] Yager, R.R. and Zadeh, L.A., An Introduction to Fuzzy Logic Applications in Intelligent Systems, Kluwer Academic Publishers, Boston, Massachusetts, 1992.

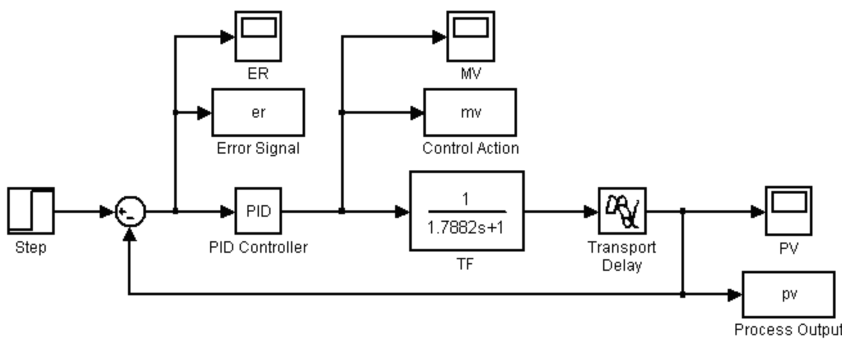
[83] Zadeh, L.A., "Fuzzy Sets", *Information and Control*, vol.8, no.3, pp.338-353, 1965.

[84] Zalm, G.M., Tuning of PID-type controllers: Literature Overview, DCT-report, nr. 2004.45,Technische Universitieit Eindhoven, the Netherland, 2004.

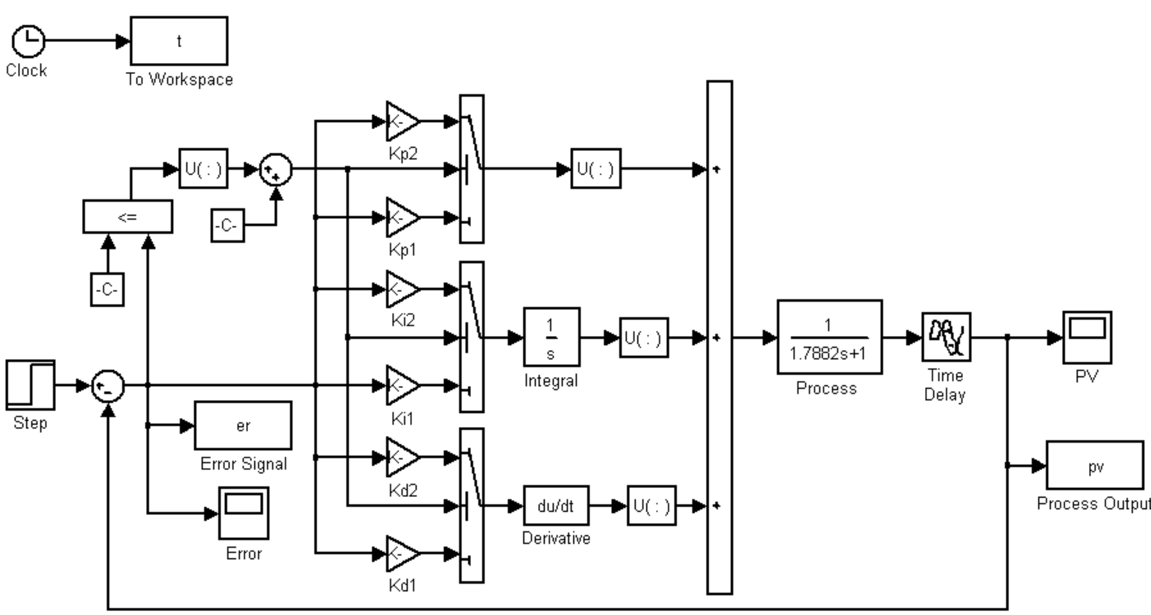
[85] Zang, C., Friswell, M.I. and Mottershead, J.E., "A Review of Robust Optimal Design and its Application in Dynamics", *Computers and Structures*, vol. 83, no.4-5, pp.315–326, 2004.

Appendix A: SIMULINK Diagrams

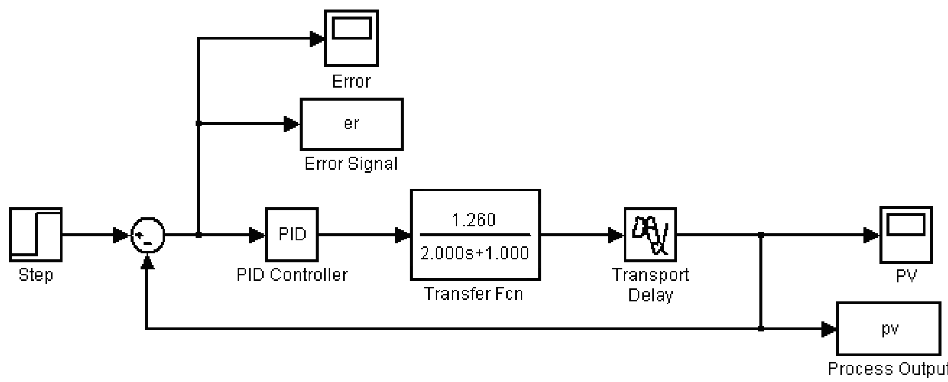
A.4.1: Block diagram for the overall system



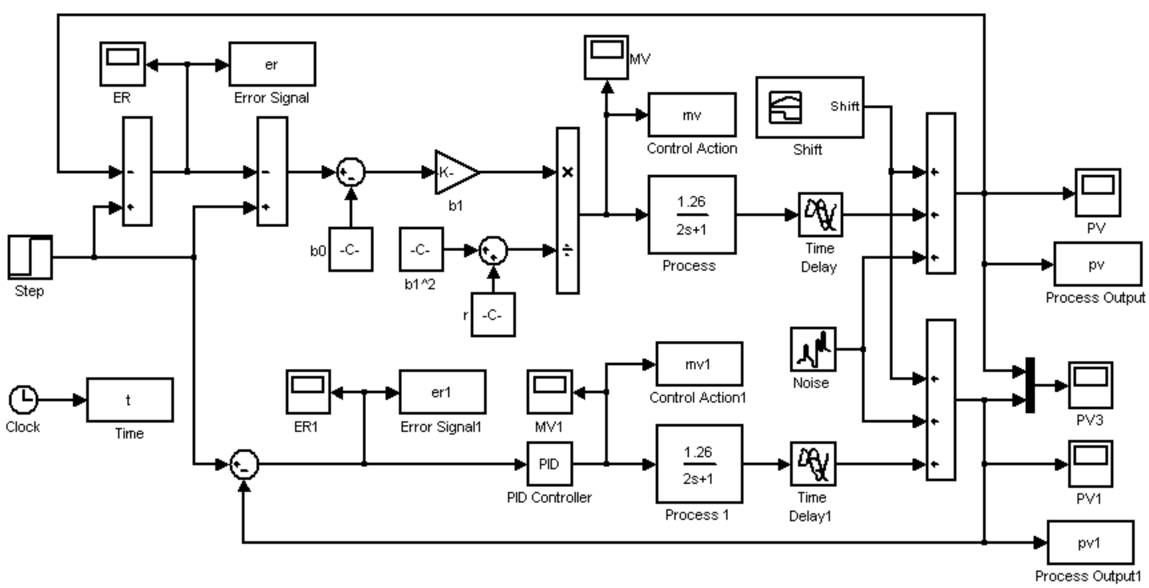
A.4.2: Block diagram for the *RGS* system



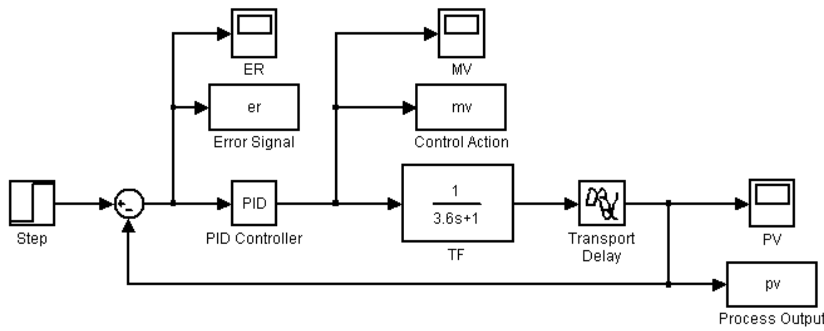
A.5.1: Process Derived by a Conventional *PID* Controller



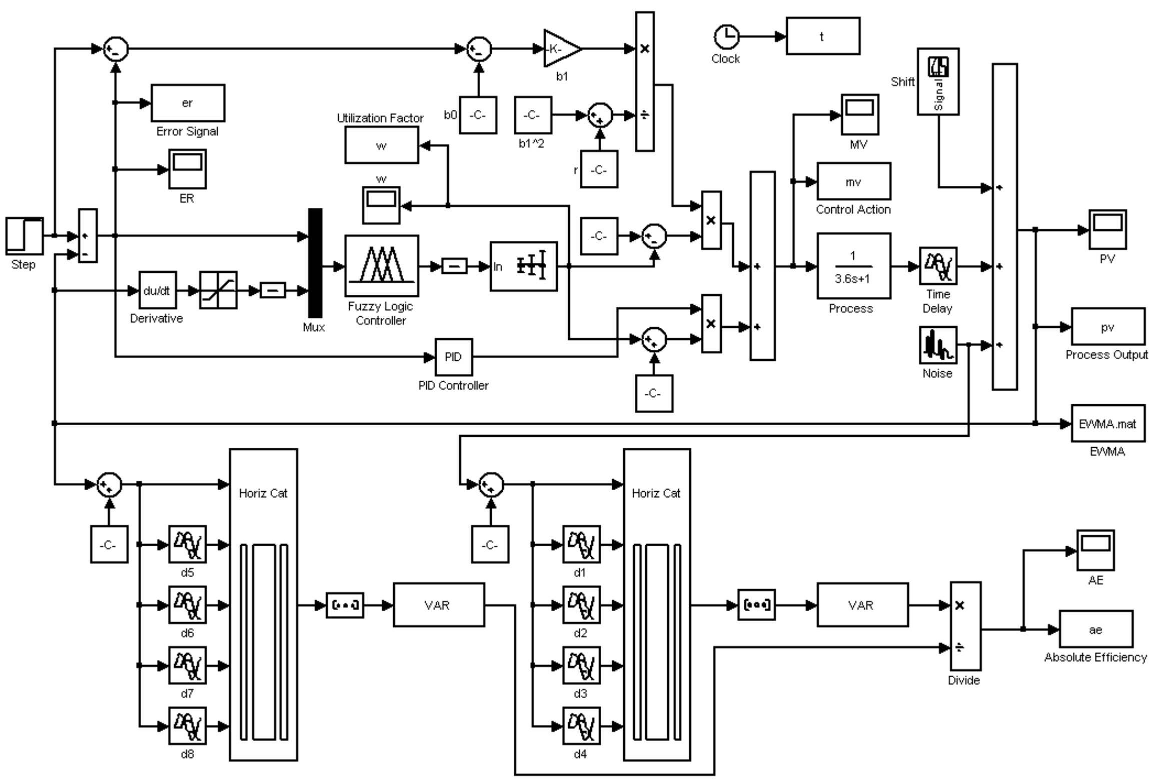
A.5.2: Process under Assignable Causes



A.6.1: Simulink block diagram for the existing pH control process



A.6.2: Simulink block diagram for the integrated *SPC/APC* system



Appendix B: MATLAB Programs

B.3.1: Matlab Code for Optimum Process Mean Problem

```
clc
clear
tl=10;   % Lower Specification Limit
tu=13;  % Upper Specification Limit
cl=65;  % Monetary loss for an item below LSL
cu=25;  % Monetary loss for an item exceeding USL
sig=0.75;        % Standard Deviation
tr=(tl+tu)/2;    % target value
k=10;            % loss coefficient
ct0=1000;

for m=9:0.01:14
   cmu=normcdf((tu-m)/sig);
   cml=normcdf((tl-m)/sig);
   pru=normpdf((tu-m)/sig);
   prl=normpdf((tl-m)/sig);
   A=cl*cml+cu*(1-cmu);
   B=k*(((m-tr)^2+sig^2)*(cmu-cml))+k*sig*((m-2*tr+tl)*prl-(m-2*tr+tu)*pru);
   ct=A+B;
   if ct<ct0;
      ct0=ct;
      Mean=m;
      Total_Loss=ct0;
   end
plot(m,ct);
hold on;
end
xlabel('Mean');
ylabel('Loss');
grid;
Mean
Total_Loss
```

B.3.2: Matlab Code for Optimum Process Mean and Production Run Length Problem

```
clc
clear
tl=9;                   % Lower Specification Limit
tu=13;                  % Upper Specification Limit
cl=35;                  % Monetary loss for an item below LSL
cu=10;                  % Monetary loss for an item exceeding USL
sig=0.76;               % Standard Deviation
tr=(tl+tu)/2;           % Target value
k=5;                    % Loss coefficient
shf=0.7;                % Shift Parameter
lnd=2;                  % Failure Rate
CT0=100;
CC=3;                   % Operating out of Control Cost
t=3;
for t=0:0.5:20
  for m=8:0.05:14
   cmu0=normcdf((tu-m)/sig);                % For In-Control Process
   cml0=normcdf((tl-m)/sig);
   pru0=normpdf((tu-m)/sig);
   prl0=normpdf((tl-m)/sig);
   cmu1=normcdf((tu-m-shf*sig)/sig);        % For Out-of-Control Process
   cml1=normcdf((tl-m-shf*sig)/sig);
   pru1=normpdf((tu-m-shf*sig)/sig);
   prl1=normpdf((tl-m-shf*sig)/sig);
   % Loss when in-control
   A0=cl*cml0+cu*(1-cmu0);
   B0=k*(((m-tr)^2+sig^2)*(cmu0-cml0))+k*sig*((m-2*tr+tl)*prl0-(m-2*tr+tu)*pru0);
   ct0=A0+B0;
    % Loss when out-of-control
   A1=cl*cml1+cu*(1-cmu1)
   B1=k*(((m-tr-shf*sig)^2+sig^2)*(cmu1-cml1))+k*sig*((m-2*tr-shf*sig+tl)*prl1-(m-2*tr-shf*sig+tu)*pru1);
   ct1=A1+B1+CC;
    % Total Loss
   CT=exp(-lnd*t)*ct1+(1-exp(-lnd*t))*ct0;
   if CT<CT0;
      CT0=CT;
      Opt_Mean=m;
      Opt_Run_Length=t;
      Loss=CT0;
   end
plot3(m,t,CT);
hold on;
end
end
xlabel('Mean');
ylabel('Run Length');
zlabel('Loss');
grid;
Opt_Mean
Opt_Run_Length
Loss
```

B.3.3: Matlab Code for Optimum Process Mean, Production Run Length and Specification Limits Problem

```
clc
clear
cl=28;          %  Scrap Cost
cu=13;          % Rework Cost
cr=9;           % Rejection cost
sig=0.75;       % Standard Deviation
tr=10;          % Target value
shf=0.8;        % Shift Parameter
lnd=3;          % Failure Rate
CC=5;           % Operating out of Control Cost
CT0=100;
for t=0:1:20
for d=0.5:0.5:3
  tu=tr+d/2;    % Upper specification limit
  tl=tr-d/2;    % Lower specification limit
for m=8:0.05:12

% For In-Control Process ~ N(m,sig)
   cmu0=normcdf((tu-m)/sig);
   cml0=normcdf((tl-m)/sig);
   pru0=normpdf((tu-m)/sig);
   prl0=normpdf((tl-m)/sig);
   A0=cl*cml0+cu*(1-cmu0);
   B0=cr/d^2*(((m-tr)^2+sig^2)*(cmu0-cml0))+cr/d^2*sig*((m-2*tr+tl)*prl0-(m-2*tr+tu)*pru0);
   ct0=A0+B0;

% For Out-of-Control Process ~ N(m+shf*sig,sig)
   cmu1=normcdf((tu-m-shf*sig)/sig);
   cml1=normcdf((tl-m-shf*sig)/sig);
   pru1=normpdf((tu-m-shf*sig)/sig);
   prl1=normpdf((tl-m-shf*sig)/sig);
   A1=cl*cml1+cu*(1-cmu1);
   B1=cr/d^2*(((m-tr-shf*sig)^2+sig^2)*(cmu1-cml1))+cr/d^2*sig*((m-2*tr-shf*sig+tl)*prl1
        -(m-2*tr-shf* sig +tu)*pru1);
   ct1=A1+B1+CC;

%Total Loss
   CT=exp(-lnd*t)*ct1+(1-exp(-lnd*t))*ct0;
     if CT<CT0;
       CT0=CT;
       Opt_Mean=m;
       Opt_Run_Length=t;
       Loss=CT0;
       Tolerance=d;
    end
    plot(m,CT,'g*');
    hold on;
end
end
```

```
end
plot(Opt_Mean,Loss,'ro');
hold on;
grid on;
xlabel('Mean');
ylabel('Loss');
Opt_Mean
Opt_Run_Length
USL=tr+Tolerance/2
LSL=tr-Tolerance/2
Loss
Tolerance
```

B.3.4: Matlab Code for Optimum Process Mean Problem for Satisfying Manufacturing Requirements

```
clc
clear
tl=40;          % Lower Specification Limit
tu=41.5;        % Upper Specification Limit
cl=55;          % Scrap Cost
cu=10;          % Rework Cost
cm=90;          % Manufacturing cost
ci=4;           % Inspection cost
sp=200;         % Selling price
sig=0.25;       % Standard Deviation
tr=40.75;       % target value
k=25;           % loss coefficient
pr0=30;
for m=39.5:0.005:42
   cmu=normcdf((tu-m)/sig);
   cml=normcdf((tl-m)/sig);
   pru=normpdf((tu-m)/sig);
   prl=normpdf((tl-m)/sig);
   A=cl*cml+cu*(1-cmu);
   B=k*(((m-tr)^2+sig^2)*(cmu-cml))+k*sig*((m-2*tr+tl)*prl-(m-2*tr+tu)*pru);
   pr=sp-A-B-cm-ci;
   if pr>pr0;
      pr0=pr;
      Mean=m;
      Total_Profit=pr0;
   end
plot(m,pr);
hold on;
end
plot(Mean,Total_Profit,'r*');
xlabel('Process Mean');
ylabel('Total Profit');
grid;
Mean
Total_Profit
```

B.5.1: Matlab code for EWMA control chart

```
function ewma(d)

d=d';
nn=size(d);
n=nn(1,2);
t=1;
l=3;
sg=std(d);
z0=t;
w=0.1;
a=14;

for i=1:1:n

    z1=w*d(1,i)+(1-w)*z0;
    ucl=t+l*sg*sqrt((w/(2-w))*(1-(1-w)^(2*i)));
    lcl=t-l*sg*sqrt((w/(2-w))*(1-(1-w)^(2*i)));
    cl=t;

 if z1 >= ucl
    plot(a,z1,'rO');
    hold on;
    plot(a,z1,'rx');
    plot(a,ucl,'bV');
    plot(a,lcl,'b^');
    plot(a,cl,'bh');

 elseif z1 <= lcl
    plot(a,z1,'rO');
    hold on;
    plot(a,z1,'rx');
    plot(a,ucl,'bV');
    plot(a,lcl,'b^');
    plot(a,cl,'bh');

  else
    plot(a,z1,'k*');
    hold on;
    plot(a,ucl,'bV');
    plot(a,lcl,'b^');
    plot(a,cl,'bh');

end
    z0=z1;
  %  a=a+0.05;
  a=a+0.05;
end
```

Appendix C: Tables and Calculations

C.4.1: Orthogonal Array of level 2 with 4 experimental runs *OA*(L_4) [50]

Run	*A*	*B*	*C*
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

C.4.2: Orthogonal Array of level 3 with 9 experimental runs *OA*(L_9) [50]

Run	*A*	*B*	*C*	*D*
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

C.5.1: Calculations on Output Data

n	u	y	$u\ y$	y^2
1	1.2367	0.1706	0.2110	1.5294
2	1.1311	0.4495	0.5084	1.2794
3	1.0452	0.6942	0.7256	1.0924
4	0.9950	0.8588	0.8545	0.9900
5	0.9499	0.9654	0.9170	0.9023
6	0.9074	1.0334	0.9377	0.8234
7	0.8708	1.0730	0.9344	0.7583
8	0.8418	1.0915	0.9188	0.7086
9	0.8200	1.0953	0.8981	0.6724
10	0.8044	1.0896	0.8765	0.6471
11	0.7939	1.0787	0.8564	0.6303
12	0.7874	1.0653	0.8388	0.6200
13	0.7840	1.0517	0.8245	0.6147
14	0.7826	1.0389	0.8130	0.6125
15	0.7827	1.0279	0.8045	0.6126
16	0.7837	1.0187	0.7984	0.6142
17	0.7851	1.0115	0.7941	0.6164
:	:	:	:	:
:	:	:	:	:
:	:	:	:	:
49	0.7936	1.0000	0.7936	0.6298
50	0.7936	1.0000	0.7936	0.6298
Sum	-	-	39.6727	34.4775
Average	0.8254	0.9761	-	-
Variance	0.0084	0.0230	-	-

b_0	2.2036
b_1	-1.4872

C.6.1: Calculations on Output Data

n	x	y	$x\,y$	x^2
1.0000	3.0403	0.1049	0.3189	9.2434
2.0000	3.0206	0.4150	1.2535	9.1240
3.0000	2.7728	0.7420	2.0574	7.6884
4.0000	2.3595	1.0314	2.4336	5.5672
5.0000	1.8703	1.2527	2.3429	3.4980
6.0000	1.3821	1.3936	1.9261	1.9102
7.0000	0.9549	1.4545	1.3889	0.9118
8.0000	0.6281	1.4456	0.9080	0.3945
9.0000	0.4199	1.3835	0.5809	0.1763
10.0000	0.3298	1.2877	0.4247	0.1088
:	:	:	:	:
:	:	:	:	:
:	:	:	:	:
46.0000	0.9921	1.0026	0.9947	0.9843
47.0000	0.9928	1.0013	0.9941	0.9857
48.0000	0.9943	1.0002	0.9945	0.9886
49.0000	0.9961	0.9992	0.9953	0.9922
50.0000	0.9963	0.9991	0.9954	0.9926
Sum	-	-	51.9603	77.6505
Average	1.1134	1.0029	-	-
Variance	0.3198	0.0451	-	-

b_0	-0.2467
b_1	1.2775

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