HIGH VOLUME CLOSED LOOP MACHINING SIMULATION

HIGH VOLUME CLOSED LOOP MACHINING SIMULATION

By

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ABSTRACT

Statistical Process Control (SPC) provides tools to monitor process quality and productivity. When coupled with closed loop control theory, SPC algorithms can be utilized to compensate for various error sources in stable, high volume, discrete part manufacturing processes. These error sources include environmental effects, tool wear, measurement, and material errors.

Closed loop machining cells must be analyzed from both Quality and Manufacturing Engineering perspectives for efficient and successful implementation. Discrete, stochastic, time event manufacturing simulation is used to analyze process organization, data flow and control system performance. SPC and Engineering Process Control (EPC) control algorithms are compared using data gathered from a high volume machining process involving steel turned components with a critical machined surface.

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NOMENCLATURE

The following terms and symbols are used in this thesis:

C_p - The Process Capability.

C_{pk} - The Process Capability Index.

d - One half the total feature tolerance, or the tolerance expressed as ±d.

δ - The part feature dimensional error.

$e_g(k)$ - The error goal, zero for parts with no dependent variables.

$e_i(k)$ - The error signal, an input of the SISO single variable controller.

e_{ss} - Steady state error.

g - Controller sensitivity gain, where $0 \leq g \leq 1$.

i - The machine number.

k - The sample number.

λ - EWMA weighting constant.

m - The target value i.e. (USL – LSL) / 2.

n - The sample size, parts in a subgroup.

n_s - The settling time.

pn - The part number.

q - Controller performance rating.

s - The estimated standard deviation of the process.

$S_i(k)$ - The cumulative sum in the CUSUM controller.

σ - The population standard deviation.

T_s - The sampling period.

T_f - The feedback period.

μ - The population mean.

$x_i(kT_s)$ - The independent variable input to the controller.

Y(k) - The controller output.

z - A ratio often used in CUSUM calculations. Also, a popular SPC index.

$$z = \frac{\overline{x_k} - m}{\sigma}$$

z_t - The EWMA control chart variable.

Glossary of Terms and Abbreviations

AIAG. **Automotive Industry Action Group.** A group of companies led by GM, Ford, and Chrysler, that develops quality standards for the North American Automotive parts industry.

AOQ. **Average Outgoing Quality.** The average quality level of production as it leaves the factory. This is often expressed in parts per million or estimated percent defective. It should be noted that unless every outgoing part is tested, this quantity can only be estimated.

APC. **Automatic Process Control.** A control mechanism that automatically corrects a process for disturbances, drift, or error. APC often refers to PI control.

A.R.L. **Average Run Length.** The number of parts required before a statistical flag is triggered. The A.R.L. varies depending on the SPC methods used, the magnitude at type of the disturbance, and the average process variation (noise).

ASPC. **Automatic Statistical Process Control.** Automatic Process Control that employs Statistical Process Control techniques.

Buffering. A delay in data transmission from the feedback signal to the machine controller. Data buffering occurs when part measurement data is provided to the control algorithm but the control action utilizing this data cannot be applied before another part is measured.

CMM. **Co-ordinate Measuring Machine.** A machine that automatically or manually measures parts by individually measuring points in an absolute co-ordinate system. These points are then processed, almost always automatically by computer, into the final dimensional measurements. Most CMMs are fully computer controlled and automatic.

CNC. **Computer Numerically Controlled.** This designation indicates the machine is computer controlled and has the capability of running programs that control the machines functions. For example, CNC Milling Machine refers to a Machining Centre and a CNC CMM refers to a Computer Controlled Co-ordinate Measuring Machine.

Common Cause Variation. The variation in a process that is normally present in a process when it is operating correctly. This is in distinction to "Special Cause Variation" which can be eliminated and occurs when something in a process breaks, malfunctions, or changes. In the case of the SPC-Based Supervisory Controller, "Special Cause Variation" would correspond to the errors introduced by tool wear that the controller attempts to correct for and eliminate. "Common Cause Variation" would correspond to measurement errors that cannot be compensated for. In SPC "Common Cause Variation" is reduced by developing a better understanding of it such that portions can become "Special Cause Variation" and be eliminated.

C_p **Process Capability.** A unitless quality benchmark that ranks uniformity of parts produced by a process.

C_{pk} **Capability Index.** A unitless quality benchmark that indicates how likely the parts being produced are within specifications. Common C_{pk} requirements are 1.33, 1.66, 2.0.

CUSUM. **Cumulative Sum.** An SPC algorithm that tracks consecutive z-indices to develop a measure of whether the process is in-control or out-of-control.

DPMO. **Defects Per Million Opportunities.** A measure of quality nonconformance.

E(IAT) **Expected Inter-Arrival Time.** The time between work items entering a process. For example, the time between customers entering a store, or the time between raw material placed in a machine. This variable is independent of the time to process the work item.

EPC. **Engineering Process Control.** Process Control determined in an engineered and often automatic manner. EPC is a super-set of APC.

EWMA. **Exponentially Weighted Moving Average.** An SPC technique based on the Exponentially Weighted Moving Average which weights each sample at a fraction of the weight of the following sample.

Fliers. A data point outside of expected ranges and not following statistical trend functions. As they do not necessarily follow common SPC curves, like the normal curve, fliers can be exceptionally difficult to predict and control.

GMI **Glueckler Metal Inc.** A manufacturer of machined automotive parts and supplier of metal stock products.

GR&R. **Gauge Repeatability and Reproducibility.** 1. The procedure used to estimate the likelihood of gauges and measuring devices repeating within a certain range. 2. The number expressed as an absolute magnitude within which a gauge is expected to repeat 95% of the time measuring the same part and assuming a normal distribution. The 95% number varies depending on the distribution, GR&R technique, and whether the difference is expressed relative to the previous sample (95%) or the average (98-99%).

GR&R%. **Gauge Repeatability and Reproducibility Percent.** A unitless number representing the GR&R divided by the specification tolerance of the part. By the QS-9000 MSA standard, a 10% or less GR&R% is considered good. A GR&R% between 10% and 30% is considered satisfactory but improvement is recommended. A GR&R% greater than 30% is considered unacceptable.

GWMA. **Geometrically Weighted Moving Average.** The same as EWMA.

In-control. A process that is performing within the SPC specifications set for it.

I.D. **Inside Diameter.** The distance across a drilled or machined hole.

Fixture. The device used to hold a production part in place. Fixtures are used during both machining and measurement.

LSL. **Lower Specification Limit.** The part-print tolerance representing the minimum acceptable condition to the customer.

Mean. The average. The sum of a group of samples divided by the number of samples.

Mitutoyo. **Mitutoyo Canada Inc.** A manufacturer of precision measurement devices, such as CMMs and surface roughness testers.

MMRI. **McMaster Manufacturing Research Institute.** The research group under which this research was conducted.

MSA. **Measurement Systems Analysis.** An AIAG manual considered a part of the QS-9000 standard that specifies a standard method of interpreting quality specifications and performing a GR&R.

Nakamura. A manufacturer of CNC turning machines.

Nominal. The ideal value of a part-print dimension. Normally it is the average of the upper and lower specification limits. It is 10.000 in a dimension of the form 10.000 ± 0.005.

O.D. **Outer Diameter.** The distance across an outside circular feature like a cylinder.

Outliers. Points outside the second or third standard deviations from the mean, depending on the SPC techniques used.

Out-of-control. A process that is not performing within the SPC specifications set for it.

Out-of-Spec. Outside of Specification. 1. A dimension that is not within part-print tolerances. 2. A part that has one or more dimensions that are not within part-print tolerances.

Overcorrecting. Responding to an error with an excessively large correction. This results in error caused by the correction. Similar to Overcontrolling.

Overcontrolling. When the control actions result in an increase in the process variability. This is usually caused either by inaccuracy in the feedback signals or by a controller overcorrecting for error.

Part-print. The QS-9000 controlled document that describes the part measurements. While the part-print can be an electronic document, generally it is a physical piece of paper. This allows the operator, the quality department, the supplier and the customer to all work from the same set of specifications. Generally, the part-print contains all critical dimensional information on the part being manufactured.

PI. **Proportional Integral.** A form of control that computes the control action based on a proportional and integral term derived from the error between the desired output and the actual output.

PID. **Proportional Integral Derivative.** A form of control that computes the control action based on a proportional, integral and derivative term derived from the error between the desired output and the actual output.

Ppb. **Parts per billion.**

QS-9000. A quality standard used by the North American automotive industry and maintained by the AIAG.

Queue. A Simul8 model element. It acts as a buffer stage for parts to accumulate while a work station is blocked or a required resource is occupied.

Repeatability. The variation present when the same gauge measures the same parts within the same operators in the same conditions. Repeatability may be influenced by external variables. Ideally these variables are controlled and specified, but these variables may not always be known, understood, controllable, or specified.

Reproducibility. The variation present when other operators, or laboratories attempt to measure the same parts in similar conditions. In a GR&R test, a specific "operator" or "laboratory" is used to refer to the external variables being tested.

Route. A path between model elements dictating the flow of work items in a SIMUL8 model.

Sensitivity. 1. The controller's ability to respond to small signal levels. 2. A controller parameter that limits the response of the controller to small signal levels.

Set-point. The point at which the process is set. The output of the controller. In theory every process should have an optimal set-point at which the C_{pk} is maximized.

SIMUL8. A program that uses a discrete, stochastic event solver for manufacturing simulation produced by the SIMUL8 Corporation.

Six Sigma. A process management system developed by Motorola. It aims to improve quality by reducing defects and process variability.

Special Cause Variation. Opposite of Common Cause Variation. See Common Cause Variation.

Std. Dev. **Sample Standard Deviation.** A mathematically statistical computation described widely elsewhere.

SPC. **Statistical Process Control.** The application of statistical techniques to control a process. Generally, this is used for manufacturing; however, it can be used in many industries.

Stochastic. A variable or process that has a random probability distribution. This is opposite of deterministic, where the variable is known or fixed.

Subgroup. A sample group of 3 or more consecutive parts used for SPC purposes.

Subgrouping. The act of dividing parts into consecutive sample groups of 34 or more for SPC purposes.

UCLR. **Upper Control Limit for the Range Chart.** The UCLR is a warning line in a Shewhart X Bar R SPC chart.

USL. **Upper Specification Limit.** The part-print tolerance representing the maximum acceptable condition to the customer.

Undercorrecting. Generating an insufficient correction response in a controller. This generally results in stable but not optimal process control.

Unitless. A quantity that does not require units (metre, gram, etc.) Unitless quantities need no unit conversion. An example is the Process Capability, C_p, the Capability Index, C_{pk}, and the z-index.

Variability. Every process should exhibit variation. Depending on the SPC technique, the mean "common cause" variation in a process is referred to as variability. It should be noted that variation can vary significantly from subgroup to subgroup. Changes in the variability metric should indicate meaningful changes in the process.

Variation. Changes in part dimensions from part to part or within subgroups. Variation can vary widely between subgroups due to random process and measurement effects.

Visual Logic. A built-in conversational programming language used to customize SIMUL8 simulation models.

VSI. **Variable Sampling Interval.** An SPC technique in which the sampling interval between subgroups varies and is not fixed. Generally, in–control processes use less sampling than out-of-control processes.

VSS. **Variable Sampling Size.** An SPC technique in which the sample size of each subgroups varies. Generally, in–control processes use smaller subgroups than out-of-control processes.

VSI/VSS. **Variable Sampling Interval / Variable Sampling Size.** An SPC technique in which both the sample size and sampling interval can vary. Additional sampling is triggered for out-of-control processes.

Chapter 1

1 Introduction

1.1 Overview

The objective of this thesis is to provide a method to optimize the quality output of high volume, discrete part machining operations. This was achieved by tuning an existing Statistical Process Control (SPC) based supervisory controller using discrete, stochastic process simulation. SPC theory was applied in conjunction with closed loop control theory to improve the process capability of this application.

A case study will be used to analyze an SPC closed loop control system and the interaction of the control algorithm on the quality and productivity of the system. The case study will focus on the turning operation of a precision automotive component manufactured by Glueckler Metal Inc. (GMI). GMI is located in Barrie, Ontario and focus onsteel bar stock production and on high quality precision part manufacturing from bar stock. As a supplier for the automotive, aerospace, power generation, healthcare, mining, and agriculture industries, their strengths include lean manufacturing, precision machining of steel components and excellent customer service. They are also diversified covering a wide range from steel processing to finishing operations.

Approximately 250,000 parts are produced per month in a custom automated production cell that covers 3,300 square feet. The cell utilizes ten multi-axis Nakamura Tome, Computer Numerically Controlled (CNC) lathes, with underground scrap metal removal. Parts are conveyed through a cleaning station and then a number of inspection stations where various features are checked for burrs, flaws and dimensional accuracy.

Every third part produced from each machine is fully inspected against the part-print specifications on a Co-ordinate Measuring Machine (CMM). The critical bearing surface dimension is inspected on every part using an air gauge. The data from the air-gauge inspection is then fed back into the control algorithm. The SPC Based Supervisory Controller decides whether an adjustment is required and the machine offset is adjusted accordingly. Any nonconforming parts found during this sequence are automatically flagged and isolated. This step eliminates contamination of good parts that may result in a costly release of bad parts to the final customer.

The SPC Based Supervisory Controller is very flexible as it can control a wide variety of manufacturing processes by providing a feedback loop from a measurement device to a machine tool. Process adjustments are made based on various control algorithms based on sampled part data. Generally, in a process controlled by an SPC Based Supervisory Controller, the number of parts sampled and the frequency of sampling can be adjusted as needed by the controller to keep the process targeted on the part-print nominal. The controller must also be able to manage the process and measurement noise, also known as common cause variation. The system is deemed a Supervisor, because it deals with the higher level closed loop communication between the measurement system and CNC, rather than specific machine motion and function control.

In the automotive industry, the standard quality measure is the Capability Index, C_{pk}. Achieving a high C_{pk} requires the process mean to be targeted on the part-print nominal while minimizing process variance. For automotive part manufacturing a C_{pk} below 1.33 or 1.66, depending on the customer, would require 100% inspection of parts. This would normally represent a significant cost to the supplier; however, since the part-print specifies 100% inspection of the critical feature by air gauge, the cost penalty in this case is increased scrap. A key component of lean manufacturing is the minimization of scrap; therefore, it is desired to maximize C_{pk} beyond this range. In this case, output quality is verified by evaluating every part. However, the layout of the cell components may not maximize cell efficiency. Parts are produced continuously to maintain a steady production rate on the machine to avoid process variation that results from changes in machine activity. Therefore, production does not wait for the quality data of the previous part to be returned before the next part is machined. Therefore, to maximize C_{pk} the design of the cell must be considered.

GMI's setup improves profitability through lean manufacturing. The system provides increased productivity, improved quality, reduced floor space requirements and an 80% reduction in labour content. This demonstrates the benefit of integrate advanced manufacturing techniques, such as closed loop machining, into new or existing manufacturing processes.

1.2 The Parts

The automated cell is very flexible. The CNC lathes produce cylindrical parts, such as shafts, pins, or bolts. The CNCs are also equipped with multiple spindles and live tooling. Live tooling attached to the tool turret can be driven, such as a drill or milling cutter. These are used to produce off axis holes or non-cylindrical shapes and features on parts. This allows features that would not ordinarily be produced on a lathe to be achieved. The inspection stations are also flexible as each CMM machine can be configured and programmed specific for the part.

Currently, the cell is configured to machine decoupler shafts for an automotive alternator pulley assembly, as illustrated in Figure 1. The shaft is part of an assembly that allows the serpentine belt to continue moving in one direction after the engine is stopped. It also dampens torque oscillation from the crank shaft due to the combustion cycle. This reduces vibration in the alternator, extending part life, reducing cabin noise, and improving fuel economy. The critical feature on this part that requires improved quality control is a bearing surface.

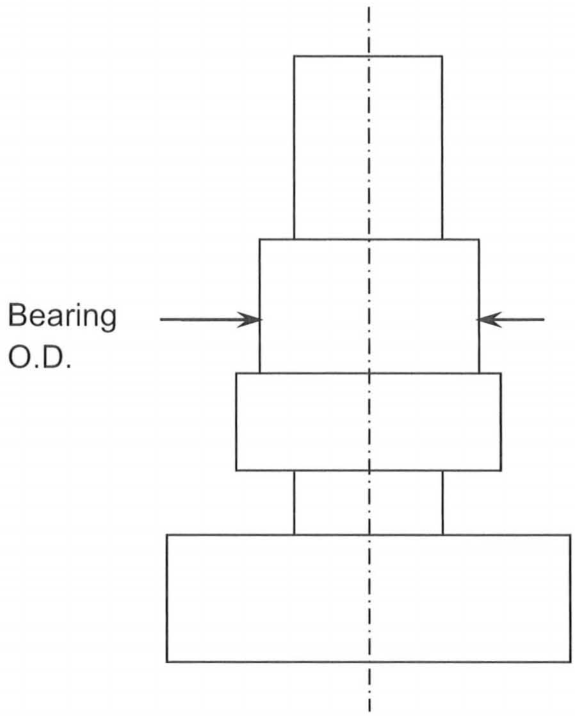

Figure 1: Diagram of GMI Part

The SPC controller must compensate for the various sources of error in the system, such as the environment, tooling, measurement and material variation.

- *Environment*

The primary impact of the environment is the effect of thermal fluctuations and thermal gradients on the machine and work pieces. Positional error occurs in the machine due to thermal growth of machine components. This gradual drift is a low frequency component that can be managed by the control system but a portion of it is generally outside of the position control loop on the machine controller. In this implementation the cell is located in an environmentally controlled area, where temperature and humidity are monitored and controlled.

Contaminants such as dust and machining debris must also be considered as they will have an impact on the performance of an air gauges and a CMM. Dirty surfaces can alter the backpressure on an air gauge and change the effective diameter of a CMM stylus. For this reason regular calibration of the measurement instruments using controlled master parts need to be performed to ensure accurate measurements.

- *Tool Wear*

Since the cutting length per part in this process is small, tool wear will primarily be a low frequency disturbance. High frequency disturbances may be present due to catastrophic cutting edge failure. The SPC portion of the controller will prevent the process from going beyond the upper and lower control limits if a small gradually changing disturbance is encountered. Large rapid changes in part dimension due to tool edge chipping will be detected by the control algorithm and the process shut down and maintenance called. Current tooling for this finishing process will be tested to analyze tool life characteristics.

- *Measurement*

Measurement error deals with the accuracy and precision of the measurement equipment. Gauge performance limits the ability of the process to control dimension within the specification limits. An improperly calibrated gauge will cause the process to shift off centre from the target mean, while poor process repeatability will cause unnecessary variability in the process when operating under closed loop process control.

Factors that influence measuring repeatability are inherent precision, calibration, thermal effects, and contamination. Contamination can occur when parts are not fully deburred or cleaned of coolant and particulate when they are measured.

- *Material*

There will be an error present due to work piece material property variability. This can be minimized through supply control and management.

1.3 Cell Overview

The production cell operates under the "push" method of manufacturing. Material is input at the beginning of the process. The completion of a stage allows the work piece to travel to the next stage where it enters a buffer, or "queue", and then moves onto the next work station if it is cleared. The cell is illustrated in Figure 2. The cell is fully automated. The only operator input required is material loading, tool changing and machine maintenance.

Parts are first machined on CNC lathes. The finished parts wait to be collected by an automated part handling system. First the parts are cleaned and a visual inspection of the threads is completed. From there, a third of the parts are measured for critical dimensions. The remaining parts go directly to a queue. Once the CMM inspection has completed, all three parts are sent to the air gauge for final inspection, if the CMM check passes. Parts that pass all stages of inspection are then loaded into pallets for secondary inspection, if required, then shipping. Any non-conforming parts are ejected from the process and isolated from parts awaiting delivery to the customer.

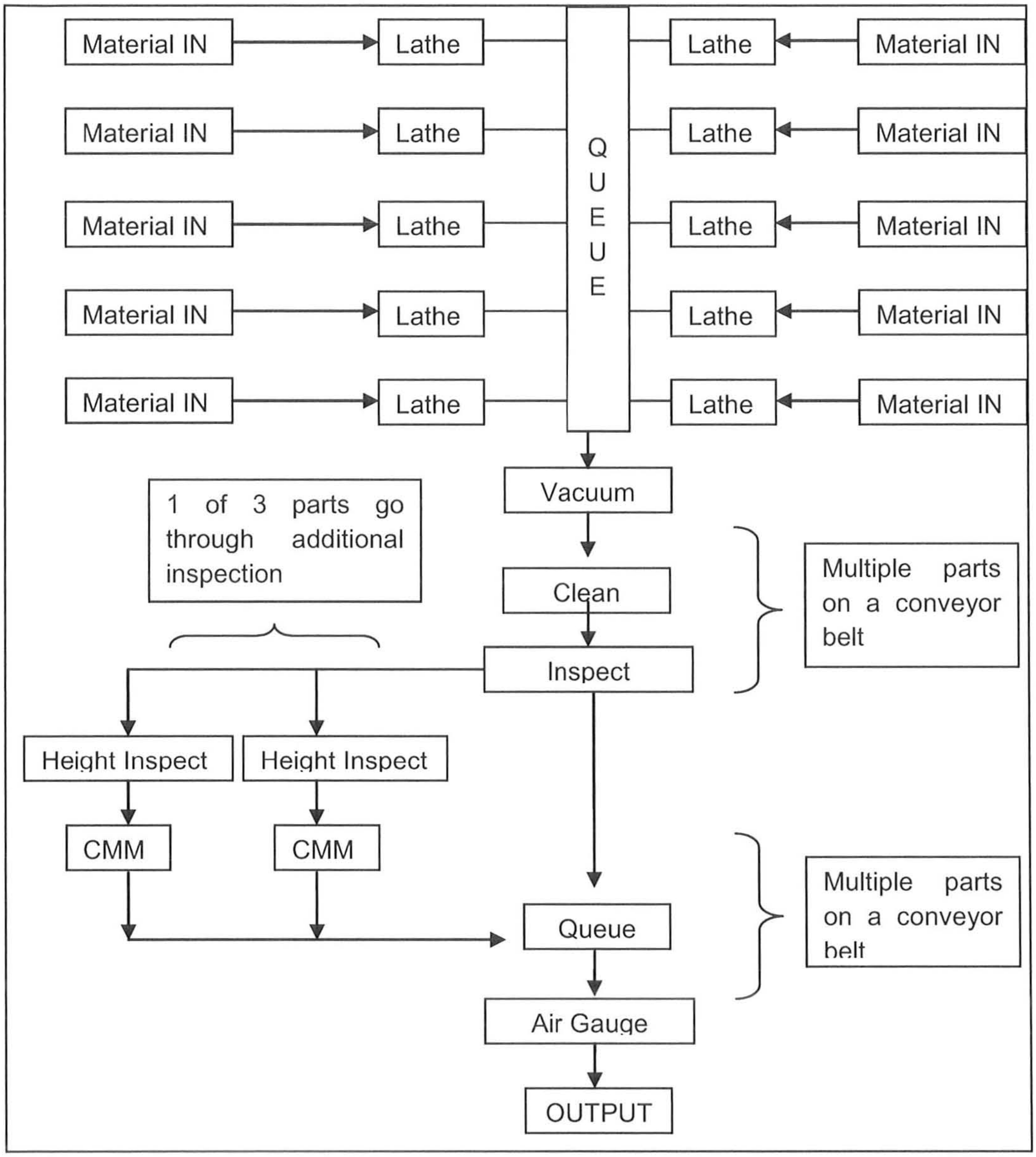

Figure 2: Cell Layout Block Diagram

1.4 Statistical Process Control

Statistical Process Control (SPC) is used for quality control and productivity monitoring. Walter A. Shewhart pioneered the application of statistics to quality control while working at Bell Laboratories in the early twentieth century.

SPC allows an operator to monitor a process and take appropriate control action to set the process mean to the part-print specification. This keeps the process "on-target". This is commonly referred to as "targeting" the process.

1.4.1 Process Capability Indices

Process Capability, C_p, and Capability Index, C_{pk}, are defined in this thesis as:

$$C_p = \frac{USL - LSL}{6\sigma} = \frac{d}{3\sigma} \qquad [1.4.1]$$

$$C_{pk} = \frac{\min(USL - \mu, \mu - LSL)}{3\sigma} = \frac{d - |m - \mu|}{3\sigma} \qquad [1.4.2]$$

These quality measures are widely used, and their performance is described in “Process Capability indices” (Kane 1986).

A comparison of C_p and C_{pk} values are presented in Figure 3 and Figure 4. The error is unitless because C_p and C_{pk} values are relative to the scale of the tolerance zone, which is ±1.0 for both figures.

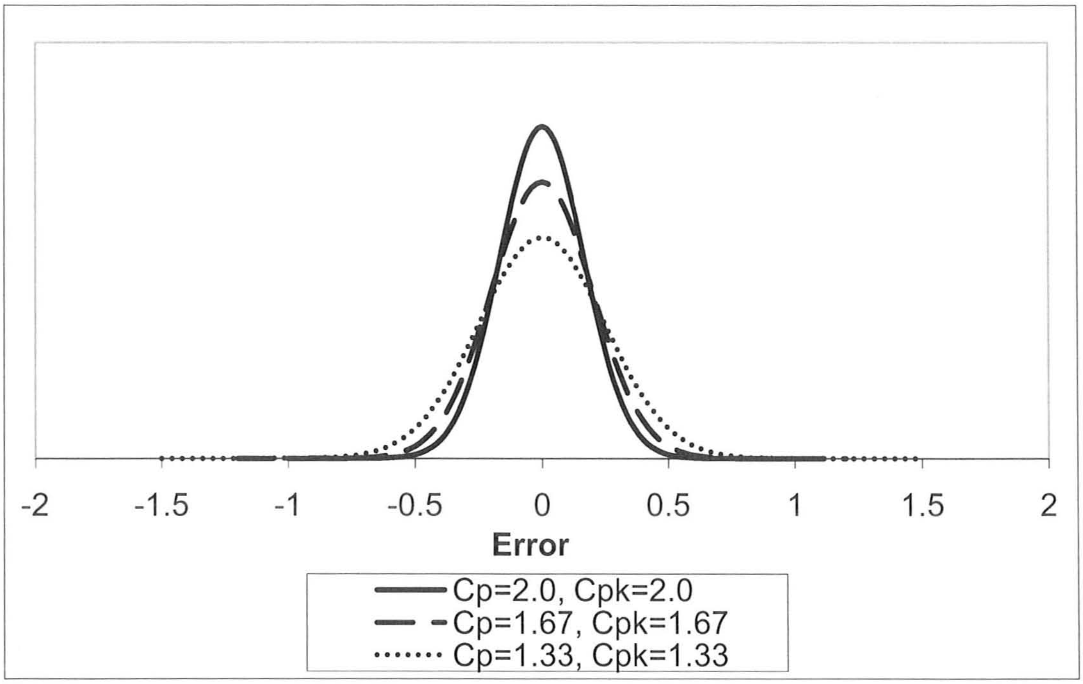

Figure 3: Process Capability Indices C_p Comparison

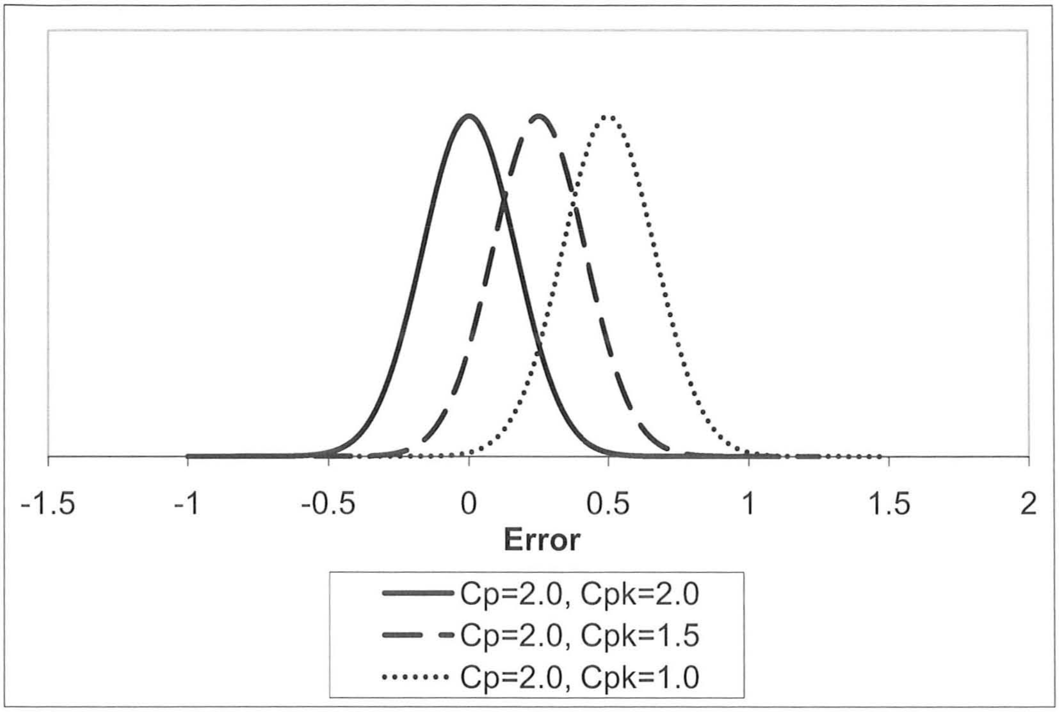

Figure 4: Process Capability Indices C_{pk} Comparison

It is assumed that process data is normally distributed about the process mean. The Process Capability, C_p, describes the range, or spread, of the statistical distribution of probable process values. Process Capability is the potential production capability if the process is centered at the target process mean. The Capability Index, C_{pk}, represents the distribution of the data with respect to the upper and lower specification limits, or the tolerance bounds, of the characteristic. Simply stated, C_p and C_{pk} quantify the repeatability and accuracy of a process, respectively. It should be noted that C_p is only a function of process variance, whereas C_{pk} is a function of both the process variance and the process mean. C_{pk} is maximized when the mean of the process equals the nominal part-print specification and the process variance is minimal. Any drift in the process reduces the C_{pk} to values less than the C_p.

The standard deviation of the process, described by C_p, is determined by the process design and process performance. The standard deviation is a result of both predictable and random error sources. An SPC Based Supervisory Controller maximizes C_p and C_{pk} by attempting to remove predictable error, such as thermal and tool wear drift to target the mean on the nominal part-print specification.

Ideally, the process is tuned to make the C_{pk} value equal to C_p, but this rarely occurs in practice. Typically, a slight mismatch is expected. Some controllers are able to target the process, but increase process variation in doing so and thus reduces C_{pk}. SPC Theory indicates that better C_{pk} performance can be achieved by allowing a process to run slightly off-target but minimizing the process variation. This is often done to account for the trends that occur in production. Generally tool wear and thermal growth are biased to one direction type changes. Typically, SPC process control is conducted by a Quality Engineer. Process control charts track process changes that provide information about the process that can be used to identify trends or increases in process variability. The Quality

Engineer can then adjust process parameters to improve quality output by targeting a process or reducing process variability.

A process controller automates the task of targeting, reducing labour input to a process. Process operators are still required to monitor a process for variability changes, as these often indicate mechanical issues requiring maintenance or replacement. The process controller can utilize various algorithms or control schemes, such as the Shewhart X Bar R Chart described in the following section, to compute the recommended process adjustment based on sampled part data.

1.4.2 Control Charts

The X Bar R Control Chart is very popular in industry. It consists of a top graph depicting the average of the data points in the corresponding subgroup, symbolized by X Bar ($\bar{x}$) and a lower graph showing the range of the data points, symbolized by R. A plot of random data points, simulating process quality data, is shown in Figure 5. Each set of 5 points represents a subgroup of data. The resulting Shewhart X Bar R Control Chart is shown in Figure 6.

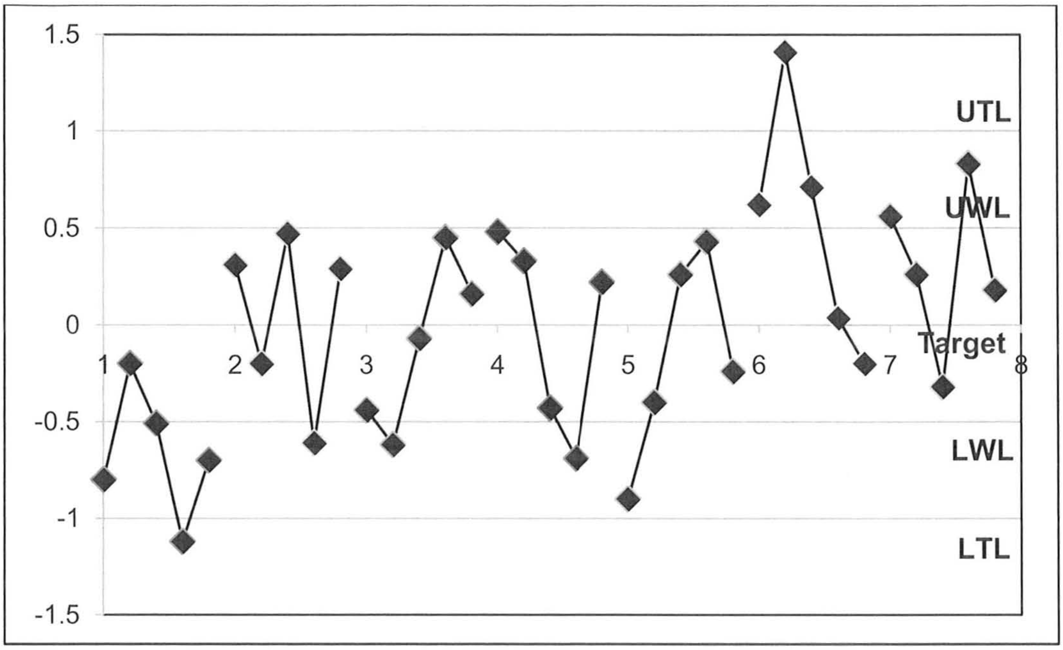

Figure 5: Plot of Random Data Points

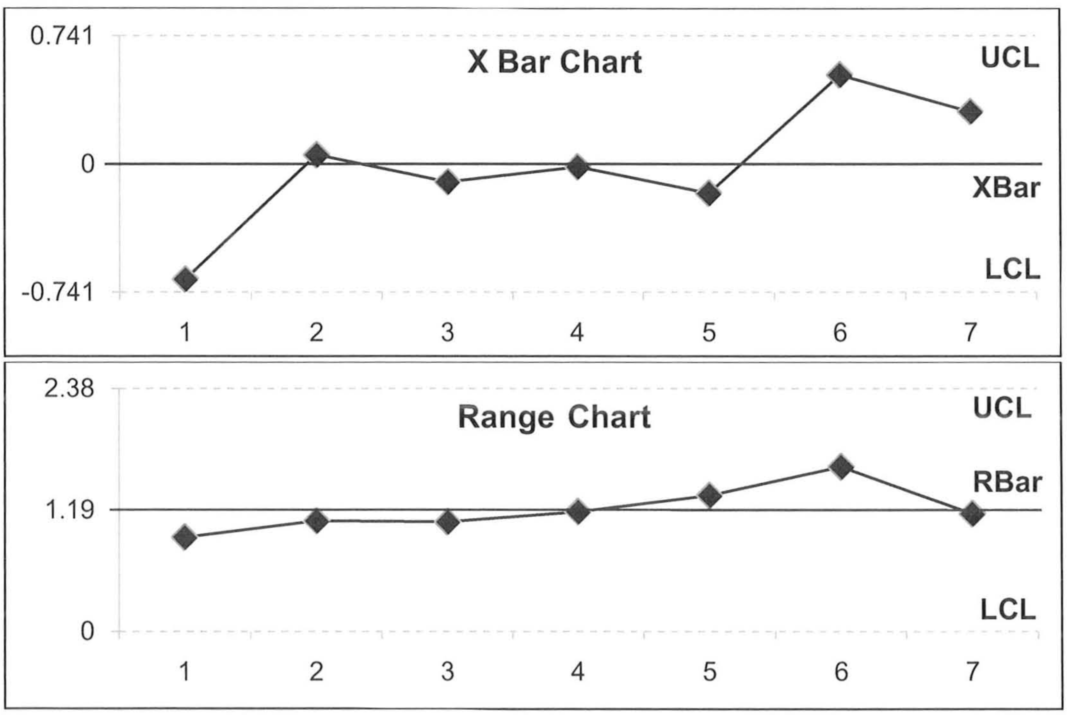

Figure 6: Shewhart X Bar R Control Chart

One chart is used to track each incoming part characteristic. An operator must read, update and interpret the chart before making a process adjustment. This becomes a very complex and time consuming task for complex parts with many critical dimensions. This was the original motivation for developing an automated SPC Based Supervisory Controller.

The upper X Bar graph alerts the operator to trends in the average of the subgroups. The operator can adjust the process to bring it back to target based on this information. This maximizes the Capability Index, C_{pk}.

The lower R Chart alerts the operator to variation in the process. Increases in the process variation can indicate an issue that requires a root cause analysis and resolution. The range is loosely correlated to the standard deviation. Thus the R Chart displays trends in the Process Capability, C_p. Variation displayed in this chart cannot be improved by controller action, but rather through process development or mechanical adjustment or repair of the equipment.

The SPC Based Supervisory Controller analyzes trends in the X Bar Chart and automatically makes adjustments to the process. The controller must alert the operator if increased process variation occurs.

Furthermore, for a stable process, C_{pk} will not be maximized if the controller adjustments increase process variation.

One of the goals of SPC is to react to trends not individual data points, as reacting to outliers can significantly increase process variation when sampling intervals are large. For example, a deadbeat controller may respond to an outlier with a 100% correction. This may cause high scrap rates due to a sample interval of 100 or more parts. In this case, this effect is minimized by reducing sampling intervals. This effect can be minimized by taking measurements from several sequential parts, or a subgroup, then using the average error as the controller input. If 100% inspection is occurring in the cell, the effective sampling interval may not be constant due to delays in the feedback data. This is caused by data flow delays and buffering induced by cell layout design.

1.5 MANUFACTURING SIMULATION

A sample set of production data was gathered to evaluate the effect various compensation algorithms have on the productivity indices C_p, C_{pk}, and scrap rate. The following algorithms will be analyzed: deadbeat, moving average, exponentially weighted moving average, and cumulative sum. Normally, in SPC, these algorithms are implemented in the form of control charts to monitor process changes.

In this application, the control chart is used as the control algorithm and the gauge provides the feedback signal, as shown in Figure 7.

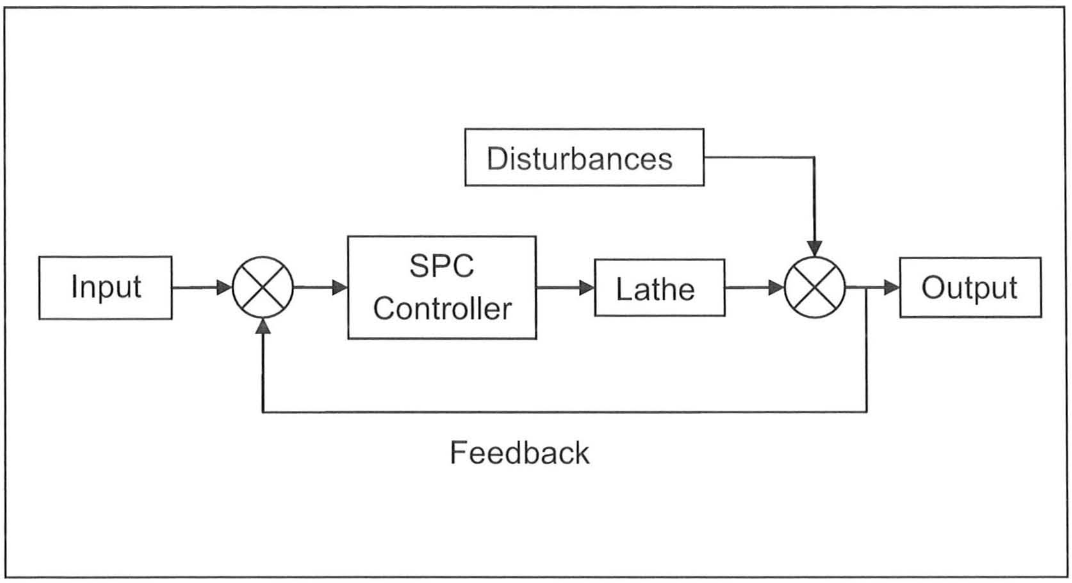

Figure 7: Control System Block Diagram

A sample data set that is representative of typical production is used for lathe error output as a function of part count at each machine. It begins at a tool change and continues until it is replaced, encompassing a single day of production. The data experiences drift due to tool wear, as well as a random noise due to external error sources, as described in section 1.2. White noise is superimposed onto the drift data to account for variation typically seen in machining operations. Different random number sets are used at each machine to reflect different states of maintenance for each machine.

Sample statistics are calculated from this sample set. The production data was uncompensated based on commanded tool offsets for the simulation. An initial offset is provided to centre the data at the production target mean, as would occur with a tool change. Production capability indices are used for comparison, as they would not accurately reflect the performance of a longer term data set, due to the reduced occurrence of outlier data points.

Each algorithm also includes a proportional gain element to minimize the induced variation on the process, such that C_p and C_{pk} are maximized. The control adjustments are limited to three times the standard deviation of the process to prevent outliers and large disturbances, such as tool failure, causing the system to become unstable.

The control system can be optimized by overlaying the control system on a discrete, stochastic, time event simulation of the process. This allows the timing of part production, measurement, and data input to the controller to be evaluated. This data would otherwise be difficult to estimate and may incorrectly be assumed to be constant. Design of the controller algorithm and parameters will be improved with this data, which in turn maximizes the potential quality output of the system.

1.6 Key Topics in this Thesis

The work in this thesis is divided into three main topic areas:

1. Analysis of Measurement Data. The feedback signal to the controller is given by the measurement device. The Process Capability, C_p, is limited by the device's accuracy. The Gauge Repeatability and Reproducibility (GR&R) technique will provide an evaluation of the current and alternative measurement devices.

2. Simulation of the Manufacturing Cell. Design of the cell layout and component positioning can impact the controller performance. Feedback delays reduce the quantity of data being communicated to the controller. Discrete, stochastic time event simulation utilizing process and quality system modelling will allow for the optimization of the cell layout and controller parameters. This allows the Capability Index, C_{pk}, to be maximized. Current and alternative cell configurations will be analyzed to determine key performance characteristics.

3. Control Algorithm Selection & Tuning. Various SPC and EPC based controllers are available. The control algorithm of the SPC Based Supervisory Controller will be evaluated against the performance requirements of this application. It will be tuned to maximize the Capability Index, C_{pk}, and the productivity of the process.

Chapter 2

2 Literature Review

2.1 Overview

This chapter discusses previous work on topics related to Measurement, Closed Loop Manufacturing, SPC, and Manufacturing Simulation. The objective of this research is to show that manufacturing cell productivity and quality can be increased with the use of closed loop feedback control. In this research SPC techniques will be applied to minimize part variation due to underlying process variation and the benefit of detailed manufacturing simulation will be highlighted for configuring and operating a cell.

2.2 Measurement Methods

The AIAG Measurement Systems Analysis Manual (AIAG 1995) is the industry QS-9000 recommended publication on measurement systems. The analysis of measurements is covered in detail.

"Air gauges as a part of the dimensional inspection systems" (Rucki, Barisic and Varga 2010) discussed modern advances in air gauge technology and application for in-process control. This report highlights the robustness of air gauges on the plant floor.

"Accuracy Limitation of Fast Mechanical Probing" (Vliet and Schellekens 1996) discussed issues associated with high-speed mechanical probing. Increased productivity requirements drive faster CMM cycle time requirements when used in production environments, which intensifies the issues identified.

2.3 Closed Loop Projects

In "SPC-Based Supervisory Controller for Closed Loop Machining" (Bering 2003), Bering developed and implemented an SPC Based Supervisory Controller for precision machining aluminum die-cast parts. The effects of the feedback measurement device's Gauge Repeatability and Reproducibility on average output quality (AOQ) is emphasized. Various control algorithms are available depending on the process to which it is applied. This controller is currently used in the automated cell under investigation.

"Error Compensation in CNC Turning Solely from Dimensional Measurements of Previously Machined Parts" (Liu and Venuvinod 1999) Liu and Venuvinod analyzed the problem of compensating a CNC turning process. A CNC lathe was used to turn complex curved profile segments in both low carbon steel and aluminum materials.

Parts were measured on the machine using an on-line touch probe. A CMM was used off-line to calibrate and verify touch probe accuracy. A "Case Based Reasoning" algorithm utilizing historical adjustment data was used to control the feedback loop. This method was able to increase dimensional accuracy to ±5 μm from the uncompensated program error of over 70 μm. Although this method may provide the required machine accuracy, it is not ideal for high volume machining due to increases in cycle time for multiple on-machine measurements per part.

Most machine tool position compensation research modifies tool offsets. Asao, Mizugaki, and Sakamoto (Asao, Mizugaki, and Sakamoto 1992), updated the CNC program to compensate for tool path error. A predictive formula is used to develop program corrections. In this application, the part geometry is very basic, so the controller does not require this capability.

However, Asao, Mizugaki, and Sakamoto's research provides a valuable conclusion. They found that tool movement was reliable up to resolutions of 1µm, meaning a command of positive 1µm resulted in machine movement of approximately 1µm. This is a necessary condition for system stability.

"Autonomous Coordinate Measurement Planning with Work-In-Progress Measurement for TRUE-CNC" (Ng et al. 1998) describes a full closed-loop feedback system implemented with CNCs and an in-line CMM. The TRUE-CNC system does not implement SPC concepts. The CMM and CNC programs were optimized to minimize cycle time for high volume manufacturing.

The TRUE-CNC system updated CNC tool path programs to correct for dimensional errors. This type of system is difficult to implement in production due to the difficulty of interfacing with many types of CNC, CMM and CAD software packages. The SPC Based Supervisory Controller simplifies this process by updating tool position offsets via standardized machine tool interface protocol.

Ament and Goch (Ament and Goch 2001) analyzed a manufacturing process as a series of "holonic cells". The quality of each cell was optimized using both control law and neural network approaches. The process was analyzed as a series of discrete steps. Up-stream quality variation could be minimized by feed-forwarding process information to later down-stream secondary operations.

2.4 SPC Papers

The Shewhart X Bar R chart was introduced in 1.4.2. Two other SPC control chart based algorithms were tested; the EWMA and CUSUM methods are described below. One goal of SPC is not to induce extra variation into the process. This is done by reliably identifying out-of-control processes using control or action limits. Once an out-of-control process has been identified, appropriate control action is applied, based on the selected algorithm.

2.4.1 Shewhart SPC Algorithm

A Shewhart X Bar R Chart tracks trends in averaged process data. If an out-of-control process is identified, corrective action can be taken. The control action is based on the previous subgroup average. An out-of-control process is identified when the subgroup average is charted outside of the upper or lower control limits (UCL, LCL). Ryan (Ryan 1991) defines these limits as:

$$UCL/LCL = \mu \pm k \qquad [2.4.1]$$

where:

k is the distance of the control limits from the process mean, and

μ is the process mean estimate.

The process standard deviation estimate is difficult to estimate during the process. This is simplified by estimating the standard deviation from the expected C_{pk} performance. Six Sigma production standards dictate that six standard deviations fit between the target and the upper or lower tolerance limit. Therefore, for the purposes of simulation, the standard deviation can be assumed as:

$$s = \frac{d}{6} \qquad [2.4.2]$$

where:

d is the distance part-print tolerance specification, and

s is the process standard deviation estimate.

2.4.2 EWMA SPC ALGORITHM

An alternative to the Shewhart X Bar R Chart is the Exponentially Weighted Moving Average (EWMA) SPC Algorithm. This is also referred to as the Geometrically Weighted Moving Average (GMWA) algorithm by Jackson (Jackson 1977). The Shewhart X Bar R Chart equally weights each sample data point when determining the required control response. The EWMA algorithm gives more weight to the most recent sample data in a geometrically decreasing pattern. Twigg and Thomson (Twigg and Thomson 1995, 84) define:

$$z_t = \lambda x_t + (1 - \lambda) z_{t-1} \quad [2.4.3]$$

where:

z_t is the EWMA value from the current iteration,

z_{t-1} is the EWMA value from the previous iteration,

x_t is the sample value from the current iteration, and

λ is the sensitivity parameter of the algorithm and the weight of the current sample.

The input data point, x_t, can be an individual sample data point, x, or the average of a subgroup, $\overline{x}$.

The EWMA action and warning limits are also defined by Twigg and Thomson as:

$$\boldsymbol{Action\ Limit} = \pm 3\sigma\sqrt{\frac{\lambda}{(2-\lambda)}} \qquad [2.4.4]$$

and

$$\boldsymbol{Warning\ Limit} = \pm 2\sigma\sqrt{\frac{\lambda}{(2-\lambda)}} \qquad [2.4.5]$$

where:

σ is the process standard deviation.

During operation, the standard deviation must be estimated. EWMA control chart design is discussed in more detail by Crowder (Crowder 1989) and Ng and Case (Ng and Case 1989).

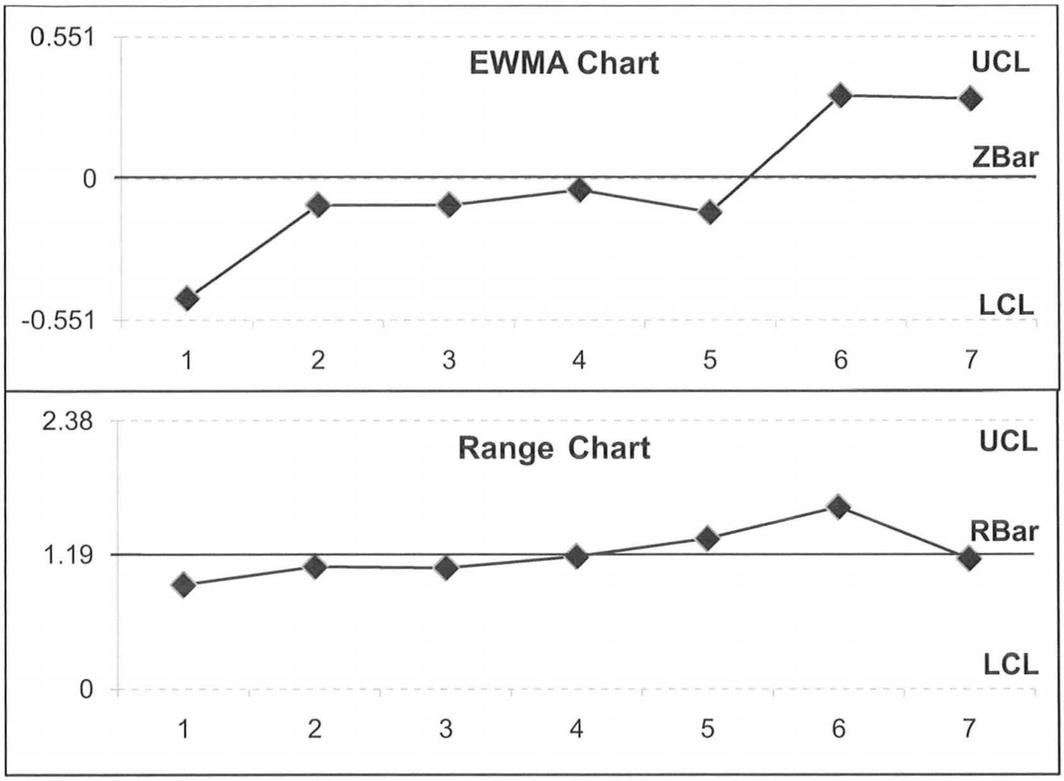

Figure 8: EWMA Control Chart

An EWMA Control Chart based on data presented in Figure 5 is shown in Figure 8 above. The upper graph displays the Z values for each subgroup, as calculated by [2.4.1]. The EWMA chart can be compared to the X Bar R Chart displayed in Figure 6. The EWMA chart does not respond as quickly to a sustained step change, which occurs after group 1. Furthermore, the EWMA chart is affected more by outliers, as the sample in subgroup 6 causes a larger response in subgroup 7.

The EWMA algorithm can be used with Variable Sample Size (VSS) and Variable Sample Intervals (VSI), as described by "EWMA

Control Charts with Variable Sample Sizes and Variable Sample Intervals" (Reynolds and Arnold 2001). Variable Sample Sizes is utilized when data may be missing from a subgroup. Variable Sample Intervals are useful for increasing sampling speed when the process variability increases or the process becomes "out-of-control". In this case, the standard EWMA algorithm is employed.

2.4.3 CUSUM SPC ALGORITHM

A VSS/VSI Cumulative Sum (CUSUM) algorithm is described in Arnold and Reynolds (Arnold and Reynolds 2001). The CUSUM terminology and notation differs from that presented by Ryan (Ryan 1991). This algorithm is used when sampling frequency is low.

A sample CUSUM control chart is shown in Text Box 1. The algorithm alerts the operator of a process change when either the positive Y^+ CUSUM statistic or the negative Y^- CUSUM statistic exceeds the warning limits. The change limit is on the order of *4n* or *5n*, where *n* is the sample subgroup size. The CUSUM chart is computed in a tabular form and no operator graph is displayed. The CUSUM algorithm is very sensitive to process shifts. In this example, a process change of less than one standard deviation was detected in 8 subgroups. However, often a process shift can be detected before a reliable adjustment recommendation can be determined.

Sub-group	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	z-Index	Y^+	Y^-
1	0.951	1.069	0.997	1.041	1.078	0.465	2.33	2.33
2	0.910	0.998	0.980	1.047	0.960	-0.359	0.53	-1.80
3	0.992	0.996	0.950	0.913	1.092	-0.195	-0.44	-0.97
4	1.067	0.956	0.948	1.083	1.100	0.527	2.63	2.19
5	0.985	0.908	1.037	1.018	0.998	0.185	1.71	-0.92
*** A process shift of 0.05 is introduced to the system.								
6	1.073	1.058	1.117	0.954	1.052	0.869	2.74	5.95
7	1.124	1.054	1.031	0.968	1.018	0.667	4.47	4.94
8	1.081	0.95	1.085	0.985	1.026	0.434	5.04	3.78
9	1.127	0.993	1.01	0.978	1.045	0.523	6.05	4.22
10	1.104	1.11	1.117	0.981	1.142	1.553	12.22	9.37
11	1.023	0.995	1.059	1.085	0.697	0.441	12.82	3.81
12	1.1	1.102	0.999	0.977	1.134	1.067	16.55	6.94
13	1.15	0.967	1.122	1.074	1.017	1.129	20.59	7.25
*** Y^+ is greater than the Threshold, a positive process shift has been detected.								

Nominal, m	1.000
Tolerance, d	0.300
c_3	0.0625
Standard Deviation Estimate	0.058
Average Subgroup Size, n	5
h	4
Threshold (h*n)	20

Text Box 1: CUSUM Control Chart

In the application under investigation, a simplified CUSUM algorithm was implemented because the sampling frequency is high. This version of the algorithm provides a process adjustment recommendation. The simplified algorithm used a cumulative sum of each part's error and reported when the positive or negative thresholds were exceeded. This version of the CUSUM algorithm is described by Downing and Sorenson (Downing and Sorenson 2002).

2.4.4 Average Run Length (A.R.L.)

Average Run Length (A.R.L.) is used to characterize SPC algorithms. This metric describes the algorithms ability to detect a process change, where, generally a shorter A.R.L. indicates better performance. The A.R.L. represents the number of parts required before a statistical flag is triggered. The A.R.L. varies depending on the SPC methods used, the magnitude and type of the disturbance, as well as the average process variation (noise). A controller's overall performance must also be judged on its ability to provide a recommended response to a process change.

Average Run Lengths are an integral part of SPC research. A comparison of Shewhart X Bar R and CUSUM algorithm performance are given by Ryan (Ryan 1991). Average Run Lengths from algorithms with smaller sample sizes and no subgrouping is discussed in "Monitoring Process Dispersion Without Subgrouping" (Acosta-Mejia and Pignatiello 2000). "CUSUM Charts for Signalling Varying Location Shifts" (Sparks 2000) looks at two sophisticated CUSUM algorithms.

Average run length is also a function of chart sensitivity. Chart sensitivity is discussed in "Evaluate Control Procedures by Examining

Errors in Process Adjustment" (Jackson 1977). Possible control chart responses are differentiated into four categories:

> "$\gamma 1$ – probability of undercorrecting
> $\gamma 2$ – probability of overcorrecting, but still improving
> $\gamma 3$ – probability of overcorrecting in excess
> $\gamma 4$ – probability of adjusting in the wrong direction" (Jackson 1977).

Jackson's analysis includes the Shewhart X Bar R, EWMA (GWMA) and CUSUM control charts. Simulations were used to model the likelihood of each situation, and the relationship between sensitivity and overcorrection. Introducing a sensitivity parameter for each control chart, similar to proportional gain, allows for the tuning of the controller response to increases the algorithm's performance.

2.4.5 Process Control and SPC

SPC theory was introduced by Shewhart and Deming prior to World War II (Shewhart 1939). Recently, the relationship between conventional control theory and SPC theory has been examined in more detail. Various terms are used to describe this area of research, such as "PI" (Proportional Integral) Control, "EPC" (Engineering Process Control), "APC" (Automated Process Control), and "ASPC" (Automatic Statistical Process Control).

2.4.5.1 Engineering Process Control (EPC)

"A Comparison of Statistical Process Control and Engineering Process Control" (Box, Coleman and Baxley 1997) discussed when each control method performs best. Statistical Process Control is defined as using a control chart to target a process, whereas, Engineering Process Control or Automatic Process Control are controllers that utilize more traditional PI (Proportional Integral) control techniques.

Box, Coleman, and Baxley (Box, Coleman and Baxley 1997) argued that complex SPC analysis can be eliminated when a conventional PI controller converges on a solution quickly. Traditional SPC analysis looks for a trend, identifies causes, and makes a long-term correction. SPC techniques excel in processes where little drift occurs with time, and the active PI controller performs well with processes that display continuous drift.

"Integrating Statistical Process Control and Engineering Process Control" (Montgomery et al. 1994) examined the relationship between SPC and EPC, in the context of chemical and continuous processing plants. They concluded:

> "The integrating of EPC and SPC has potentially desirable results. EPC can be used to minimize deviations from target due to disturbances that occur continuously and are part of the process itself, and SPC applied to the output deviation from target can be used to identify and subsequently eliminate assignable causes" (Montgomery et al. 1994).

The SPC Based Supervisory Controller developed by Bering (Bering 2003), utilizes both alarm (SPC) and control (EPC) functionality in its SPC algorithms. However, the SPC Based Supervisory Controller does not include a PI based controller. This thesis examines the performance of a PI controller, in addition to the existing SPC algorithms available.

Further discussion on this topic is found in (Janakiram and Keats 1998), (Box and Kramer 1992), (Jian and Tsui 2000), and (Wiel et al. 1992).

2.4.5.2 PID SPC-Based Continuous Time Controllers

Twigg and Thomson (Twigg and Thomson 1995) employed a Control Loop Supervisor algorithm using SPC techniques with a PID feedback loop in a heat exchanger controller. The supervisory controller determined the PID control mode based on SPC events. When the process was stable, no control action was used. If drift or a trend was identified, integral action was used to slowly re-target the process. If warning or action limits were exceeded, then aggressive PID control action was used to bring the process back in control.

The SPC Based Controllers used in this work are discrete-time controllers. Castillo (Castillo 2000) proposed a variance-constrained self-tuning PI controller. This type of controller must balance the process variance with the variance induced by adjustments. Optimal algorithm parameters are determined by the controller when constrained by the process variance. A self-tuning controller is not ideal because step response time performance is decreased because the controller does not begin with optimal algorithm parameters. Closed loop manufacturing simulation allows the quality engineer to determine optimal parameters *a-priori*.

2.4.6 Alternative Compensation Mechanisms and Control Strategies

Various in-process machine tool position compensation strategies have been analyzed to improve CNC accuracy. Typically, previous parts or real-time measurements were used to improve machine position accuracy.

- "A Study on the Development of a Three Dimensional Linear Encoder System for In-Process Motion Error Calibration and Compensation of Machine Tool Axis" (Yamazaki et al. 2000)
- "A Method for Enhancing the Accuracy of CNC Machine Tools for ON-Machine Inspection" (Mou and Liu 1992) used reference parts to develop error models for machine tool position compensation.
- "Geometric Error Measurement and Compensation of Machines" (Sartori and Zhang 1995) discussed the evaluation of measurement effectiveness and examined error compensation methods and strategies.
- "In-Process Control of Workpiece Dimension in Turning" (Shiraishi 1979) used a laser system to determine the position of the workpiece.

- "CNC Machine Accuracy Enhancement Through Real-Time Error Compensation" (Ni 1997) used force and position feedback to compensate tool position on a horizontal milling center.

- "A Strategy for the Compensation of Error in Five-Axis Machining" (Veldhuis and Elbestawi 1995) developed a method to compensate machine position using temperature data from various elements of a machine.

- "Task Specific Uncertainty in Coordinate Measurement" (Wilhelm, Hocken, and Schwenke 2001) discuss available techniques for compensating CMM position. Some techniques are also applicable for machine tools.

- "Repetitive Measurement and Compensation to Improve Workpiece Machining Accuracy" (Liu 1999) compensated machine position based on the error between actual tool depth and the measured setup position, caused by tool wear, tool deflection and workpiece deflection.

2.5 Manufacturing Process Simulation Papers

Discrete time event simulation is a tool often used in industry to optimize productivity and minimize process costs. Most simulation programs utilize an object oriented, queuing theory based modelling environment. Modelling of the automated cell in this application was completed in SIMUL8, an industry leading, desktop, process modelling software package.

"Simulation modeling handbook: a practical approach" (Chung 2004) provides practical techniques and examples for simulation modelling which are independent of commercial software packages.

"Stochastic Simulation" (Riley 2006) is a comprehensive guide to stochastic simulation methods and algorithms. Ripley discusses random number generation, non-uniform random variables and stochastic processes.

"Handbook of simulation: principles, methodology, advances, applications, and practice" (Banks 1998) is a comprehensive resource for discrete-event simulation with applications to various industries. Recent advances in simulation methods and various simulation software packages are discussed. Techniques for best-fit distribution were used to select appropriate probability distribution functions to measured process data.

In "Discrete event simulation and cost analysis for manufacturing optimisation of an automotive Liquid Composite Moulding component" (Kendall, Mangin, and Ortiz 1998), discrete event simulation is coupled with a technical economic cost model to evaluate various process scenarios and production line layouts.

In "Choice of inspection strategy using quality simulation" (Tannock 1995), uses the Taguchi method (Taguchi 1981) to calculate quality costs of various inspection strategies, i.e. no inspection, sample inspection, or full inspection, for a range of quality levels based on the Capability Index, C_{pk}. Tannock's results show no differentiation between inspection strategy costs at C_{pk} values greater than 1.

CHAPTER 3

3 THEORY

3.1 OVERVIEW

The controller utilized in this application provides three different SPC algorithms for the user to select based on the process under control. These are: Moving Average, EWMA and CUSUM. An additional Proportional Integral control algorithm is included for comparison.

SPC process control charts are used to alert the operator of process changes that may require corrective action. An experienced operator is required to determine the appropriate response to an alert. The SPC-Based Supervisory Controller automates the process of detecting and responding to changes in the process mean. Changes in process variability are less frequent, and are left for operator investigation.

The controller acts as a Single-Input Single–Output (SISO) controller for each machining center. This functionality is the focus of this chapter.

3.2 Part-Print Specifications

The QS-9000 quality system is used in the automotive industry. This system requires that all part drawings are monitored and controlled to ensure final part production meets critical part-print specifications. Critical characteristics are listed on a part-print, for supplier or customer reference.

The controller uses the part-print specification for critical characteristics in the form $m \pm d$, where m is the part-print target and d is the tolerance. This information is used to target the process and compute quality characteristics, such as the Capability Index, C_{pk}.

3.3 Targeting the Process Mean

Targeting the process mean can generally be achieved through automatic control. For example, on a CNC machine, adjustment of the tool or part offset can achieve this goal. Simple disturbances, such as tool wear, can be compensated for automatically in this manner.

Alternatively, reducing process variability is more difficult to correct automatically, as most root causes of variation require operator or maintenance level intervention. An example of a large variability change is catastrophic tool failure, where an operator must change the tool. An example of a gradually growing variability is a worn ball screw that can be ignored until it needs to be replaced by maintenance. Low process variability readings can also be a concern, as it could indicate a control system or feedback loop malfunction.

3.4 SPC ANALYSIS

Generally, SPC reduces inspection cost by eliminating 100% inspection by providing a high confidence level that future part quality will fall within the part-print specification. This reduces the cost of inspection and can often allow for an increase in productivity.

The goal of the SPC-Based Supervisory Controller is to:

1. Target the process mean on the part-print nominal, and

2. Maximize the Process Capability, C_p, and the Capability Index, C_{pk}.

The first goal is stated mathematically by defining the quality index, q, of the controller as:

$$q = \frac{|\mu - m|}{s} \qquad [3.4.1]$$

The Process Capability, C_p, is defined as:

$$C_p = \frac{USL - LSL}{6s} = \frac{d}{3s} \qquad [3.4.2]$$

The Capability Index, C_{pk}, is defined as:

$$C_{pk} = \frac{min(USL-m, m-LSL)}{3s} = \frac{d-|m-\mu|}{3s} \quad [3.4.3]$$

Substituting [3.4.1] and [3.4.2] into [3.4.3] gives:

$$C_{pk} = C_p - \frac{q}{3} \quad [3.4.4]$$

In a perfectly targeted process, the process capability equals the capability index; therefore, it is the goal of the controller to minimize q to zero.

Maintaining a q less than 1 will achieve a C_{pk} greater than 1.66. In other words, the process mean must be held within one standard deviation of the part-print target to achieve industry recommended quality standards.

Six Sigma production goals call for a C_{pk} value of 2.0, which corresponds to 3.4 defects per million opportunities (DPMO). Alternatively, this corresponds to 99.99966% of products being defect free. The recommended minimum C_{pk} for an existing process is 1.33, whereas a new process is recommended to have a minimum of 1.67.

The quality index, q, defined in this form is similar to the popular z index described in Ryan (Ryan 1991, 103) and Smith (Smith 1991, 150). Similarly, the quality index is unitless and not dependent on the part tolerance, d.

The goal of SPC is to minimize process variance. For an in-control process, the controller input may represent some of the largest process variation. Therefore, in practice, it is important to use random sampling, outside of the controller samples, to compute C_p and C_{pk}.

3.4.1 SPC CONTROLLERS

The following controllers were adapted from SPC control charts. The Moving Range Average Controller is based on the Shewhart X Bar R Chart. The EWMA and CUSUM controllers are based on their respectively named control charts. A 3 part moving range (MR3) will be used in this controller.

The error signal is calculated from the feedback loop as:

$$e_i(kT_s) = x_i(kT_s) - m - e_g(kT_s) \qquad [3.4.5]$$

where:

$x_i(kT_s)$ is the sample measurement,

m is the process part-print target mean,

$e_g(kT_s)$ is the error goal, and

$e_i(kT_s)$ is the sample error.

Since the sample time T_s is not constant, the sample error notation is simplified to $e_i(k)$.

An error goal may be used if the part feature has dependent variables that may influence the quality of the feature in later operations. In this application, the error goal is zero.

3.4.1.1 Moving Range Averaging Controller

The moving range averaging controller is based on the Shewhart X Bar control chart. In this case, a three part moving range subgroup was used. This controller translates to simple subgroup averaging when continuous sampling is not implemented. The average of the three parts in the subgroup is used. A sensitivity gain was added to the algorithm to optimize controller output quality due to reasons described in 2.4.3. Mathematically, the controller output is calculated as:

$$Y_i(k) = g \times \frac{\sum_{j=0}^{n-1} e_i(k-j)}{n} \qquad [3.4.6]$$

where:

g is the sensitivity gain,

$e_t(k)$ is the error signal input to the controller, and

n is the number of samples in the subgroup.

This is a good controller for the discrete part industry, such as automotive. Usually, the previous part is a poor indicator of the next part quality. Outliers, or "fliers", are often present in production and exhibit large random errors. By comparing values to production averages the trends become apparent and identifying fliers is easier. Production problems due to the presence of fliers drove the widespread adoption of the Shewhart X Bar R chart in industry.

If a deadbeat controller is used, one which uses the error of the previous part to correct the next, a flier will result in multiple scrap parts instead of only one. This algorithm reduces the flier effect by waiting for two consecutive subgroup averages to occur outside of the control limits, as defined by [2.4.2].

3.4.1.2 EWMA Controller

The EWMA controller implements the Exponentially Weighted Moving Average algorithm. Generally, this controller places more emphasis on process trends rather than small process changes. This controller performs well when the previous part is a good indicator of the next sample.

The Twigg and Thomson (Twigg and Thomson 1995) EWMA iteration equation, modified with sensitivity gain, g, is computed as:

$$\boldsymbol{Y_i(k) = g \times z_t = g \times [\lambda e_i(k) + (1-\lambda) z_{t-1}]} \qquad [3.4.7]$$

where:

g is the sensitivity gain,

$e_t(k)$ is the input error from the current iteration,

z_t is the EWMA output value that appears on the control chart, and

λ is the EWMA control constant.

This algorithm also reduces the flier effect by waiting for two consecutive subgroup averages to occur outside of the action limits, as defined by [2.4.4].

3.4.1.3 CUSUM CONTROLLER

The simplified CUSUM algorithm, as described by Downing and Sorenson (Downing and Sorenson 2002), is utilized in this CUSUM controller. This controller acts similarly to an integral controller, which reduces steady state error. This controller also performs well when the previous part is a good indicator of the next sample. The CUSUM controller output is calculated by:

$$Y_i(k) = g \times S_i(k) \qquad [3.4.8]$$

$$S_i(k) = S_i(k-1) + e_i(k) \qquad [3.4.9]$$

where:

g is the sensitivity gain,

$e_t(k)$ is the input error from the current iteration, and

$S_i(k)$ is the cumulative sum.

The CUSUM iteration equations for single part sampling are defined as:

$$Y^+(0) = 0 \qquad [3.4.10]$$

$$Y^{-}(0) = 0 \qquad [3.4.11]$$

$$Y^{+}(k+1) = \max(Y^{+}(k), 0) + \frac{x(k)+c_3 d}{s} \qquad [3.4.12]$$

$$Y^{-}(k+1) = \min(Y^{-}(k), 0) + \frac{x(k)+c_3 d}{s} \qquad [3.4.13]$$

Control action is taken when the CUSUM positive or negative thresholds are exceeded. This occurs when:

$$\max\left(Y^{+}(k+1), -Y^{-}(k+1)\right) \geq hn \qquad [3.4.14]$$

where:

x is the input sample data,

s is the standard deviation estimate,

c_3 is a sensitivity constant affecting the ability of the algorithm to center the process, set at c_3=1/16 for this application.

h is a sensitivity constant affecting the ability of the algorithm to detect process changes, typically either 4 or 5, set at 4 for this application, This is analogous to the UCL and LCL of the X Bar R Chart or EWMA control algorithms.

n is the number of parts in a subgroup, in this case n=1, and

$Y^{+(}$k+1) and Y^{-}(k+1) are the CUSUM iteration variables.

The CUSUM controller will perform best on normally distributed data. In practice, this is often not the case as many errors are one sided. Surface contamination will skew the distribution because debris may not be fully cleaned from the inspected surface. Tool wear drift will not be normally distributed, as the O.D. will increase as the tool wears. Furthermore, as the tool wears, more heat will be generated and consequently be transferred to the part. This may cause thermal growth of the part during machining, causing the O.D. to be consistently under sized when the part cools.

3.5 Linear Control System Analysis

The following block diagram is developed based on classic control theory:

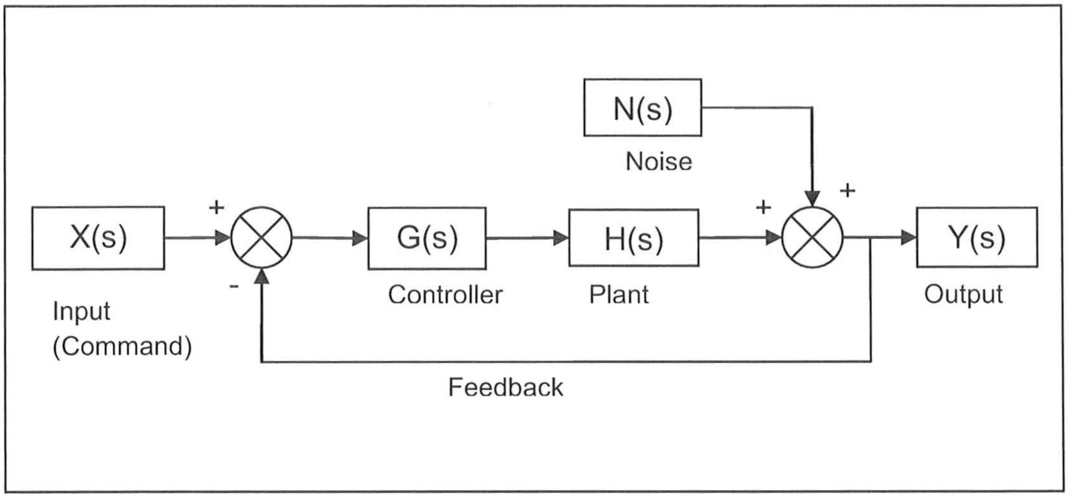

Figure 9: Simple Continuous Time Controller Block Diagram

This control system is characterized by the following transfer function:

$$Y(s) = \frac{N(s)+G(s)H(s)X(s)}{1+G(s)H(s)} \quad [3.5.1]$$

where:

x(s) is the input signal or the command signal,

Y(s) is the output signal,

N(s) represents a noise source in the system,

G(s) is the transfer function of the controller, and

H(s) is the transfer function of the plant.

From the above equation, there are three possible modes of operation:

1. $|G(s)H(s)X(s)| \gg |N(s)|$
2. $|G(s)H(s)X(s)| \approx |N(s)|$
3. $|G(s)H(s)X(s)| \ll |N(s)|$

Typically, feedback systems operate in the first mode. The feedback signal cancels the effects of noise or plant model uncertainty. The second mode occurs when small amplitude or low frequency inputs are present allowing noise to obscure the signal. The third mode of operation occurs when a fixed input signal is present and noise is a dominant source of error in the system.

The SPC Based Supervisory Controller operates in the third mode. The part-print target is known and constant; hence, it is used as the set point input, where the desired error is zero.

As with most modern controllers, the SPC Based Supervisory Controller is digitally implemented as a discrete time controller. If G and H are taken as constants, as is the case with the control algorithms described in this thesis, the following discrete time equation results:

$$\boldsymbol{y(t+1) = [x(t) - y(t)]GH + n(t)} \qquad \textbf{[3.5.2]}$$

where:

x(t) is the input signal,

y(t) is the output signal,

G and H are constants,

n(t) is the noise source,

t is the time period, and

t+1 is the next time period.

If a fixed set point, or constant input is used, it follows that x(t) = x(t+1), and if the above equation is expanded to y(t+2), the following results:

$$\boldsymbol{y(t+2) = x(t)(1 - GH)GH - y(t)G^2H^2 - n(t)GH + n(t+1)}$$

[3.5.3]

The above equation shows that n(t) is multiplied by GH. If the noise source is perfectly random, the optimal value of GH is zero such that noise is minimized.

The above situation is an example of how adaptive control algorithms "de-tune" when presented with a stable process. When a large amplitude disturbance occurs, the algorithm parameters no longer have the optimal values to provide the desired response. The optimal parameter settings vary depending on the mode of operation. Specifically, in the third mode of operation, the optimal parameter values for a PID control are zero derivative gain, a proportional gain set based on the sequential correlation between the noise samples and a small integral gain to reduce the average error to zero.

3.5.1 PI Controller

The Proportional-Integral (PI) controller is used for comparison against the SPC based algorithms. The proportional action allows for quick response to large disturbances, such as step changes due to tool change. The proportional gain should be kept low to reduce the influence of fliers. The integral action is included to correct for process drift.

The PI controller, based on the form described by Box and Luceño in “The Anatomy and Robustness of Discrete Proportional-Integral Adjustment and Its Application to Statistical Process Control” (Box and Luceño 1996), is formulated as:

$$Y_i(k) = k_0 + k_1 e_i(k) + k_2 \sum_{k=1}^{t} e_i(k) \qquad [3.5.4]$$

where:

$Y_i(k)$ is the controller output set point,

k_0 is the initial level of the controller output variable ($Y_i(0)$), typically set to zero,

k_1 is the proportional gain, and

k_2 is the integral gain.

This controller can also be formulated for incremental changes to the controller output set point, such that $y_i(k)=Y_i(k)-Y_i(k-1)$, as follows:

$$y_i(k) = c_1 e_i(k) + c_2 e_i(k-1) \quad [3.5.5]$$

with,

$$c_1 = k_1 + k_2 \quad [3.5.6]$$

$$c_1 = -k_1 \quad [3.5.7]$$

In this case, the original formulation was used.

3.6 SUMMARY

Many SPC and EPC based algorithms are available for closed loop manufacturing. The Moving Average, EWMA, CUSUM, and PI controllers are presented here. The performance of the different controllers will be compared to select the best controller for each cell layout and operating mode.

Chapter 4

4 Experimental Setup

4.1 Overview

This chapter outlines the tools and techniques used in the laboratory and for the simulation experiments. Gauge Repeatability and Reproducibility (GR&R) techniques are used to characterize measurement error. This provides a maximum limit on the quality output of the system.

An overview of the SIMUL8 modelling process is provided. The current cell layout and a second alternative layout concept are presented. The models are used to evaluate the performance of the control system and various algorithms.

4.2 Measurement Issues

The performance of the closed loop feedback system will be limited by the accuracy of the measurement device. In this implementation, an air gauge is used to measure the outer diameter of the critical feature. The use of an air gauge improves process time and eliminates some measurement error sources encountered with a CMM.

On-machine measurement is when probes mounted in the machine measure part dimensions before the part is removed from the machine. On-machine measurement techniques can eliminate feedback delay and measurement data buffering by immediately providing measurement data once the process has completed. This method can be used when part scrap costs outweigh the cost of increasing machining process time.

The machining process generates heat that distorts part geometry. Offline part measurement allows parts to reach ambient temperature before measurements are made. The machine environment also contaminates measured surfaces. Effort must be made to ensure that parts are thoroughly cleaned and temperature effects are compensated.

4.2.1 Gauge Repeatability and Reproducibility

Gauge Repeatability and Reproducibility is a process that can be used to quantify a gauge or measurement device's ability to be repeatable and reproducible. Repeatability refers to variation between measurements of the same part under the same conditions. Reproducibility refers to variation between measurements of the same part under different conditions. Typically, reproducibility represents the influence of different operators on the measurement result. With automated instruments, the operator influence should be zero. Interaction measures the influence between the appraisers and parts.

However, in practice, the reproducibility in a GR&R study is often not zero. This is due to various factors:

- Operators or robots may handle parts differently, due to subtle variation in part dimension or finish, when presenting them to a fixture or automated device, which may cause the part to nest on the fixture differently and slightly skew the results. Different operators may also handle the parts differently. This can cause temperature or cleanliness on the surface of the part to vary. This can affect surface finish and cause slight dimensional changes.

- The GR&R test will have some amount of “procedure error”. This is due to the finite number of samples taken for a statistical test which will not agree with a test taken using an infinite number of population samples. This results in a confidence interval for the GR&R results, as discussed in “Confidence Intervals on Measures of Variability in R&R Studies” (Burdick and Larsen 1997).

- GR&R testing requires repeated testing of the same set of parts. This can cause normal deformation due to mechanical and thermal stress, as well as thermal or humidity changes. Deformation can be caused by part handling or part clamping (Vliet and Schellekens 1996).

- External variables, such as temperature and humidity, may change during the test procedure. This can affect the test equipment or the parts.

Due to these effects, the total GR&R number, which includes both repeatability and reproducibility, is more representative of the process than the individual repeatability and reproducibility results of the equipment being used. A GR&R% represents the total GR&R as a percentage of the part-print tolerance band specification. A value of 10% is considered good, 10%-30% acceptable and >30% requires remedy.

4.2.2 Gauge R&R Format

For the automotive industry, the GR&R procedure is defined under the QS-9000 standard. The recommended procedure is shown in MSA (AIAG1995). The calculations on how to compute the GR&R values from the form are given in (AIAG 1995, 57-58) and (Smith 1991, 212-213).

The test conducted utilized the 2 Operator and 3 Tests per Operator format for GR&R, in which 10 sample parts are randomly chosen. Each operator measures each part 3 times. A sample GR&R sheet is displayed on the following page.

GR&R Sheet

Operator #1		**Trial #1**	**Trial #2**	**Trial #3**
	Part 1	________	________	________
	Part 2	________	________	________
	Part 3	________	________	________
	Part 4	________	________	________
	Part 5	________	________	________
	Part 6	________	________	________
	Part 7	________	________	________
	Part 8	________	________	________
	Part 9	________	________	________
	Part 10	________	________	________

Operator #2		**Trial #1**	**Trial #2**	**Trial #3**
	Part 1	________	________	________
	Part 2	________	________	________
	Part 3	________	________	________
	Part 4	________	________	________
	Part 5	________	________	________
	Part 6	________	________	________
	Part 7	________	________	________
	Part 8	________	________	________
	Part 9	________	________	________
	Part 10	________	________	________

Text Box 2: GR&R Sheet Format

4.2.3 Effect of GR&R on the Capability Index - C_{PK}

The maximum achievable capability index C_{pk} is limited by the GR&R results. A GR&R provides the 95% confidence interval for measurements of the same part. This increases to the 99% confidence interval for the part averages. Further details on GR&R are outlined in "The Nature of Repeatability and Reproducibility" (Mandel and Lashof 1987).

GR&R results are commonly specified as a percentage of tolerance. This allows correlation to the Process Capability and consequently the Capability Index, as formulated below:

$$C_{pk} \leq C_p \leq \frac{5.15}{6 \bullet GR\,\&\,R\%} \qquad [4.2.1]$$

This has several implications:

- The repeatability of the measuring device limits the maximum achievable process capability and consequently the maximum C_{pk}.
- The process will not be capable if the GR&R% is significantly large.
- The controller cannot compensate for a poor measuring device.

4.3 Simulation Model Development

For this application, a discrete, stochastic, time event simulation was used to analyze complex system dynamics and event interaction. This model was used to facilitate the maximization of cell productivity by providing a platform for experimenting with different cell configurations as well as quality control systems and settings.

The model was discrete because the number states of each variable are fixed and distinct. For example a work station representing a machine is either busy or waiting for work. Furthermore, the state variables of each element of the system change instantaneously. This is in contrast to a "continuous" model, such as the temperature of a room.

The model was stochastic because a random number generator and user input probability distributions are utilized for process event timing. Best fit probability distributions are determined from actual event time measurements. Models in SIMUL8 can also be deterministic when fixed event times are specified. This is useful for model development.

4.3.1 ELEMENT TYPES

In SIMUL8, process models were constructed from 5 basic elements: *work entry point, queue, work center, resource,* and *work exit point*. *Work items* flow between these elements via *routes,* represented by arrows. *Labels* act as global variables attached to each work item. Model function can be expanded with custom programming using the built in conversational programming language, *Visual Logic*. A basic SIMUL8 model is shown in Figure 10. The numbers above each symbol represent the number of work items, or resources, currently occupying that element.

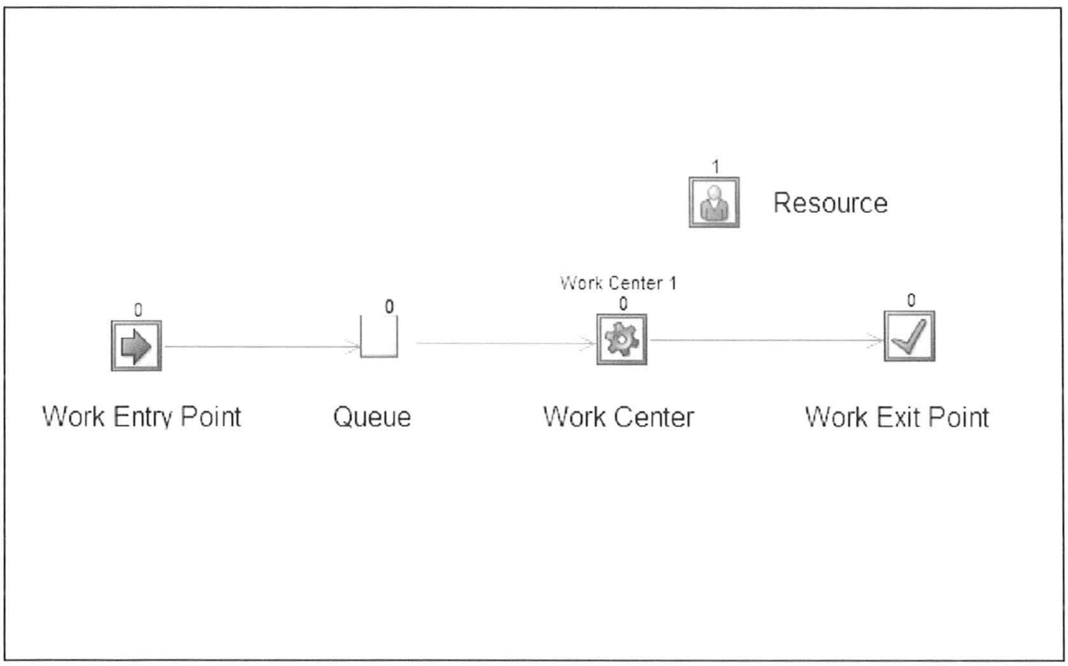

Figure 10: Basic SIMUL8 Model

1. Work Entry Point:

This element introduces work to the system at a user specified rate. In a machining process simulation, this would simulate the arrival of raw material, in this case bar stock, to the system. The main variable used in this element is the expected inter-arrival time (E(IAT)) which is the time between work being inputted to the system. For example, the time between customers entering a store.

It is possible to specify a fixed number of work items to be available to enter the system. Alternatively, unlimited work item arrivals are allowed. This was used in this simulation to allow the CNC lathe work centers to pull material into the system, as required for part production.

2. Queue:

A queue is a temporary buffer where work items are stored until they can progress downstream in the model. The queue may have limited or unlimited capacity. If a queue is full, or was not included in the model, work items will be blocked from travelling to the next element in the system. This will create a backlog upstream that can prevent work items from entering the system.

3. *Work Center:*

A work center performs a service, operation or process on a work item. The work center may require resources, such as an operator, to complete its task. A work center can combine work items if required.

Machine down time is included by defining the efficiency of the machine and the average repair time, which specifies what percentage of the time the work station is available. Alternatively, a more detailed approach is available. The user can specify probability distributions for the time between breakdowns and the time to repair.

Work centers can also collect multiple work items for processing. These items can be combined during the process or remain separate. In this simulation, a work center is used to move 3 parts from the CMM buffer queue to the air gauge inspection queue after 1 of the 3 work item has been inspected by the CMM work station. The time for this process was zero minutes as travel time was included in work center process times.

4. Resource:

A resource is an asset required by a work center to complete a task. Travel times can be specified for resources as they move between work areas. A resource is collected by a work center when a work item enters the station, and is released upon completion of the process. A work center may require a resource to be available before collecting a work item. This is useful if an operator is required to collect multiple items for the process, such as assembly.

In this case, the single CMM probe was specified as a resource. Multiple measurement fixtures can be placed in the CMM. However, for the measurement program task to be completed, the probe resource must be available.

In this case, the CMM probe resource was not required for the CMM fixture work station to collect a part. If a person is modelled as a resource, they may be required to gather work items from a bin. In this case, the resource would be required for the work item to enter the work station. This option is set in the resource options panel in SIMUL8.

Work centers representing the CNC lathes did not have resource requirements specified because the process can be completed without the presence of an operator. If a manual machine was being modeled, a resource would be specified and shift as well as break information could be included.

5. Work Exit Point:

This is where completed work items exit the simulation. This type of element provides performance statistics describing the time a work item spent in the system. Multiple work exit points were used in this simulation to separate finished good parts and rejected scrap parts.

6. Work Item:

A work item is an individual work piece or customer that requires service or processing. For example, a work item can represent a customer in a restaurant or a part in a machining process. Work item characteristics can be stored in labels and modified by work centers. Furthermore, work items can be combined or separated by a work station.

7. *Routing:*

Routes link elements in the model to provide paths for items to travel. Travel time can be specified for a route. In this case, travel time was included in processing times and route travel times were set to zero. Default route travel times are calculated based on distance as determined by the length of the route symbol in simulate. Routes are symbolized by arrows. This was undesirable for model display organization as the travel time should be independent of arrow length.

When multiple routes lead out of an element, the distribution algorithm is specified in the source element. When multiple routes are available, the routing out algorithm specifies how to distribute work items. The options vary from fixed, biased, or neutral routing algorithms. In this simulation, passive routing is used for work entering the system. Fixed percentage routing is used for scrap other than the air gauge work center. Label based routing was used to identify every third part processed by a lathe work centre. This allowed correct routing of parts to the CMM fixture work centers. Label based routing was also used at the air gauge to evaluate dimensional error, where parts out of tolerance were routed to the scrap work exit point.

8. Label:

A label can be applied to a work item when it enters the model. Labels are used by the SIMLU8 solver to track performance statistics. Custom labels can be applied to identify different types of work items that require different routing or different process timing at a work center. In this model, labels were used to record part number and quality information, such as diameter error and feedback compensation.

9. Visual Logic:

Visual logic is an integrated conversational programming language. It allows the user to expand the standard functionality of the program. In this case, it was used to model the closed loop feedback system. The controller algorithms were modeled to capture and modify label data that could be individualized based on work item part numbers.

4.3.2 Warm Up and Results Collection Period

The simulation can begin recording data immediately when a simulation begins. In some cases this is undesirable because it will skew performance results. The statistics would not be based on steady state production because the system does not have any work items present on start-up.

In this case, no warm up period was specified. This allowed the simulation to capture the unstable system dynamics after a machine is shut down for tool change or maintenance work.

4.3.3 Scrap Routing

In order to accurately capture part flow, scrap rejection was included at each inspection station. Data will be lost if a part is rejected as scrap before it has been measured by the air gauge. This may increase the feedback delay to the controller.

Production data was analyzed to determine the average percentage of scrap parts at each station. This was applied as a constant percentage output routing at the corresponding work stations in the model. Parts are then chosen randomly to meet the required routing percentages.

4.3.4 Process Timing

Upon closer inspection, the automated cell was not a perfectly synchronized assembly line. The actual timing of each operation varies randomly. The magnitude of variation depends on the process and the influence of the overall cell system dynamics. For example, the machining time for a part was consistent, but delays were introduced by random or scheduled events. Each functional station of the cell was timed to accurately capture the dynamics of the system. Probability distributions were best fit to the sample data for work station process timing in SIMUL8. Generally, model simplifications can be made where synchronized process occur, such as along a conveyor. These processes were grouped into a single work station. Alternatively, fixed process times could have be used.

4.4 Cell Layout Interaction Study Format

The existing manufacturing cell was modeled as observed at GMI. This layout will be referred to as *Cell 1*. An alternative layout design was considered. The alternative layout is referred to as *Cell 2*. In order to maximize the potential performance of the SPC Based Supervisory Controller, it was important that feedback data be provided as soon as possible. Any feedback delay to the controller would have reduced the performance of the control algorithm.

By simulating the closed loop feedback control in unison with a manufacturing simulation, the interaction between the manufacturing system dynamics and controller performance can be analyzed. Ideally, this type of simulation would occur at the design phase of an automated closed loop manufacturing cell such that cell layout can be optimized. As shown here, this type of simulation allowed tuning of an existing control system implementation for maximum productivity and quality performance.

4.4.1 Cell Designs

The following cell layouts are representative of an actual manufacturing process in place at GMI. It is important to provide enough detail when creating manufacturing simulation models to accurately capture complex system dynamics and event interactions. SIMUL8 provides an option for high volume work station processing, but individual work stations were used to allow for added label based quality data programming with Visual Logic.

The Cell 1 model began with a work entry point representing bar stock feeders for the lathes. Each lathe work center was modeled individually to allow the use of custom Visual Logic programming. Parts were identified based on sequence and machine for tracking the feedback data. All parts routed out of the lathe block entered a queue before entering the cleaning and visual inspection line. This queue represented the part handling system. This process time was included in the lathe process time. No queues were placed before the cleaning and visual inspection work centers as these stations operated on a sequenced conveyor system. A fixed percentage of scrap parts were routed to a separate work exit point from each inspection work center. One third of each machine's parts were routed to one of two height gauge and CMM fixtures. The remaining parts were buffered pending CMM approval. Once the parts were released from the buffer, they entered a queue representing a conveyor leading to the air gauge. The air gauge was the last work station in the cell before parts were palletized at the work exit point. At the air gauge, custom Visual Logic programming read the diameter error data label value and fed it back to the corresponding lathe control algorithm. Any parts with diameter errors outside of tolerance were routed to the scrap exit point.

The Cell 2 layout is a modified version of Cell 1. The air gauge was moved upstream from its previous location to the cleaning and visual inspection line. It was important that the parts were cleaned and had time to reach a stable temperature before being inspected to minimize gauge error. Furthermore, this location was the first quality inspection station. Therefore, no part data was lost if other features failed further quality inspection criteria resulting in removal from the system. Cell 1 and Cell 2 layouts as modelled in SIMUL8, are illustrated in Figure 11 and Figure 12, respectively, on the following pages.

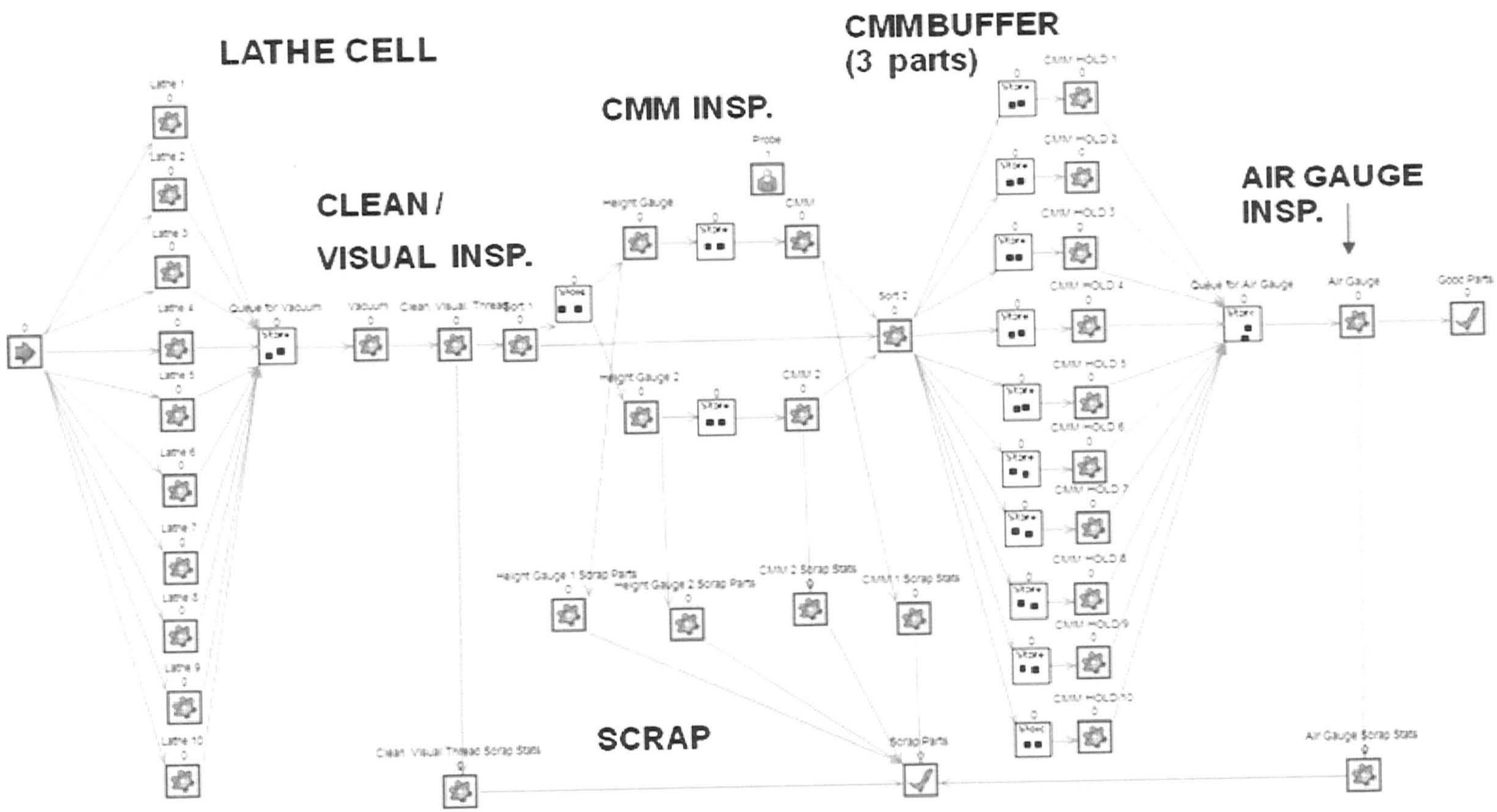

Figure 11: Cell 1 Layout

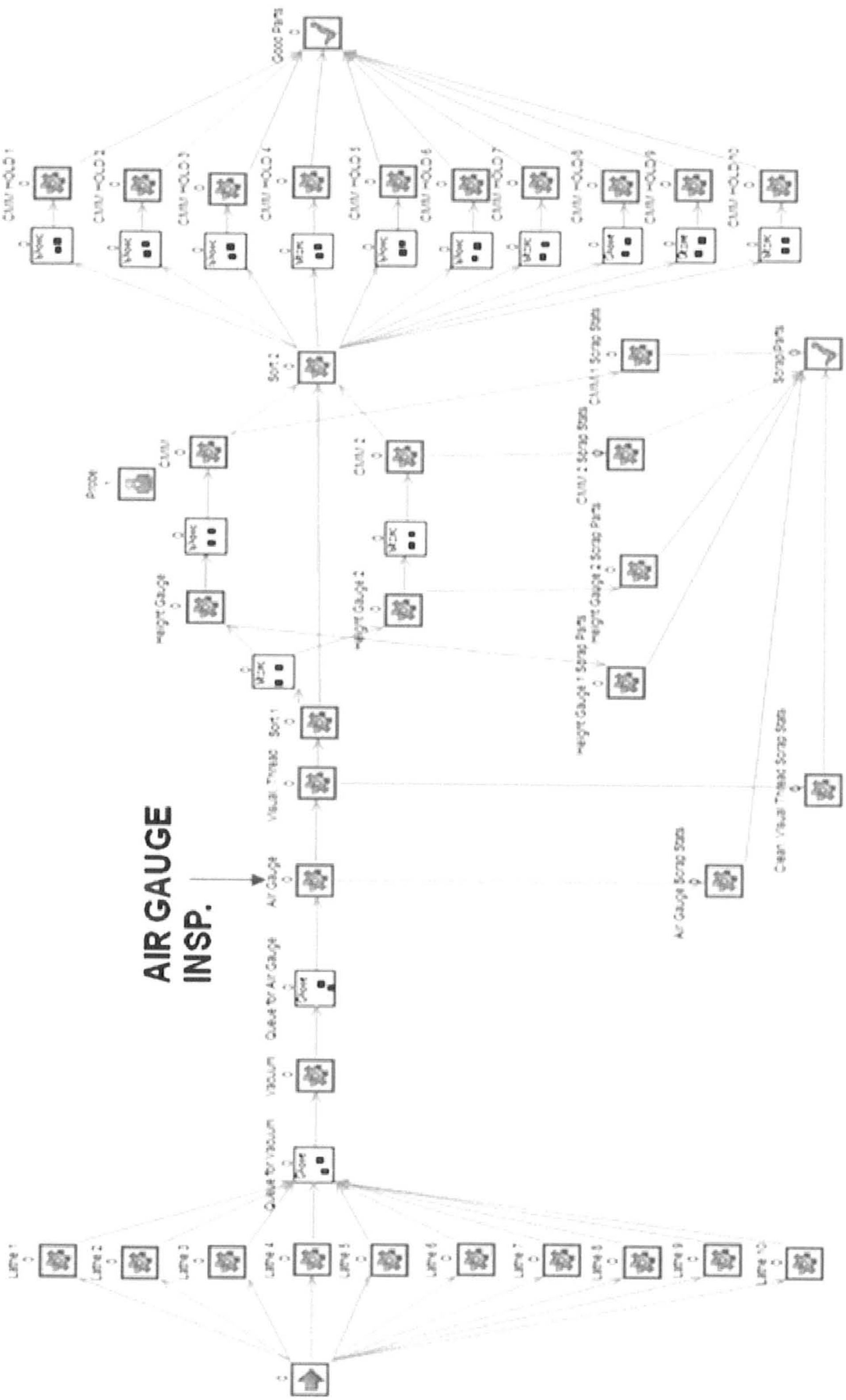

Figure 12: Cell 2 Layout

4.4.2 Feedback Delay

Feedback delay was determined by the number of parts produced between the measured part and the part that was machined using that data point. For each machine, at the start of the part machining cycle, the new part number was compared to the most recently measured part number from that machine. This is expressed mathematically as follows:

$$\boldsymbol{Delay} = \boldsymbol{pn_{current,i}} - \boldsymbol{pn_{measured,i}} - \mathbf{1} \qquad [4.4.1]$$

where:

pn is the part number and

i is the machine number.

4.5 Controller Selection and Tuning

The controllers, presented in 3.4.1 and 3.5.1, were integrated into the SIMUL8 model using the built in programming language, Visual Logic. The controllers were tested against two types of disturbance inputs: a square wave input error function and a drift error function. Both functions were tested with and without white noise added to the signal. This was done to test the robustness of the controller to process noise. The sensitivity gain, g, will also be tuned for optimal response.

4.5.1 Step Response

A square wave input function, as shown in Figure 13, was used to evaluate the response time and steady state error characteristics of the control algorithms. The function uses an abrupt error of 0.01mm from part 5 to 29 and returns to zero at part 30. The lower function is the same square wave with zero average, normally distributed white noise superimposed.

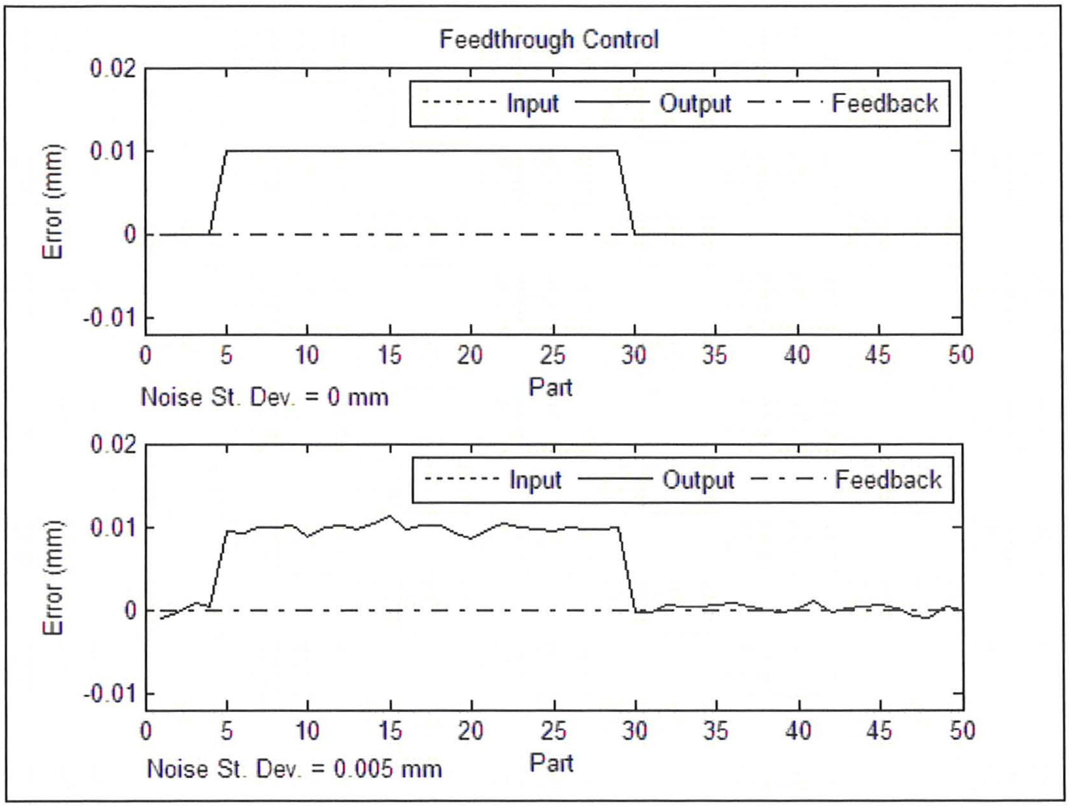

Figure 13: Square Wave Input Function

4.5.2 Process Drift Response

A process drift function was used to test the controller's ability to target a process by minimizing the steady state error. This achieved the goal of minimizing the process quality index, q, which maximized the Capability Index, C_{pk}.

To simulate the process drift encountered in the actual process, a drift function was developed using a tool wear curve. The tool wear curve was generated experimentally using the measured process parameters, materials and tooling, as described the following section.

4.5.2.1 Tool Life Analysis Format

For outer diameter features, such as the bearing surface being studied, the dimensional error resulting from tool wear is an increase in diameter of the feature. Tool life is quantified by productivity. Flank wear is compared to length, or time, in cut. However, in high volume manufacturing the tool life is more commonly compared to the number of parts per cutting edge.

The flank wear was not directly useful for simulating the dimensional error resulting from tool wear. The flank wear needed to be related to rake wear, as shown in Figure 14, to determine the resulting dimensional error. This was calculated as:

$$\text{Rake Wear} = \text{Flank Wear} \times \boldsymbol{tan}(\boldsymbol{Effective}\ \mathit{Clearance\ Angle}) \qquad [4.5.1]$$

The diametric error, δ, resulting from tool wear was then:

$$\boldsymbol{\delta} = \mathbf{2} \times \text{Rake Wear} \qquad [4.5.2]$$

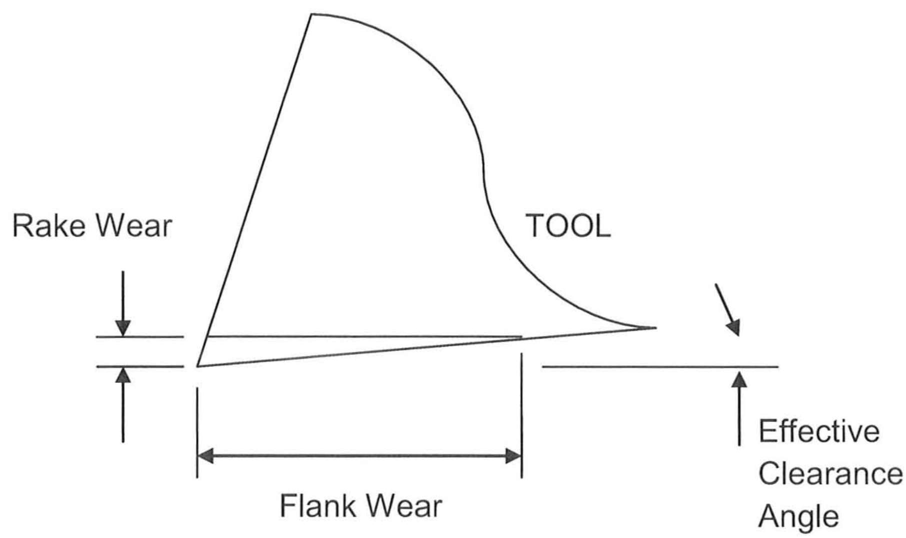

Figure 14: Diagram of Flank and Rake Wear

Production cutting parameters and part material bar stock was used to test the tool wear characteristics and develop a representative tool wear curve. The test was conducted by repeating small cuts over the length of the bar to match the volume of material removed during the finishing pass on the bearing surface of each part, while maintaining correct depth of cut. As the bar diameter reduced, the length of cut increased accordingly. This provided a comparison of tool life to number of parts produced.

Surface roughness was also specified on the part-print. The tool must be able to machine the part surface within the specification limits throughout its life. The tool life would be reduced if this specification was not met. The surface roughness was measured using a Mitutoyo Surface tester during tool wear measurement intervals.

4.5.2.2 Tool Life Analysis Results

The resulting tool wear data is presented below in Table 1. The rake wear was calculated from flank wear measurements as described in the previous section. The tool was expected to produce 1000 parts per cutting edge. The tool was tested past this limit to ensure that the wear remained consistent beyond this threshold. This was indeed the case, indicating a conservative tool life estimate.

# Parts	Tool Flank Wear (mm)	Tool Rake Wear (mm)	Diameter Error (mm)
0	0	0.0000	0.0000
84	0.046	0.0040	0.0080
167	0.078	0.0068	0.0136
251	0.093	0.0081	0.0163
334	0.094	0.0082	0.0164
418	0.095	0.0083	0.0166
501	0.095	0.0083	0.0166
585	0.095	0.0083	0.0166
668	0.098	0.0086	0.0171
752	0.098	0.0086	0.0171
835	0.098	0.0086	0.0171
916	0.1	0.0087	0.0175
996	0.1	0.0087	0.0175
1076	0.104	0.0091	0.0182
1147	0.104	0.0091	0.0182

Table 1: Tool Wear Test Results

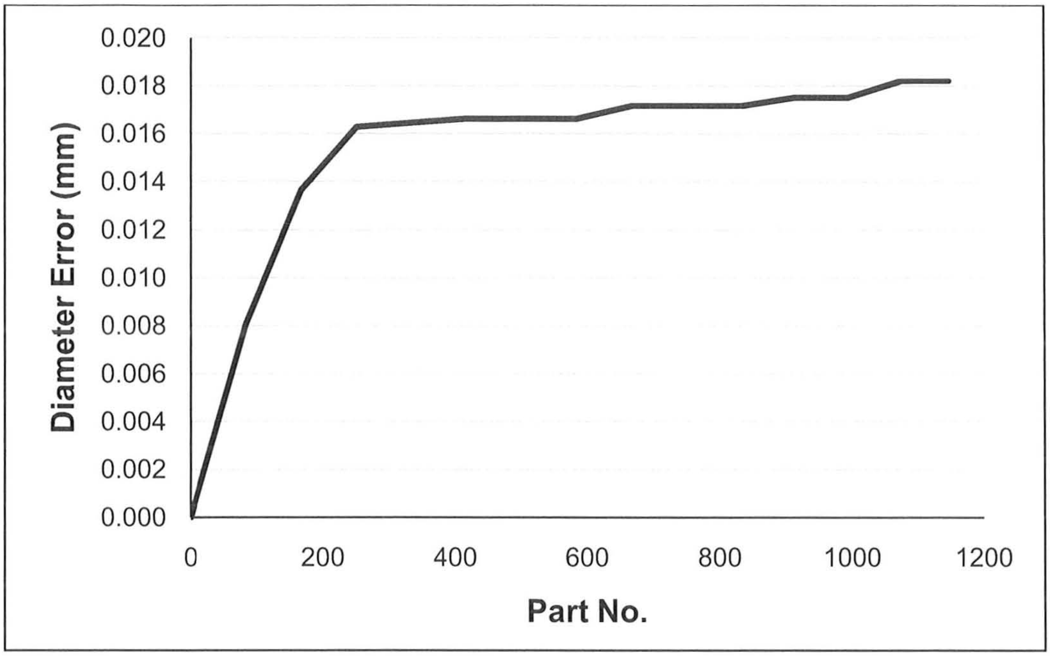

Figure 15: Experimental Tool Wear Curve

The wear mechanism of the cutting tool is of interest as well. If a tool did not wear consistently, additional variation would be introduced into the process. This could make closed loop control difficult and would limit the maximum achievable process capability. Therefore, a slow stable tool wear rate was desirable. This would introduce small errors on a part to part basis that can be easily accommodated by the control algorithm. As seen in Figure 15, this is certainly the case. The tool wear reached a steady plateau after approximately 200 parts and progressed in a stable manner.

Visual inspection of the tool did not find any significant chipping or other signs of catastrophic tool failure. This ensured that surface finish remained within specification. Surface finish was measured throughout the test. The results can be seen in Table 2. The surface roughness was within the part-print specification of a maximum of 3 micrometers Ra, throughout the life of the tool.

# Parts	Surface Roughness Ra (µm)
84	1.6
167	1.4
251	1.48
334	1.25
418	1.78
501	1.7
585	1.87
668	1.7
752	1.92
835	1.97
916	2.03
996	1.92
1076	2.12
1147	2.17

Table 2: Surface Roughness Test Results

4.6 SUMMARY

GR&R testing was done to ensure that a measurement device can provide acceptable output quality measurements. The fixture and measurement error, as described by the GR&R%, limit the maximum achievable Process Capability, C_p, and the maximum achievable Capability Index, C_{pk}.

A discrete, stochastic time event model was developed using SIMUL8. This model allows integration of the SPC Based Supervisory Control system into the simulation environment. The model was calibrated by measuring process times in the automated cell.

Cell 1 represents the current cell configuration. Cell 2 represents an alternative cell layout where the air gauge is moved upstream to reduce feedback delay.

The models are used to select and tune various SPC Based control algorithms. A step response function and process drift error, developed using actual tool wear data were used for process error inputs.

CHAPTER 5

5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 OVERVIEW

This chapter demonstrates the benefit of integrating the simulation of final part quality in a discrete, stochastic, manufacturing simulation. The value added to the task of manufacturing cell design comes from the insight provided on the relationship between quality data and part flow as well as critical cell operating states. Quality output and consequently, productivity, is maximized with controller selection and tuning, as well as reducing feedback delay through process layout at the start of the cell design process.

The results of the controller tuning and selection using the square wave step function and process drift input errors is presented. The results of the Gauge R&R study determine the maximum achievable C_{pk} of the process.

5.2 Gauge R&R Analysis

Three different measurement methods were evaluated using the Gauge R&R technique: hand gauge, air gauge, and CMM. The air gauge and CMM tested in the Gauge R&R study are equivalent to those used in a typical manufacturing cell. A hand gauge was also tested for comparison. The Gauge R&R test data is presented in Appendix A, 9.1, 9.2, and 9.3.

5.2.1 Gauge R&R Test Results

The results of the Gauge R&R study are presented below. The part-print tolerance specification was ±0.01.

	Instrument (mm)		
	Hand	**Air**	**CMM**
Repeatability	0.0131	0.0047	0.0040
Reproducibility	0.0016	0.0006	0.0000
Interaction	0.0084	0.0008	0.0023
R&R	0.0157	0.0048	0.0046
GR&R%	78%	24%	23%
Max C_{pk}[1]	1.1	3.54	3.73

Table 3: GR&R Test Results

[1] Calculated using [4.2.1].

The hand gauge did not perform well in this test. The instrument had a very poor GR&R% of 78% of the tolerance band. This may improve with better operator training, as indicated by a high interaction result. The maximum C_{pk} of a process using this instrument is 1.1, which would not meet the minimum requirement of 1.33. This instrument would not be recommended for manual SPC control of the process.

The air gauge and CMM displayed acceptable GR&R% values of 24% and 23%, respectively. The corresponding maximum achievable Cpk values are well above the Six Sigma goal of at least 2.0. Therefore, the air gauge and CMM are both capable of controlling this process to the required quality standard, in an automated environment. An air gauge was utilized in this application because of its faster cycle time for measuring a single feature.

5.3 FEEDBACK DELAY RESULTS

The CNC lathes operate continuously, meaning once a part is ejected from the machine, the machining cycle immediately resets and begins producing the next part. Therefore, in this mode of operation, there will always be, at least, a one part delay from when quality data is available to adjust the machine controller.

Measuring the bearing surface prior to ejection from the machine would eliminate the feedback delay. However, since this is a high volume automotive application, this is not acceptable due to the increased cycle time this would impose on the process. In applications where part scrap cost is significant, such as aerospace, the cost of increasing machining process time would be small compared to the cost of making a scrap part..

The feedback delay for Cell 1, during steady state production, is displayed below in Figure 16. In Cell 1, the feedback delay displayed a saw tooth pattern in groups of three. For the first part produced in a group, the most recent feedback data entered into the controller was from two parts prior indicating a one part delay. The second part had a two part delay and the third a three part delay. This indicates that the control action for all three parts was based on the same part produced four cycles previously. The pattern then repeated. This data buffering delay pattern was caused by the air gauge queue where groups of parts wait to be approved by the CMM.

In some cases, the delay reached four parts due to a part being ejected from the system due to nonconformance found at an upstream inspection. The data from parts rejected by upstream inspection stations from the air gauge were lost and not applied to the controller.

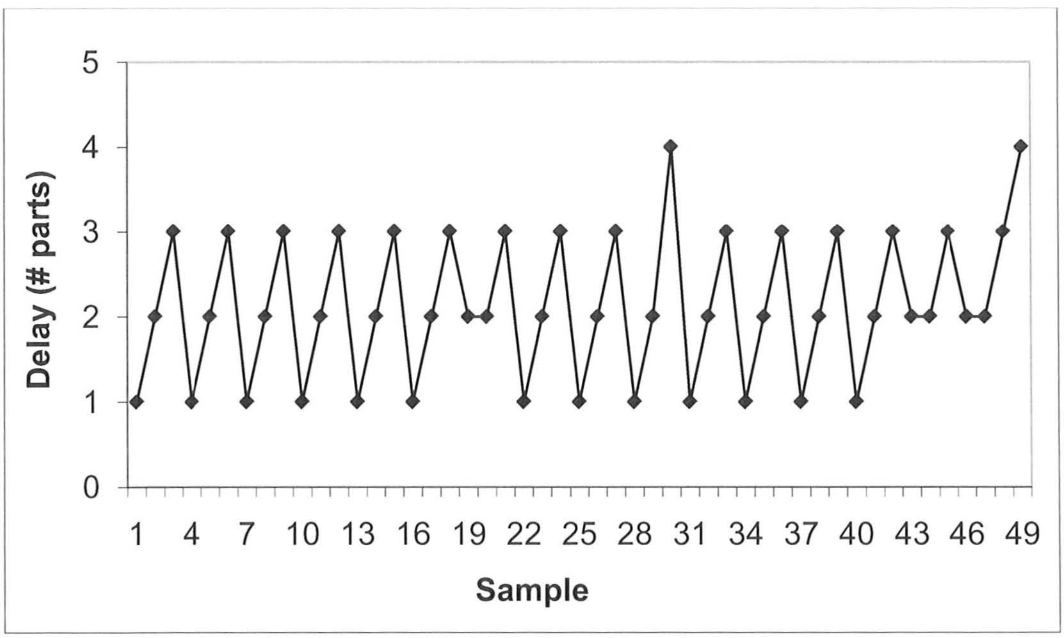

Figure 16: Cell 1 Feedback Delay

The feedback delay for Cell 2, during steady state production, is displayed below in Figure 17. With the air gauge relocated upstream of the CMM in the Cell 2 layout, the data buffering phenomenon was resolved. There was a one part delay for each part as described earlier.

Furthermore, no part data is lost due to nonconformance at other inspection stations.

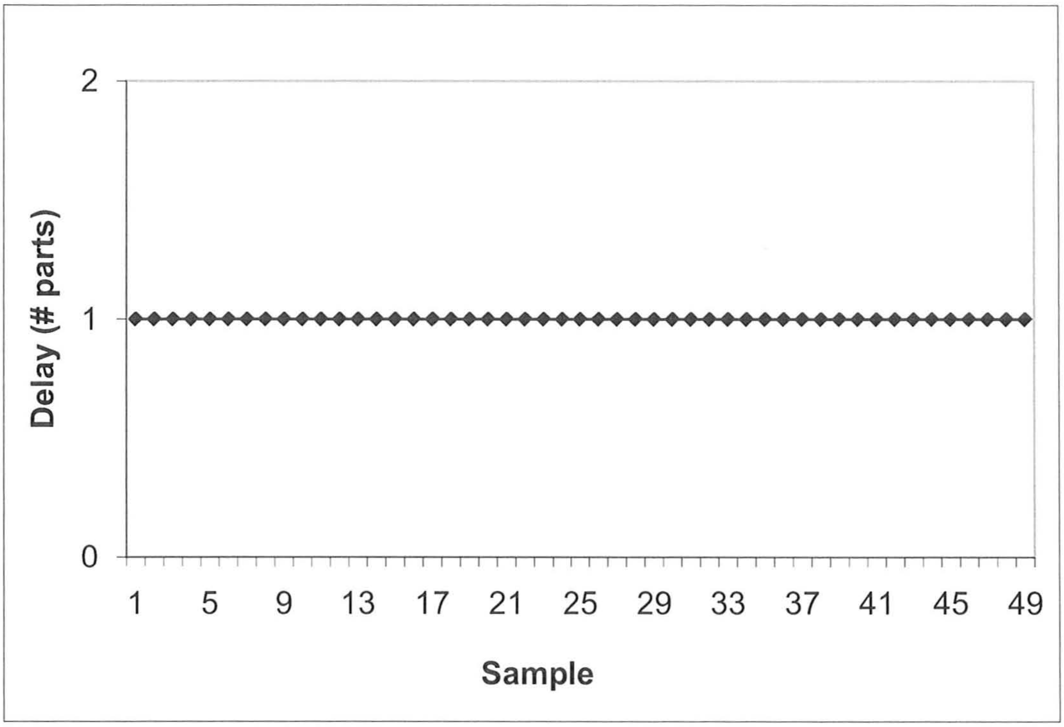

Figure 17: Cell 2 Feedback Delay

Reducing feedback delay and eliminating lost part data improves the performance of the controller, as will be displayed in the following section.

5.4 SPC Controller Selection Study Results

This section discusses the results of the controller performance study for each cell layout. Quality data are presented for the superimposed noise error input for a more realistic representative of a typical process. The controller parameters are set to maximize C_{pk} and settling time from a square wave step response. These parameters are used to study the controller's performance to tool wear drift input error. The system response graphs, which summarize the results, are presented in Appendix B for reference.

The Capability Index results reported in this section are what would be expected with a 0% GR&R%. The actual production Capability Index will be limited by gauge measurement variation as previously described in 4.2.3. In this case the air gauge had a 23% GR&R%, which results in a maximum achievable Cpk of 3.73, well above the six sigma standard minimum of 2.

5.4.1 Step Response

It is important that the controller respond quickly to step changes that occur during the machining process. Selecting a controller algorithm that quickly corrects the process to the target mean will minimize scrap by maximizing C_{pk}. Controllers were evaluated on the number of parts required to reach steady state production, also referred to as settling time, n_s, and the steady state error, e_{ss}. Settling time, n_s, was evaluated as the number of parts required for a controller to return the process mean to within one standard deviation of the target mean from a step response input.

Step changes can be introduced into the process offset in several ways. During a tool change, the tool offset is initially calibrated by the tool setter or operator. Several sources will contribute to the error. A small error often occurs during tool setup. In many cases parts are measured during setup with manual gauges, which are not as repeatable as the automated gauges used during production. Also, thermal effects can come into play due to the fact that the machine is not running during a tool change. During a tool change the machine will cool from its previous state during continuous machining. Thermal errors can also occur if cold coolant is introduced into the system abruptly.

The step response input, output, and feedback signals are graphed for each cell and controller combination listed below. Various gain and controller parameters were simulated. Parameter sets that maximized Cpk were used for comparison. Optimal controller parameters will vary based on system configuration. Confidence intervals were calculated based on ten trials using different randomly generated noise series. These are presented in 10.1. The results for Cell 1 and Cell 2 configurations are summarized in Text Box 3 and Text Box 4, respectively.

	Controller Parameters	C_p	C_p ±95th P.	C_{pk}	C_{pk} ±95th P.	n_s	e_{ss} (mm)
Input	-	0.67	0.006	0.33	0.003	-	0.01
MR3	g = 0.9	0.72	0.01	0.68	0.01	6	0.001
EWMA	g = 0.9, λ = 0.8	0.86	0.01	0.83	0.01	4	0.001
CUSUM	g = 0.4	0.86	0.01	0.85	0.01	10	0
PI	P = 0.4, I = 0.4	0.99	0.02	0.99	0.02	3	0

Text Box 3: Cell 1 Step Response Summary

	Controller Parameters	C_p	C_p ±95th P.	C_{pk}	C_{pk} ±95th P.	n_s	e_{ss} (mm)
Input	-	0.67	0.006	0.40	0.003	-	0.01
MR3	g = 0.2	0.75	0.004	0.72	0.003	8	0.001
EWMA	g = 0.4, λ = 0.9	0.86	0.01	0.85	0.02	5	0.0005
CUSUM	g = 0.5	1.04	0.01	1.04	0.01	3	0
PI	P = 0.3, I = 0.4	1.10	0.02	1.10	0.02	3	0

Text Box 4: Cell 2 Step Response Summary

5.4.2 Process Drift Response

The algorithm must be able to maximize C_{pk} by compensating for drift in the process mean. Drift will occur due to tool wear and low frequency thermal changes in the environment. Over the day, temperature and humidity changes will alter the machine profile. A tool wear profile was developed for use in the simulation to represent a typical drift input error.

The step response input, output, and feedback signals are graphed for each cell and controller combination listed below. Confidence intervals were calculated based on ten trials using different randomly generated noise series. These are presented in 10.2. The results for Cell 1 and Cell 2 configurations are summarized in Text Box 5 and Text Box 6, respectively.

	Controller Parameter	C_p	C_p ±95th P.	C_{pk}	C_{pk} ±95th P.	e_{ss} (mm)
Input	-	0.70	0.002	0.0	0.0	0.02
MR3	g = 0.9	3.39	0.04	2.03	0.03	0.003
EWMA	g = 0.9, λ = 0.8	2.32	0.21	1.66	0.15	0.001
CUSUM	g = 0.4	5.18	0.16	5.18	0.16	0
PI	P = 0.4, I = 0.4	4.37	0.12	4.34	0.12	0

Text Box 5: Cell 1 Drift Response Summary

	Controller Parameter	C_p	C_p ±95th P.	C_{pk}	C_{pk} ±95th P.	e_{ss} (mm)
Input	-	0.70	0.002	0.0	0.0	0.02
MR3	g = 0.2	3.30	0.17	2.22	0.11	0.003
EWMA	g = 0.4, λ = 0.9	3.35	0.11	2.43	0.08	0.002
CUSUM	g = 0.5	5.26	0.16	5.22	0.16	0
PI	P = 0.3, I = 0.4	5.09	0.22	5.05	0.22	0

Text Box 6: Cell 2 Drift Response Summary

5.4.3 Effect of Controller Selection

Controller performance, for a step or drift input, varies based on the desired control strategy. SPC based controllers, MR3, EWMA, and CUSUM, utilize control limits to reliably detect shifts in the process mean. SPC control limits reduce unnecessary process correction and increases in process variability caused by fliers. However, this reduces the ability of the controller to quickly respond to step changes in the process compared to the EPC based PI controller. This controller characteristic manifested as delayed feedback response to step changes and saw-tooth output signals to process drift with steady state error, as seen in Figure 18 and Figure 20, respectively.

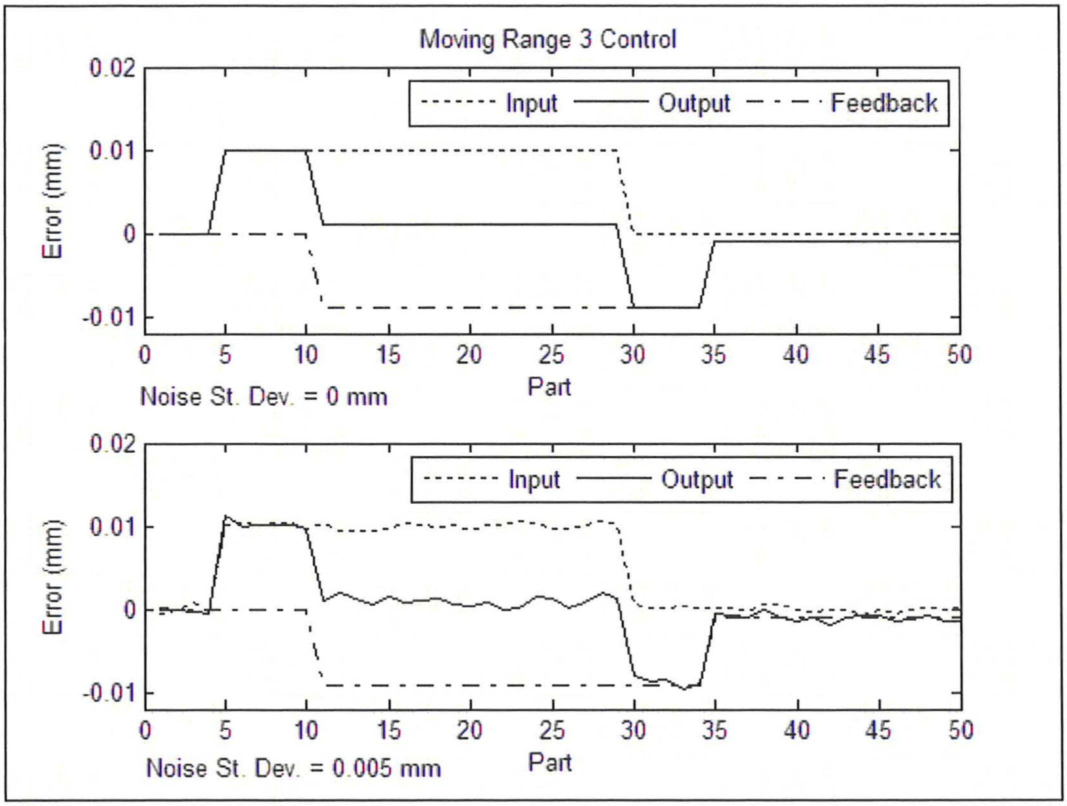

Figure 18: Cell 1, MR3 (g=0.9) Step Response

SPC based controller responses exhibited similar step response characteristics exemplified by the moving range controller response in Figure 18. The settling time was slow while the controller determined if a significant process change had occurred. Once control action was applied, the error was brought back into control within the specified control limits. Once the process mean was within the control limits, no corrective action is taken to reduce process variation. This often resulted in steady state error.

If a process change is expected, such as after a tool change or on machine start up, an operator can alert the controller to this operating state. This reduces the burden on the controller to validate process changes, allowing more aggressive control action. The CUSUM and PI controllers demonstrated excellent step response results with zero steady state error. The PI controller response displayed less oscillation than the CUSUM control response in Figure 30. Therefore, a more aggressive EPC based controller should be used during transient operational states, such as tool changes or after machine maintenance to quickly and accurately re-target a process.

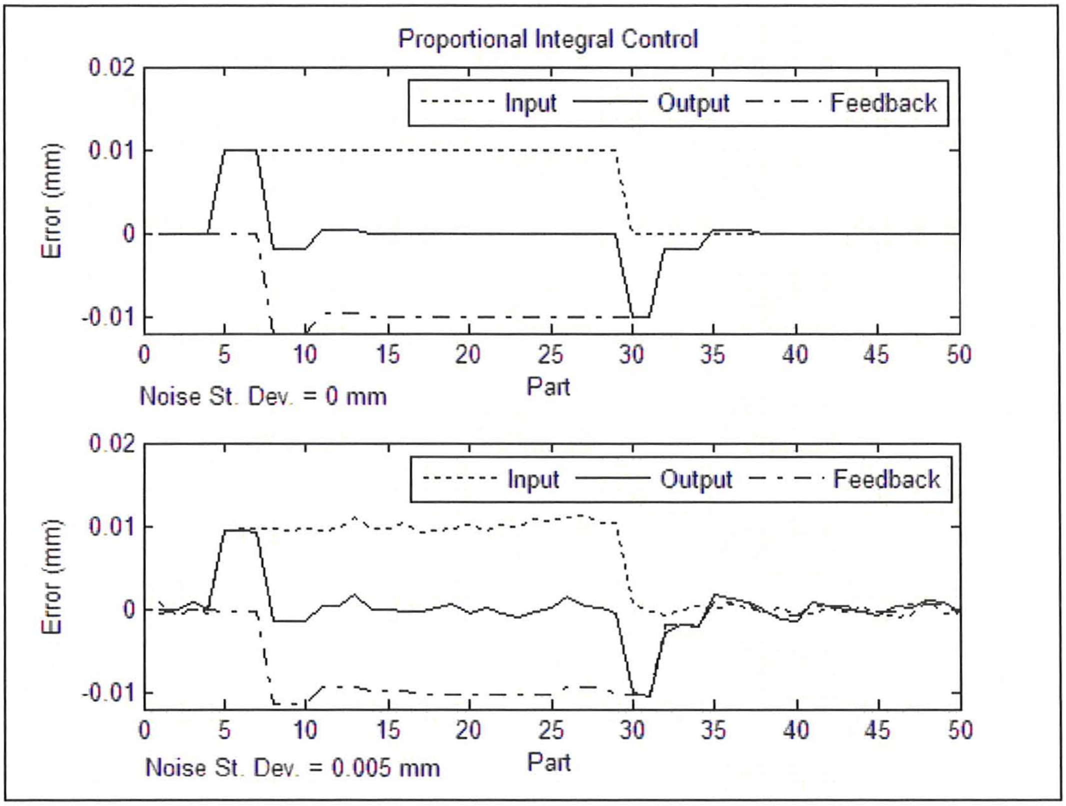

Figure 19: Cell 1, PI (P=0.4, I=0.4) Step Response

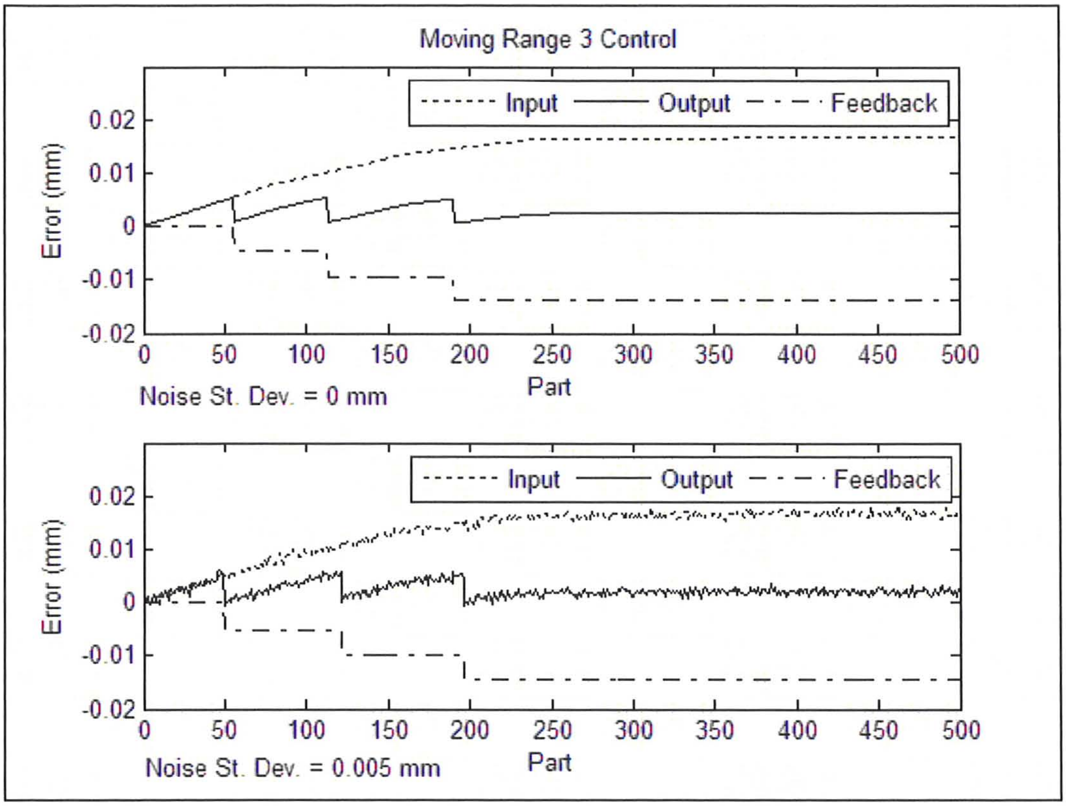

Figure 20: Cell 1, MR3 (g=0.9) Drift Response

When the SPC based moving range controller response, shown in Figure 20, is compared to the PI controller response, shown in Figure 21, the SPC based moving range controller feedback signal did not contain process noise; whereas, the process noise was amplified in the PI controller feedback signal. In this case, the PI controller outperformed the SPC based moving range, EWMA, and CUSUM controllers due to its ability to track drift disturbances. This benefit would be reduced if the noise amplitude increased. Therefore, an SPC based controller should be used to control a process with large common cause variation during steady state operation.

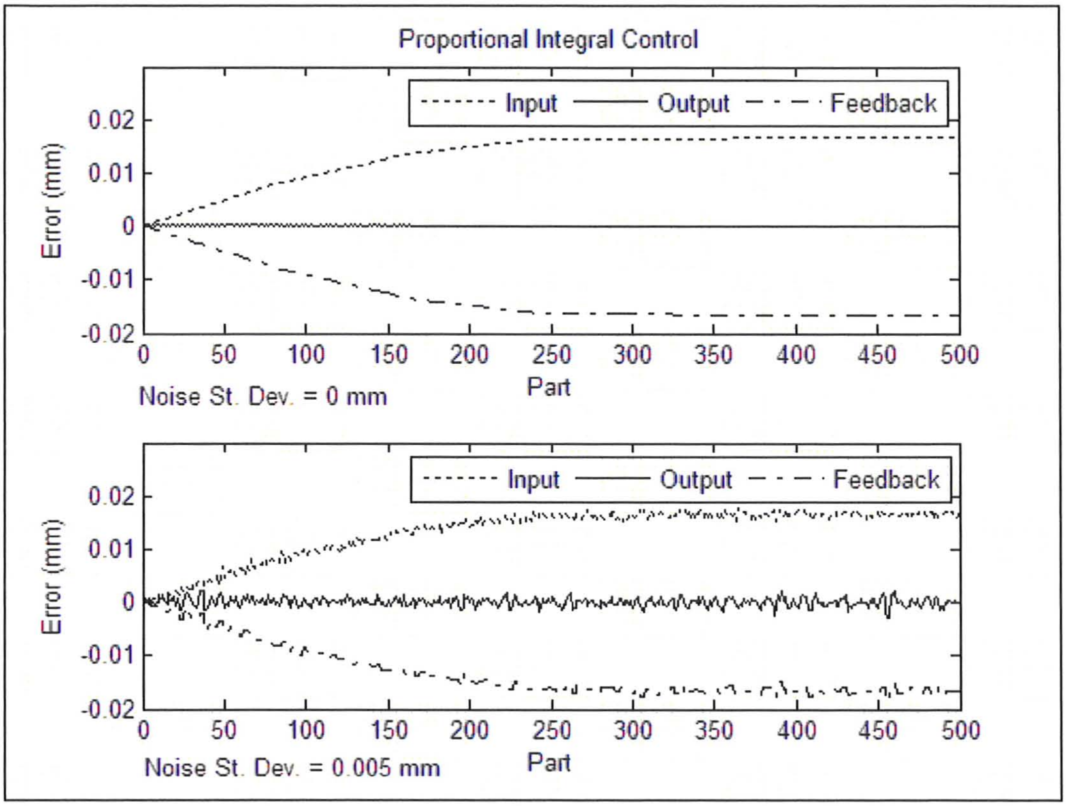

Figure 21: Cell 1, PI (P=0.4, I=0.4) Drift Response

The results for Cell 1 drift response, with moving range control, demonstrate the SPC principle of running a slightly off centre process to achieve a higher C_{pk}. Decreasing the magnitude of process corrections using a low sensitivity gain, g, resulted in a higher C_p. The quality index, q, was reduced by increased steady state error, but a significantly higher C_{pk} is achieved compared to the EWMA control response with a lower steady state error.

The drift response performance of the EWMA controller can be improved by reducing the controller parameter, λ. The control limits of this controller are proportional to λ, allowing process shifts to be detected sooner. However, this resulted in very poor step response performance. This is not desirable in this application due to the increase in scrap rates that would occur. Furthermore, fliers would cause increased false alarms triggering unnecessary process corrections.

5.4.4 Effect of Cell Layout

Generally, reorganization of the cell layout to minimize feedback delay provided a statistically significant improvement to quality output for both disturbance types. This was achieved by decreasing the feedback delay and data buffering. Data buffering occurs when part measurement data is provided to the control algorithm but the control action utilizing this data cannot be applied before another part is measured. This phenomenon is displayed in 4.4.2. Results illustrated improved settling time to step errors due to reduced oscillation. Improved data flow to the controller allowed faster and more accurate process adjustments. This is best demonstrated in the settling time improvement for the CUSUM controller step response displayed in Figure 22 and Figure 23. The data buffering in Cell 1 caused discrete step changes, as would have been expected with a lower sampling rate; however, all data was included in controller correction computation. Removing data buffering with the Cell 2 layout resulted in a smoother and faster step response.

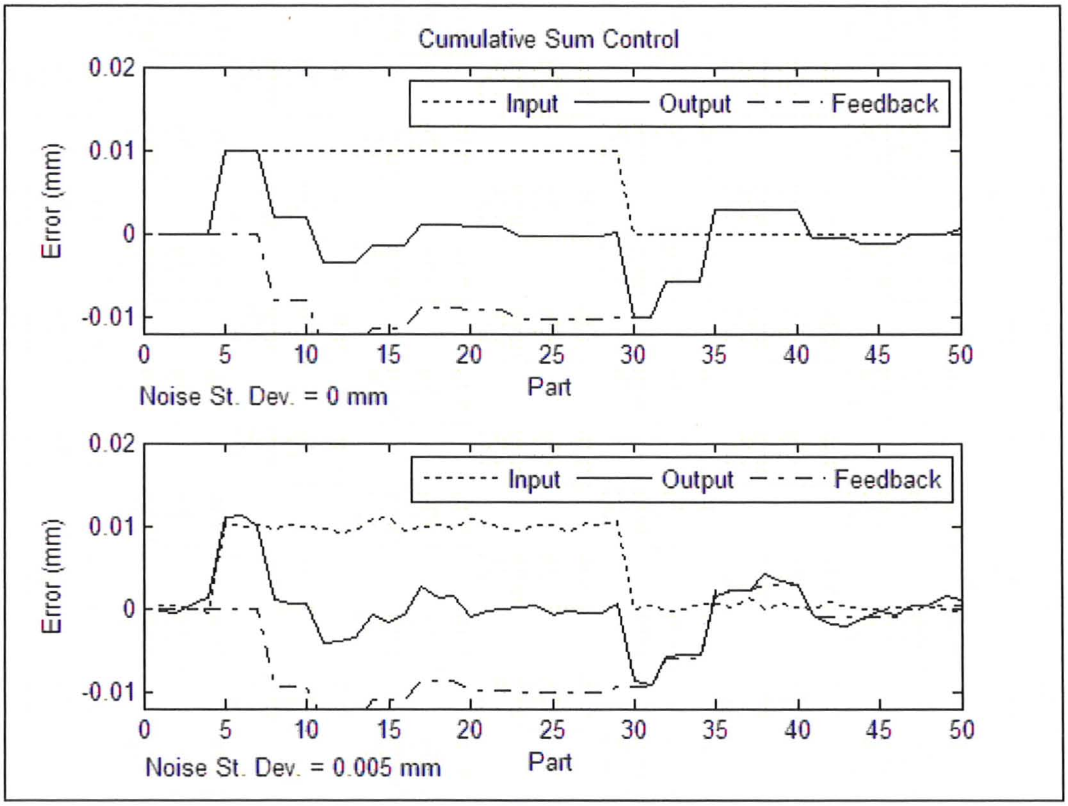

Figure 22: Cell 1, CUSUM (g=0.4) Step Response

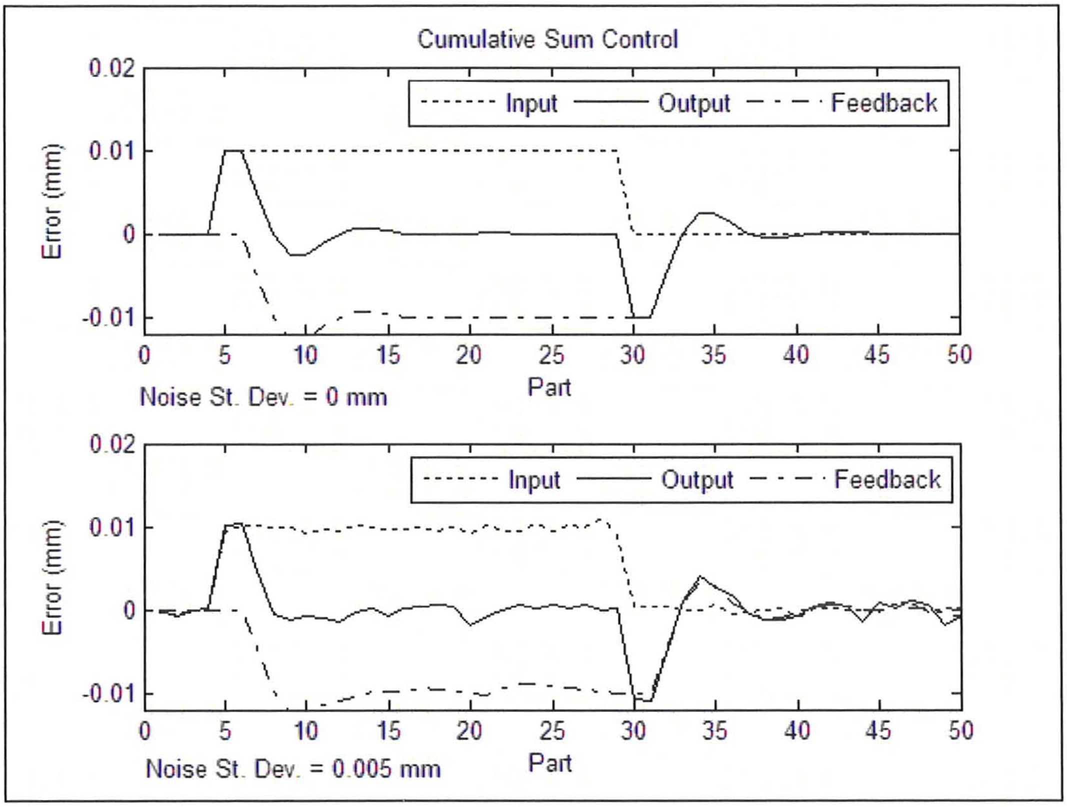

Figure 23: Cell 2, CUSUM (g=0.5) Step Response

Studying data flow during a discrete, stochastic manufacturing process simulation provided insight into the relationship between cell layout and the feedback system. Reducing the number of stations and buffers between part production and inspection minimized feedback delay and data buffering. Providing more feedback data faster to the controller provided better control response and improved quality output.

5.4.5 Effect of Sensitivity Gain

Improper sensitivity gain settings may cause instability due to feedback delay. In Cell 2, the moving range algorithm performance decreased with high sensitivity gain. This occurred when the feedback became out of phase with the machine controller due a single part delay. This is illustrated in Figure 24 below. Reducing the sensitivity gain eliminated the response oscillation, shown in Figure 25.

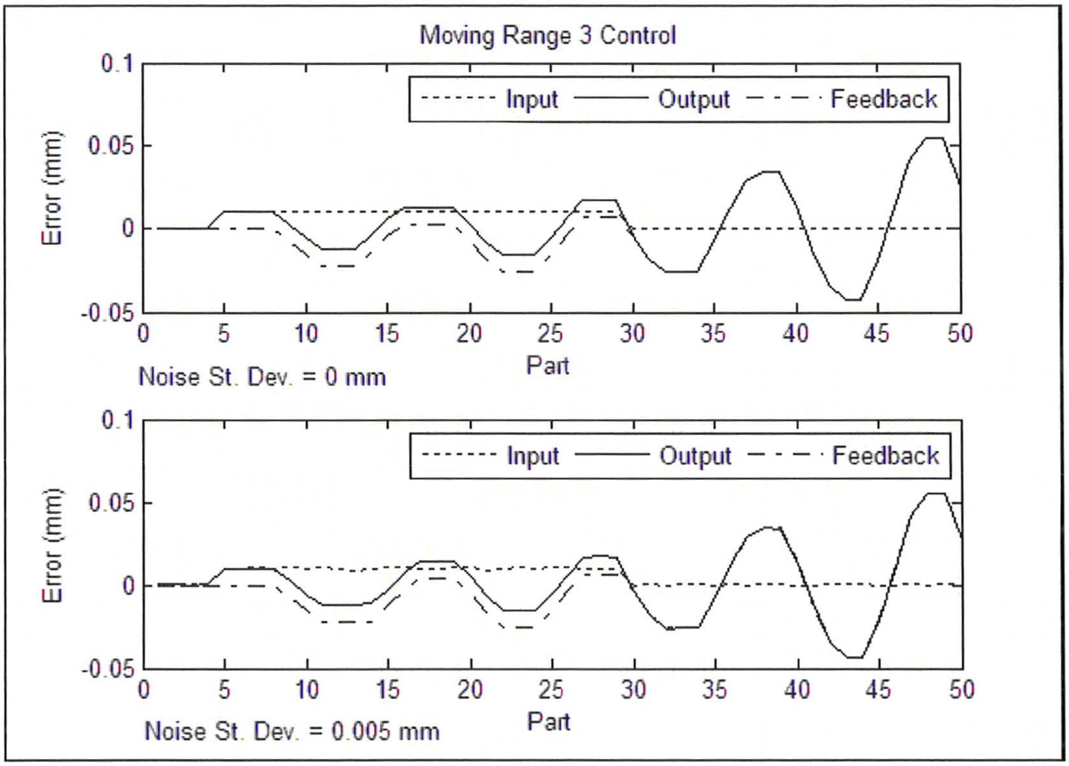

Figure 24: Cell 2, MR3 (g=0.8) Step Response

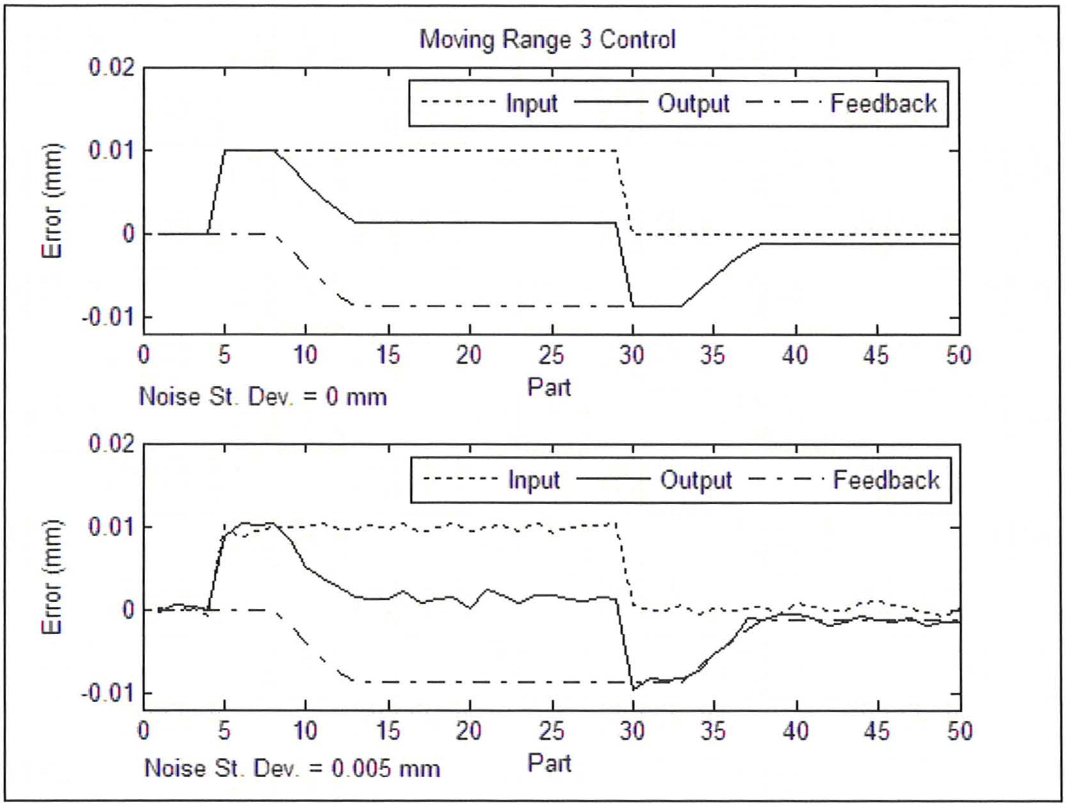

Figure 25: Cell 2, MR3 (g=0.2) Step Response

5.5 SUMMARY

This chapter presented the Gauge Repeatability and Reproducibility study results that included a hand gauge, air gauge, and CMM. Simulation results for feedback delay and controller performance to step and drift disturbances are summarized and discussed.

A maximum C_{pk} of 3.5 and 3.7 can be achieved by processes utilizing an air gauge or CMM, respectively. This is well above the Six Sigma goal of a minimum C_{pk} of 2.

Simulation results show the potential for improved performance of the EPC based PI controller over traditional SPC based algorithms. SPC based controllers balance step and drift response performance, whereas EPC excels in both scenarios. SPC based controllers should be considered for use during steady state with process that have high common cause variation. Furthermore, simulation allows quality engineers to identify controller parameters that may cause system instability.

CHAPTER 6

6 CONCLUSIONS

Combining manufacturing and quality simulation for high volume closed loop machining process design proved successful. This process is useful during the cell design process or when retrofitting an existing cell with closed loop control. This method of process simulation provides efficient analysis of closed loop machining systems because it realizes lean manufacturing goals by utilizing Quality and Manufacturing Engineering principles and techniques to improve both quality output and productivity.

Manufacturing simulation is typically used to maximize process productivity through cell layout design. Further process productivity improvements can be realized by maximizing quality output through cell design and informed control algorithm selection and tuning. This technique excels when traditional control system analysis techniques are too labour intensive or fail due to the inability to capture the complex and stochastic nature of manufacturing processes. Various SPC and EPC based control algorithms are available for closed loop machining applications.

Chapter 7

7 Future Directions

A high volume discrete part manufacturing process was used to demonstrate the combined quality and manufacturing simulation method. Developing process models with SIMUL8, an industry leading process modeling software package, allows flexibility to study various process types and configurations. Further work could be done to extend this method to different applications, such as manufacturing processes which are not fully automated where operator action impacts process timing leading to significant variation in feedback timing.

Various SPC and EPC based control algorithms are presented for use with a SPC Based Supervisory Controller. The EPC based PI controller showed promising results for improving quality output of the high volume discrete part manufacturing process under investigation. Further development of this control type is required to fully optimize its performance and integrate it into the commercial SPC based control package for in-process testing.

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APPENDIX A

9 APPENDIX A: GAUGE R&R TEST DATA

9.1 HAND GAUGE

GR&R Test Data - Hand Gauge			
Operator #1	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.966	41.969	41.967
Part 2	41.97	41.965	41.969
Part 3	41.971	41.962	41.971
Part 4	41.966	41.971	41.971
Part 5	41.966	41.969	41.973
Part 6	41.965	41.972	41.968
Part 7	41.966	41.971	41.97
Part 8	41.965	41.969	41.968
Part 9	41.964	41.965	41.964
Part 10	41.965	41.967	41.972
Operator #2	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.972	41.977	41.975
Part 2	41.972	41.975	41.976
Part 3	41.968	41.971	41.97
Part 4	41.966	41.97	41.971
Part 5	41.968	41.97	41.967
Part 6	41.963	41.968	41.964
Part 7	41.971	41.971	41.972
Part 8	41.967	41.966	41.967
Part 9	41.966	41.964	41.963
Part 10	41.966	41.967	41.967

Table 4: GR&R Test Data - Hand Gauge

9.2 Air Gauge

GR&R Test Data - Air Gauge			
Operator #1	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.967	41.966	41.963
Part 2	41.964	41.965	41.964
Part 3	41.963	41.963	41.963
Part 4	41.963	41.963	41.963
Part 5	41.962	41.962	41.963
Part 6	41.96	41.96	41.959
Part 7	41.961	41.963	41.961
Part 8	41.961	41.961	41.962
Part 9	41.959	41.958	41.957
Part 10	41.96	41.961	41.959
Operator #2	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.964	41.963	41.963
Part 2	41.964	41.964	41.964
Part 3	41.963	41.963	41.962
Part 4	41.962	41.963	41.962
Part 5	41.962	41.962	41.962
Part 6	41.96	41.96	41.96
Part 7	41.962	41.962	41.963
Part 8	41.96	41.961	41.962
Part 9	41.961	41.958	41.958
Part 10	41.963	41.96	41.959

Table 5: GR&R Test Data - Air Gauge

9.3 CMM

GR&R Test Data - CMM			
Operator #1	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.962	41.962	41.963
Part 2	41.962	41.961	41.961
Part 3	41.96	41.96	41.959
Part 4	41.958	41.959	41.96
Part 5	41.957	41.958	41.959
Part 6	41.955	41.957	41.956
Part 7	41.959	41.958	41.959
Part 8	41.958	41.957	41.958
Part 9	41.954	41.955	41.955
Part 10	41.955	41.957	41.956
Operator #2	**Trial #1**	**Trial #2**	**Trial #3**
Part 1	41.962	41.963	41.962
Part 2	41.961	41.961	41.962
Part 3	41.96	41.959	41.96
Part 4	41.959	41.96	41.958
Part 5	41.958	41.959	41.957
Part 6	41.957	41.956	41.955
Part 7	41.958	41.959	41.959
Part 8	41.957	41.958	41.958
Part 9	41.955	41.955	41.954
Part 10	41.957	41.956	41.955

Table 6: GR&R Test Data - CMM

APPENDIX B

10 APPENDIX B: CONTROLLER SELECTION STUDY DATA

10.1 STEP RESPONSE CHARTS

The following charts are summarized in 5.4.1.

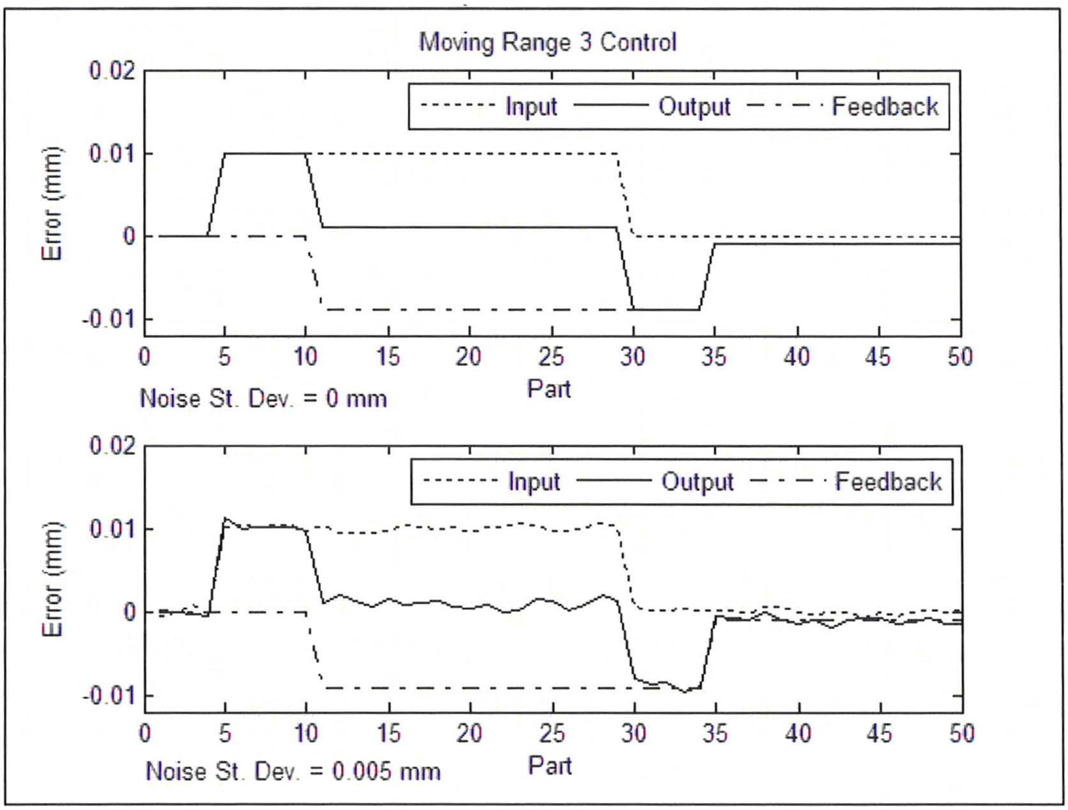

Figure 26: Cell 1, MR3 (g=0.9) Step Response

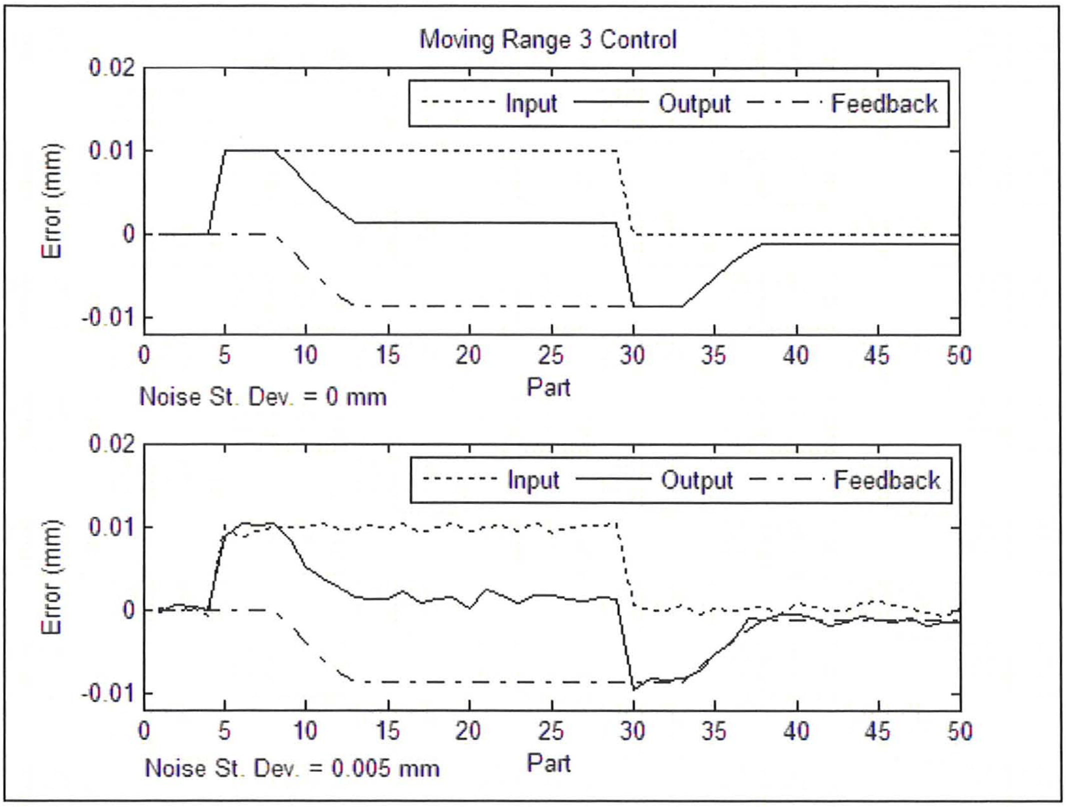

Figure 27: Cell 2, MR3 (g=0.2) Step Response

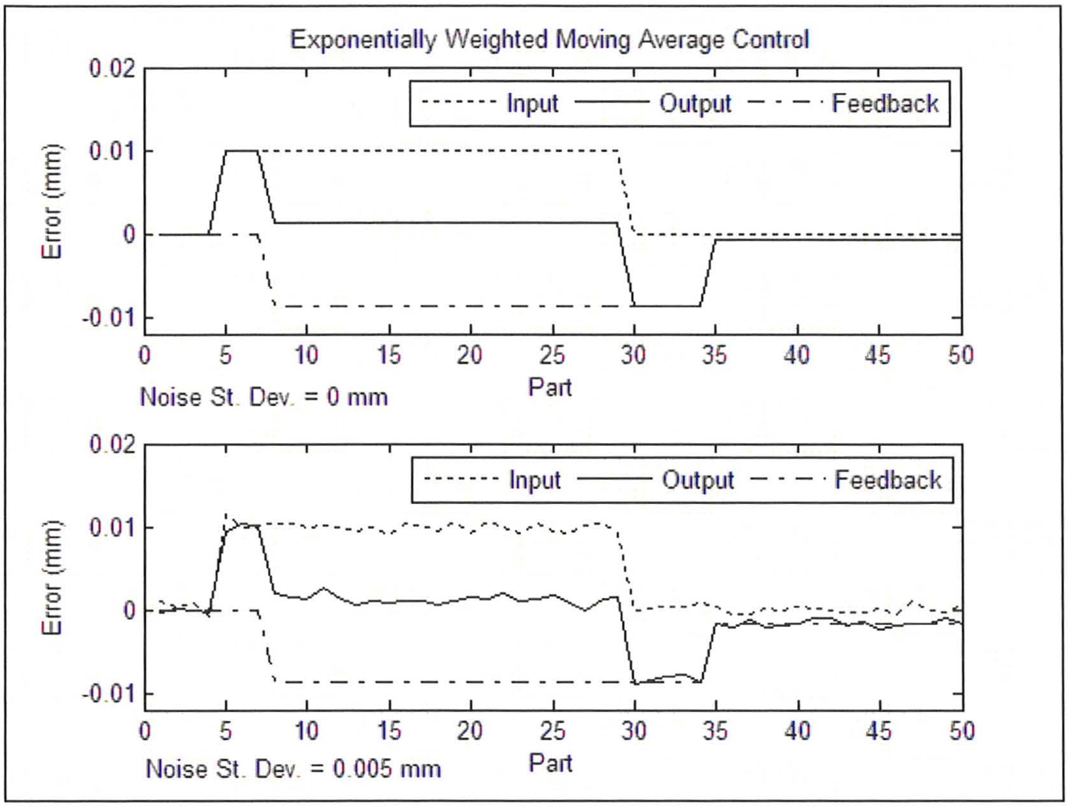

Figure 28: Cell 1, EWMA (g=0.9, λ =0.8) Step Response

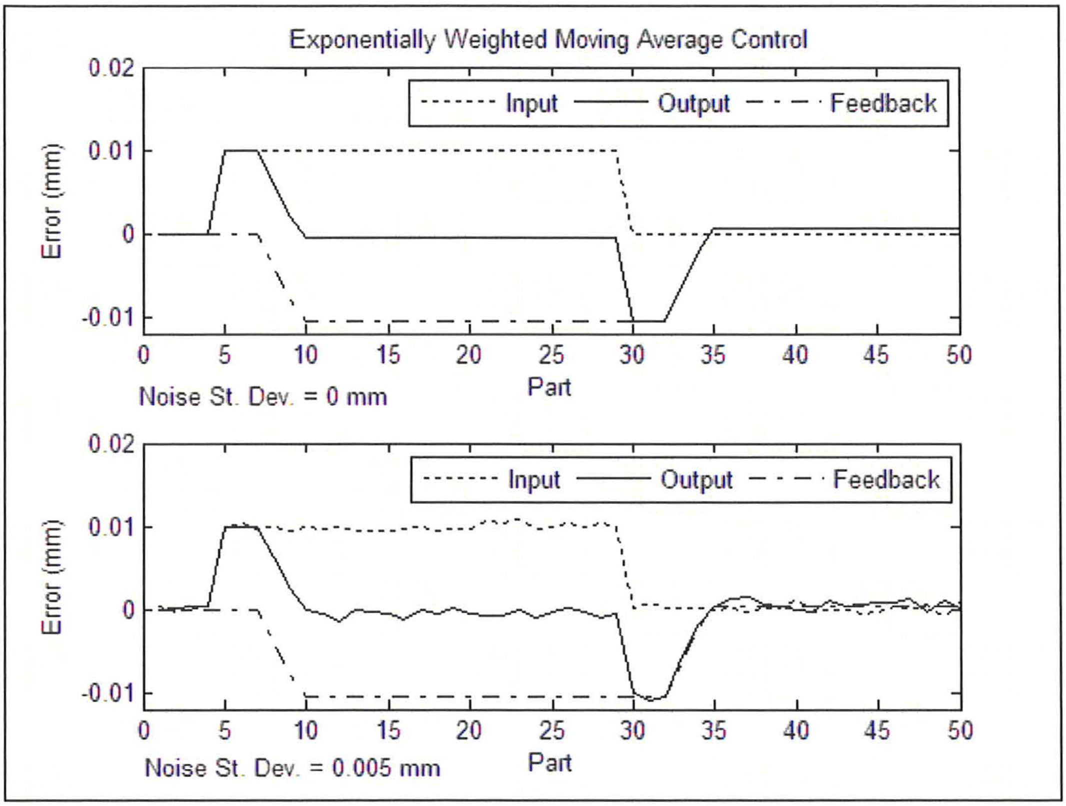

Figure 29: Cell 2, EWMA (g=0.4, λ =0.9) Step Response

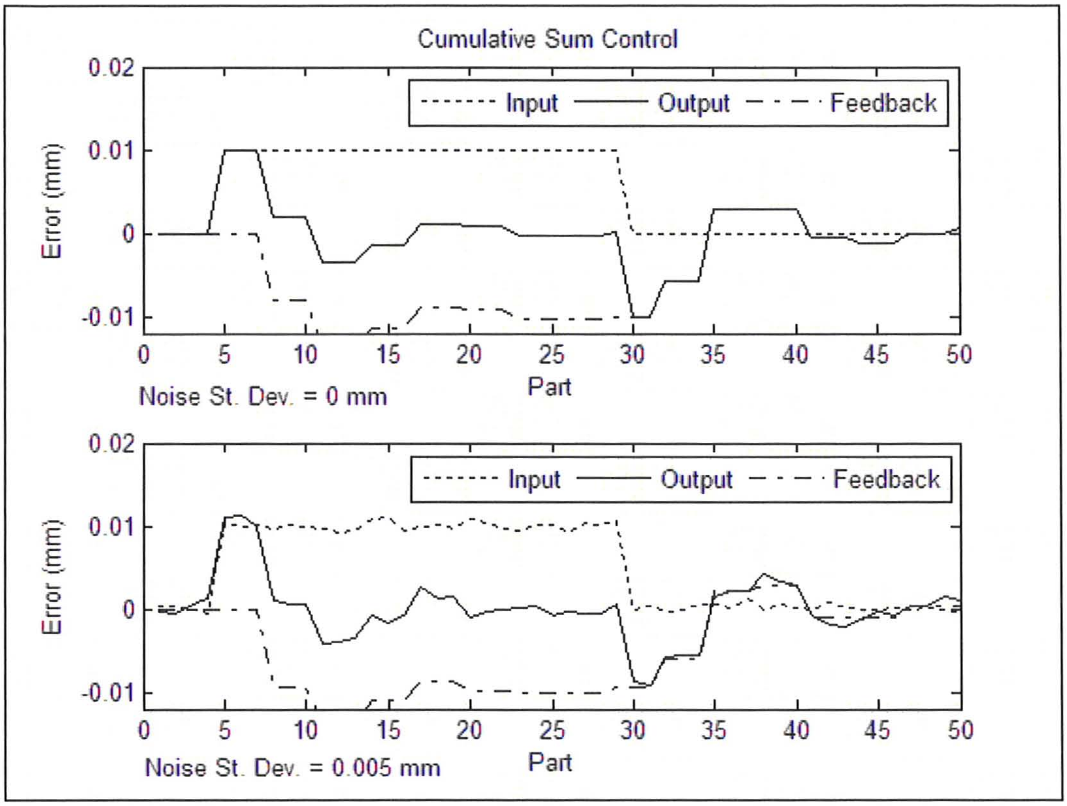

Figure 30: Cell 1, CUSUM (g=0.4) Step Response

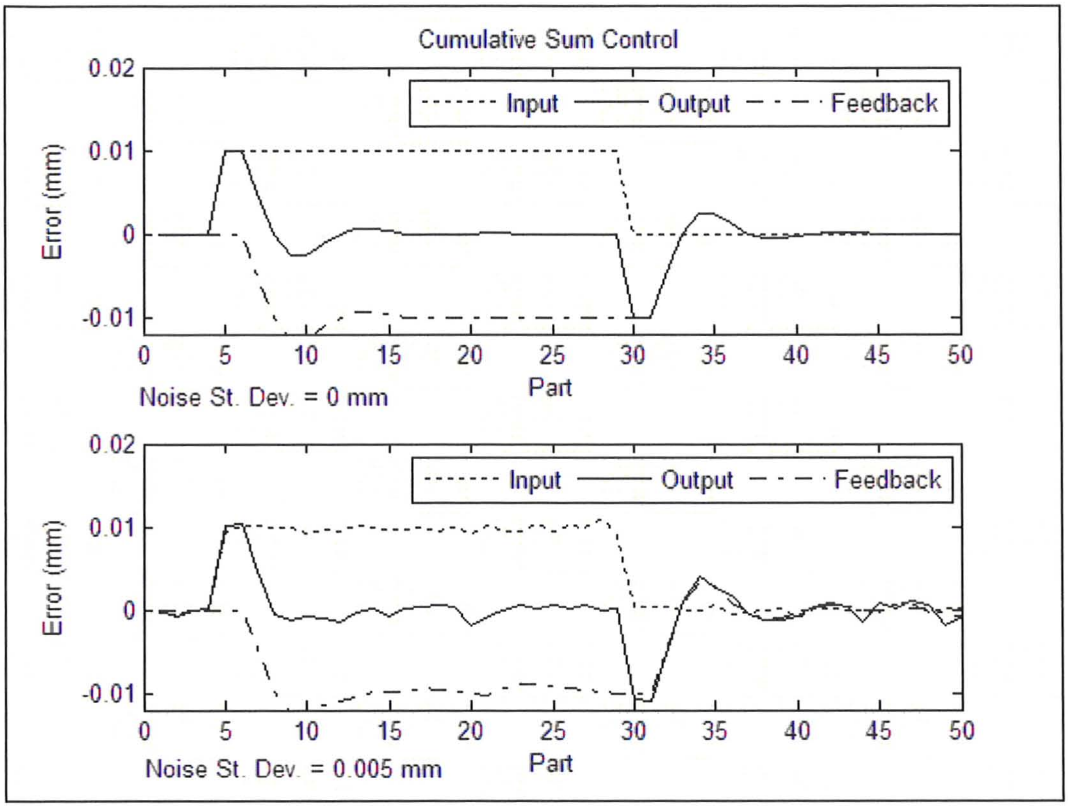

Figure 31: Cell 2, CUSUM (g=0.5) Step Response

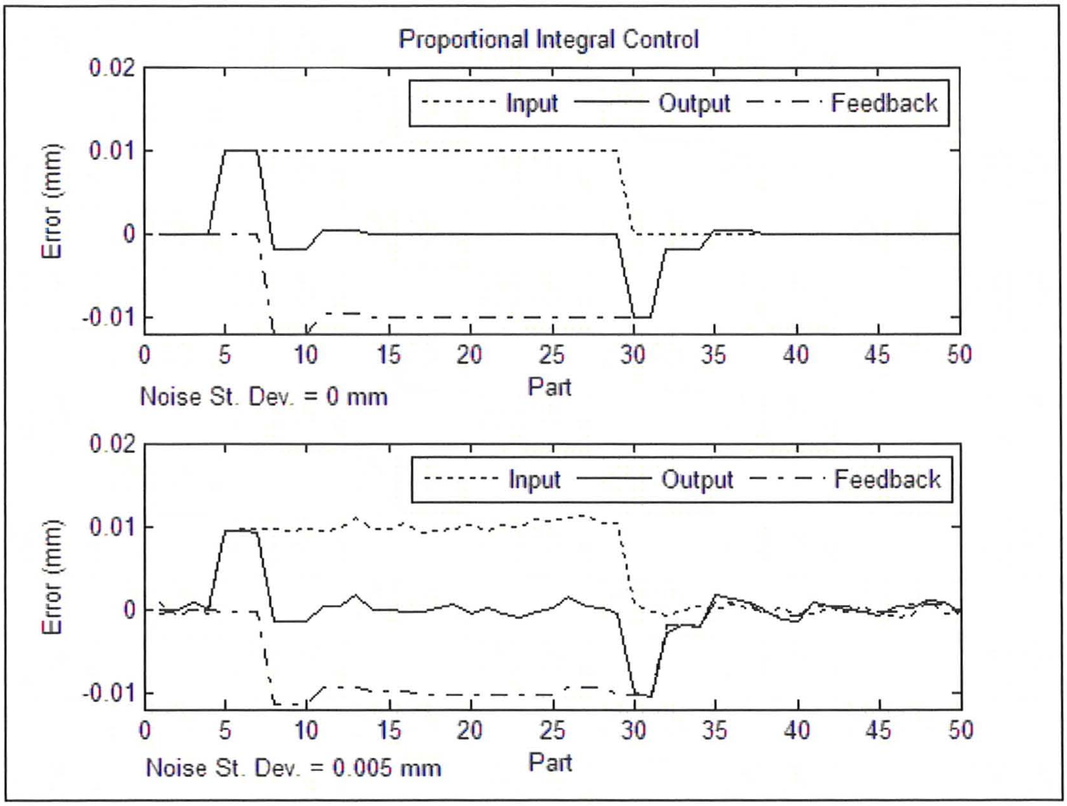

Figure 32: Cell 1, PI (P=0.4, I=0.4) Step Response

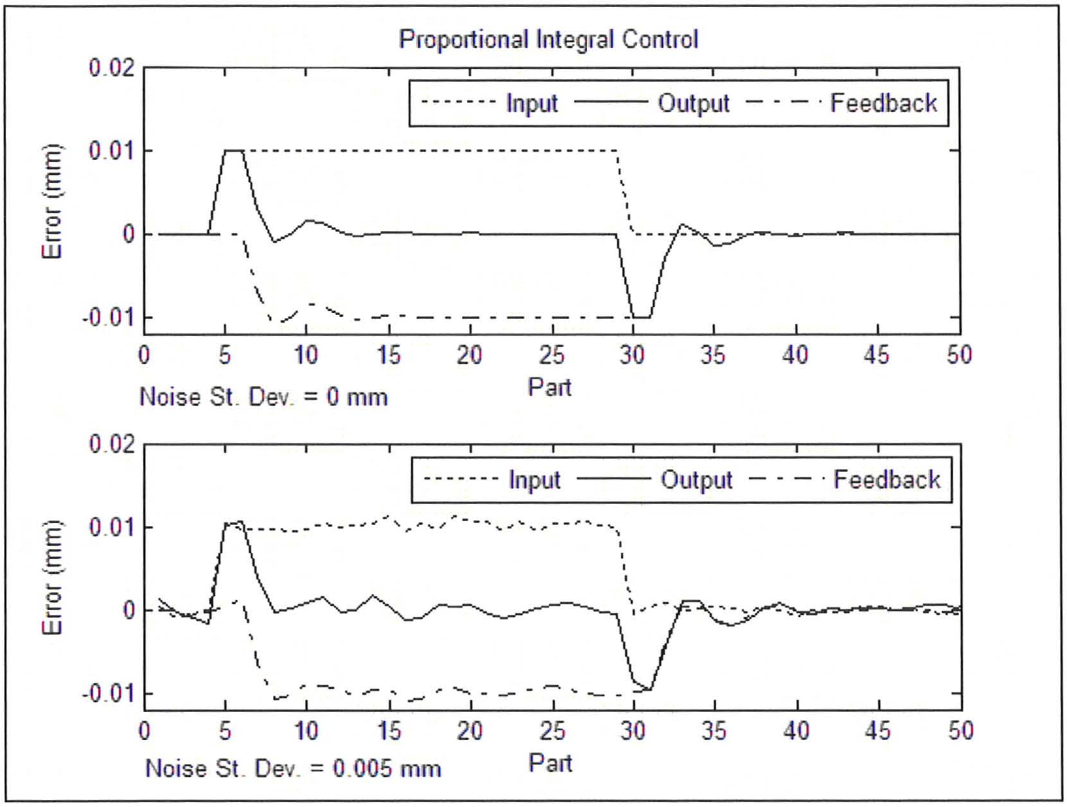

Figure 33: Cell 2, PI (P=0.3, I=0.4) Step Response

10.2 Drift Response Charts

The following charts are summarized in 5.4.2.

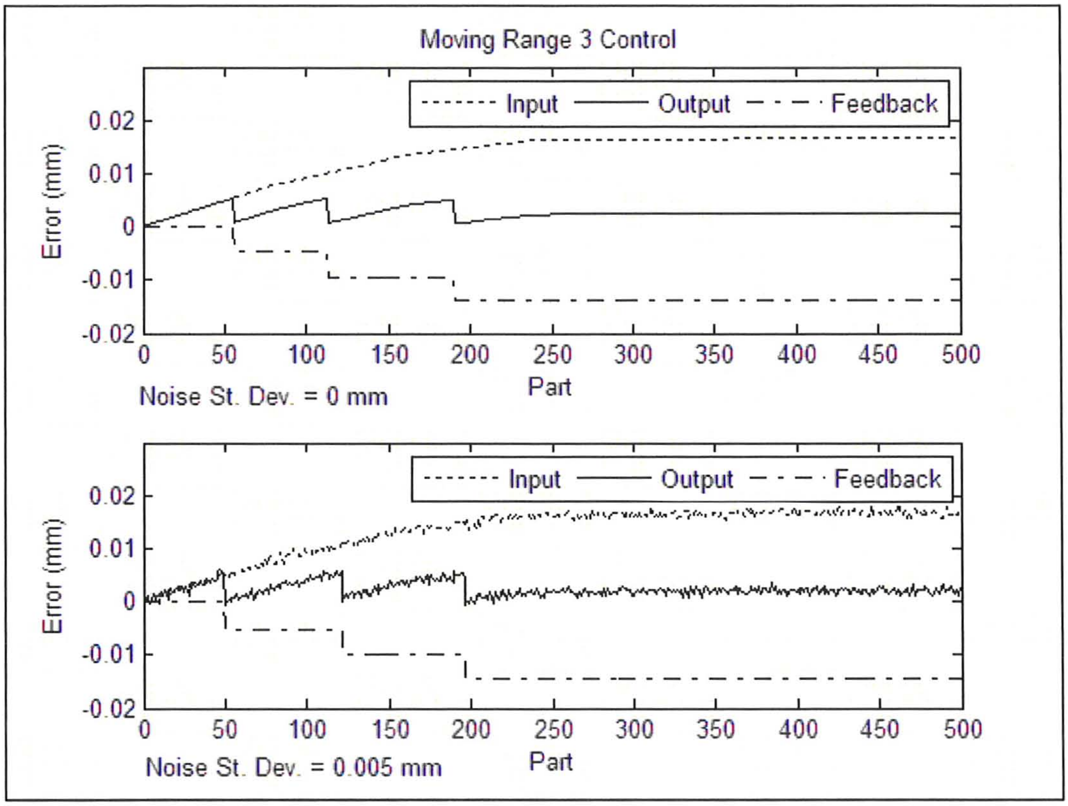

Figure 34: Cell 1, MR3 (g=0.9) Drift Response

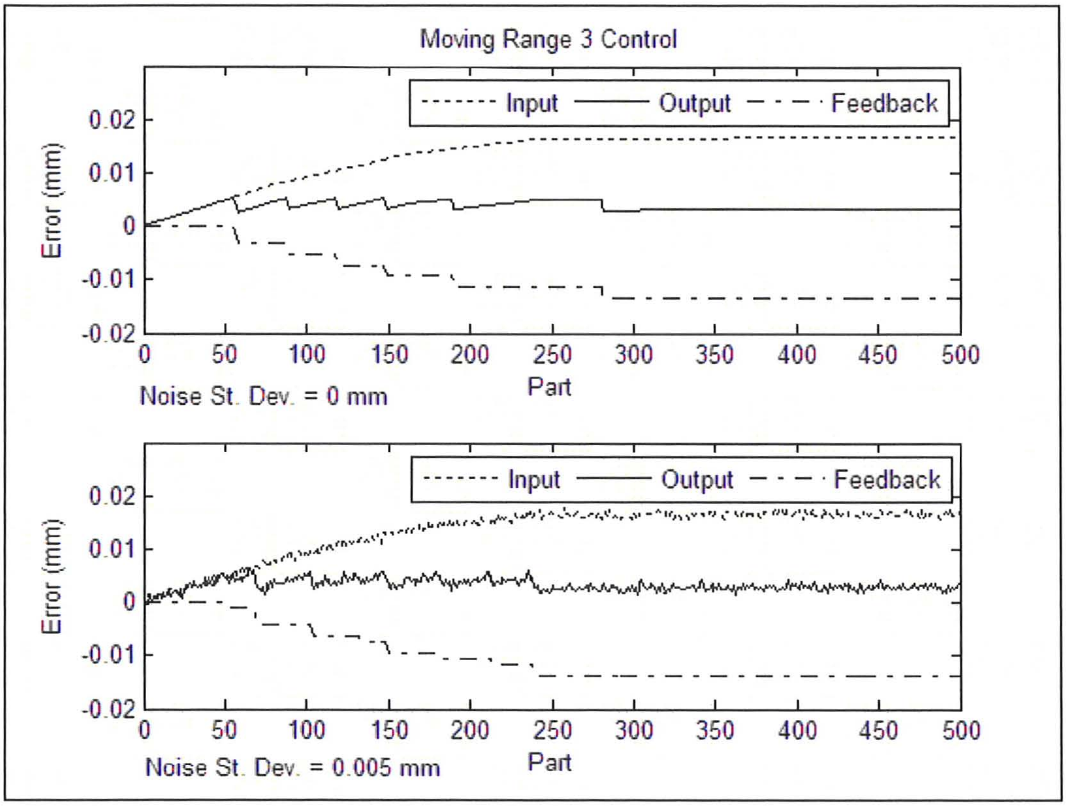

Figure 35: Cell 2, MR3 (g=0.2) Drift Response

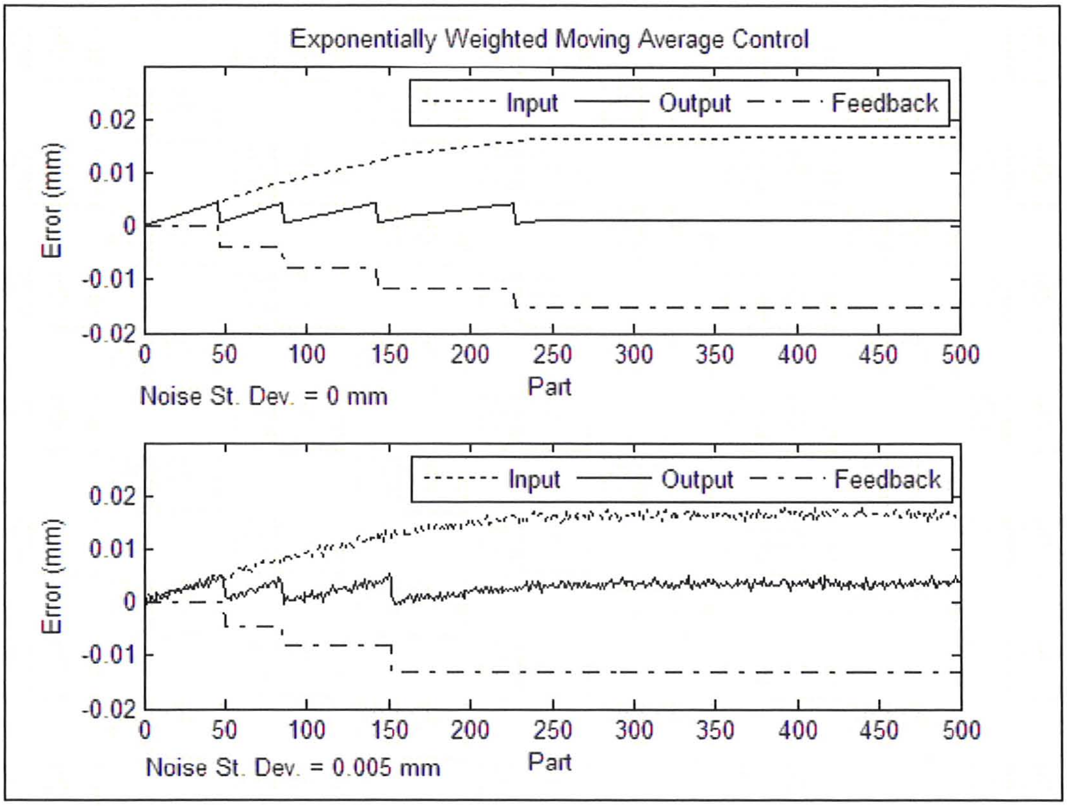

Figure 36: Cell 1, EWMA (g=0.9, λ=0.8) Drift Response

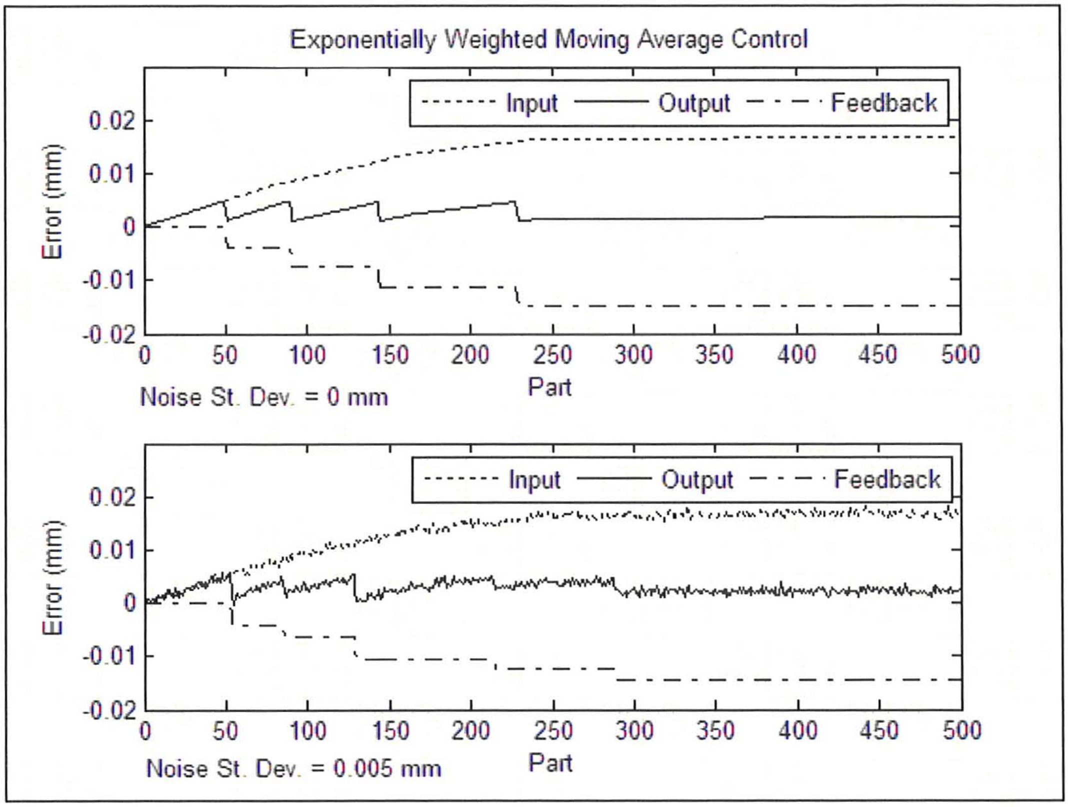

Figure 37: Cell 2, EWMA (g=0.4, λ=0.9) Drift Response

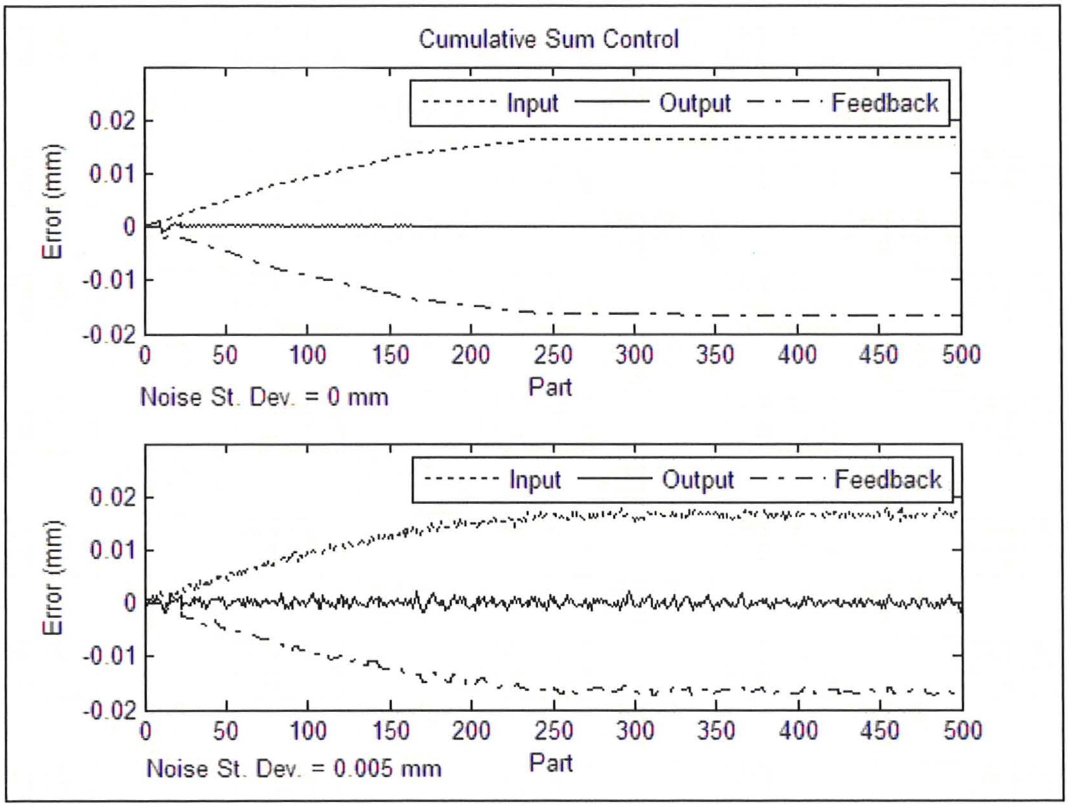

Figure 38: Cell 1, CUSUM (g=0.4) Drift Response

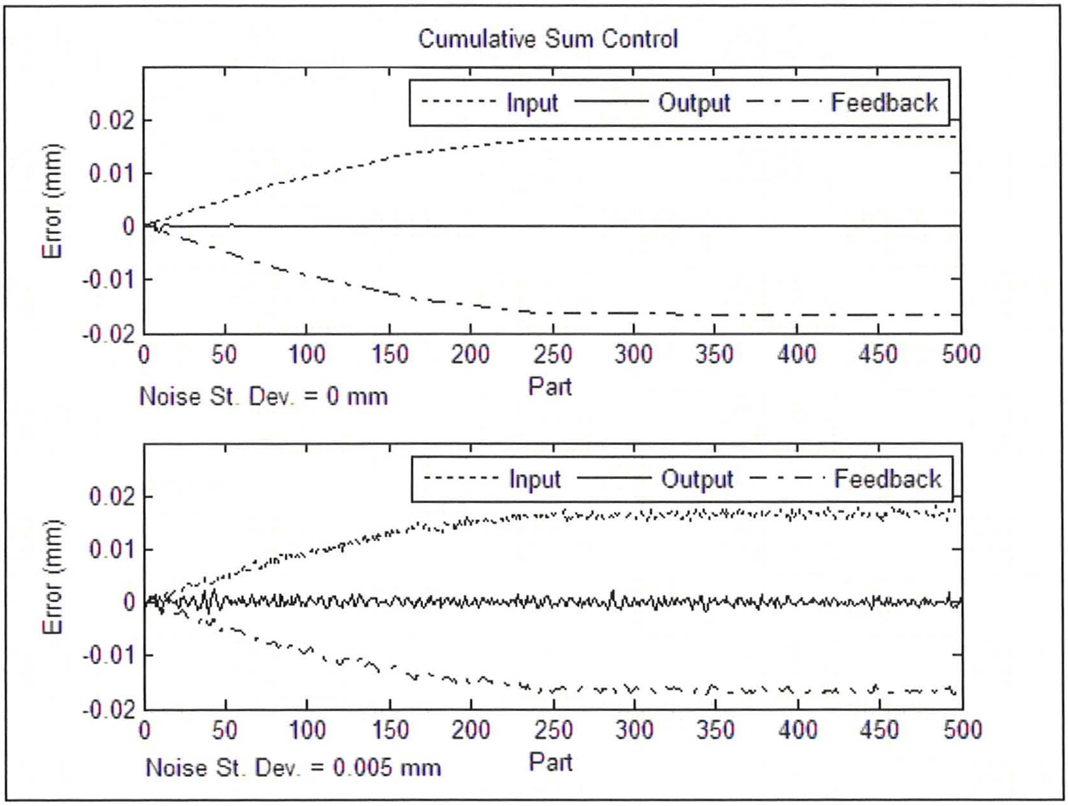

Figure 39: Cell 2, CUSUM (g=0.5) Drift Response

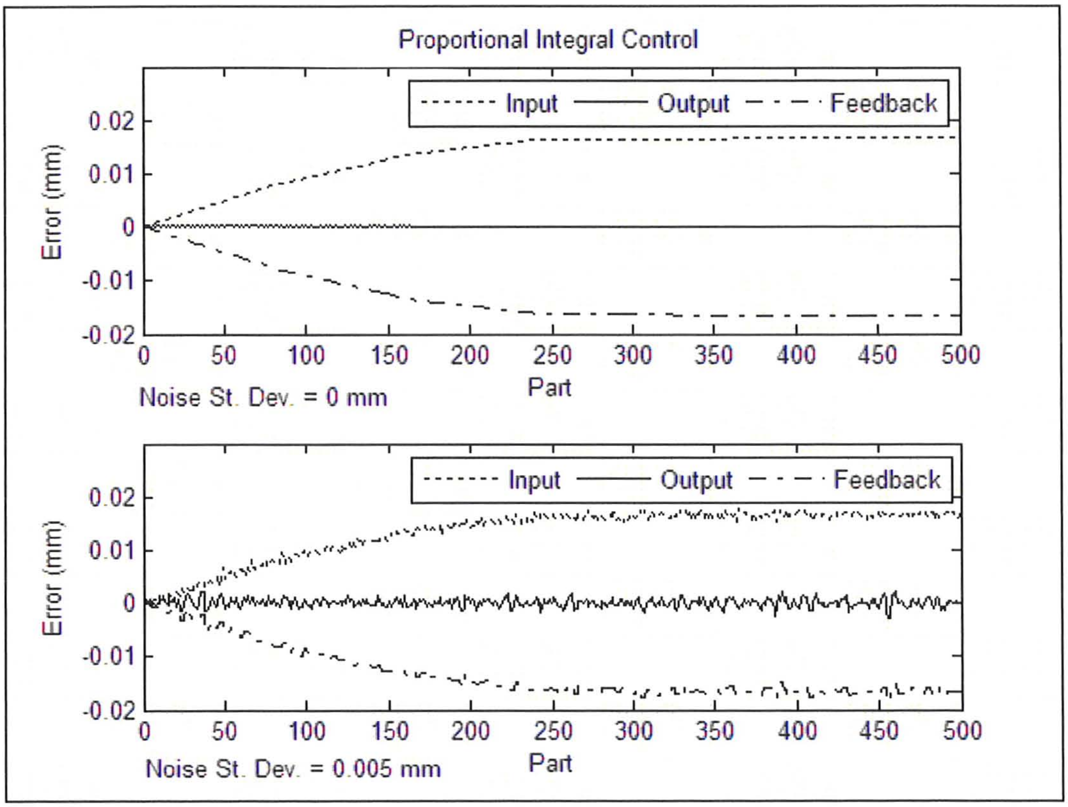

Figure 40: Cell 1, PI (P=0.4, I=0.4) Drift Response

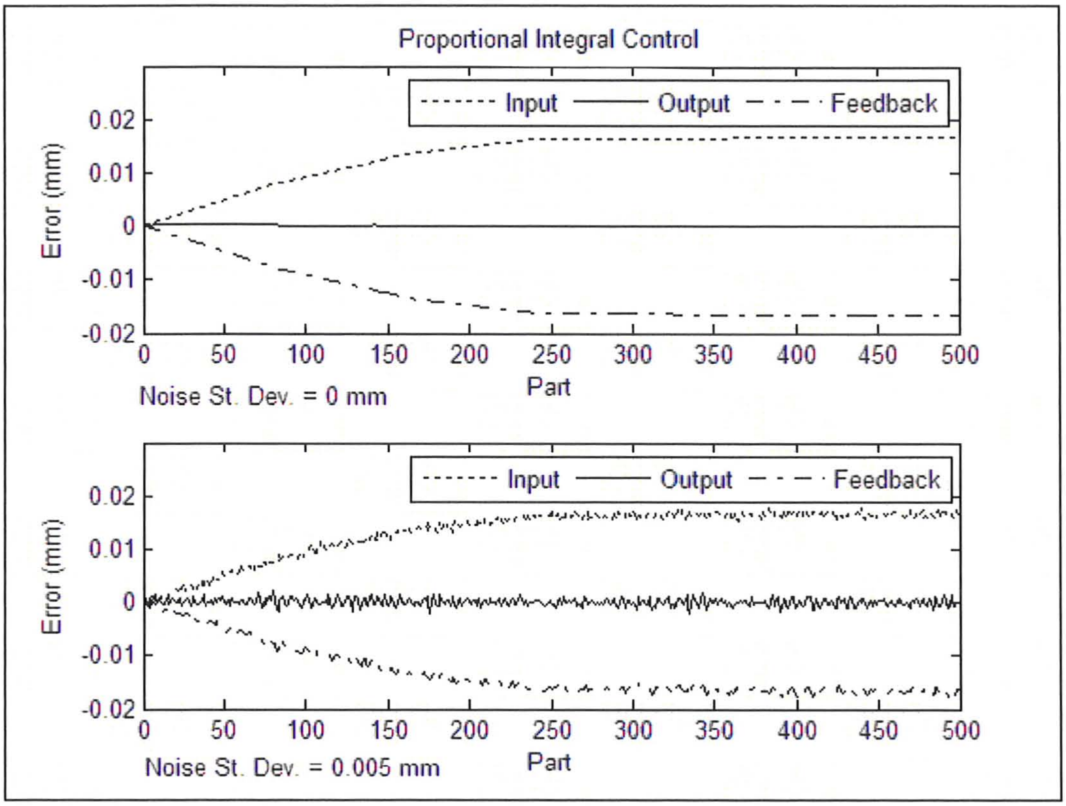

Figure 41: Cell 2, PI (P=0.3, I=0.4) Drift Response