Statistical Methods for Process Control in Automobile Body Assembly

by

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Abstract

The large data streams generated in modern manufacturing environments demand automated data processing techniques to extract useful information for process event detection and variation reduction. To meet the process control objective of reduced variability, it is helpful to quantify the contributors to the existing variation. Variation in automobile body assembly can be decomposed into high frequency, low frequency and occasional extreme point contributors. This decomposition enables a more effective process event detection algorithm. Additionally, these statistical contributors can often be associated with physical phenomena by a process expert. This association can be exploited for the purpose of accelerated problem solving. Several statistical methods are discussed and analyzed. A specific search algorithm is developed that conducts tests for specific types of process events: mean shifts, variation changes, and outliers. Process events are prioritized through comparison to a baseline data set. Trends and distribution changes are evaluated on a less frequent basis. A control algorithm based upon the exponentially weighted moving average is developed. This algorithm meets the desired objectives of being insensitive to batch to batch variation and detecting large process events rapidly. Principal component analysis and multivariate control chart methods are presented. The statistical methods are placed within a decision flowchart to facilitate rapid, effective problem solving and organizational learning.

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1. Introduction

The standards of world class dimensional characteristics in the automobile industry continue to demand improvements in the control of manufacturing processes. The key product characteristics of body panel fit are a function of many processes, ranging from product design through the manufacture of tooling to sheet metal fabrication and finally to assembly. One important strategy in the achievement of this world class standard is the improvement of dimensional feedback systems. This improvement in feedback systems must address the processing of measurements into useful information for problem solving and process improvement.

1.1 Objectives of the Study

This project addresses process control and variation reduction methods with a focus on the challenges and opportunities created with advancing technology. New measurement systems raise the traditional tradeoffs between speed and accuracy in obtaining dimensional feedback on the shop floor to a new level. The capabilities of these new measurement systems bring an associated challenge to the manufacturing environment. In the effort to obtain better control of production processes, data is being generated on more parameters and at a faster rate than ever before. A common quote heard across industries is "we have lots of data, but no information." The high sampling rates and the large number of monitored parameters render the methodology developed for a data poor environment inadequate (Hahn 1989). One challenge revealed through the measurement of every part has been the introduction of time dependence to body shop data, resulting in a difficult distinction between a time pattern of data and a true 'out-of-control' condition. This difficulty relates to recent "efforts to develop robust methods for testing summary measures of the underlying distribution such that the tests retain desirable statistical properties over a range of possible distributional forms" (Barnett and Lewis 1994). Along with the challenges, advances in computer technology have made feasible the automated, real-time, analysis of process data. The technical objective is to develop an automated statistical processing algorithm, that can be utilized for real-time detection of process events, can support rapid problem solving through supplemental data characterizations, and can support overall variation reduction efforts by informing process experts of unusual patterns or characteristics of the data.

The management objective is to place this tool within a disciplined approach to dimensional process control that facilitates rapid response to critical situations, accurate diagnosis of true root cause, and organizational learning to support proactive improvement and defect prevention.

1.1.1 Immediate Objectives - Facility Driven

The manufacturing plant where this research was conducted approaches the challenges of manufacturing with a focus on technology. An aggressive approach to measurement technology resulted in the acquisition of optical coordinate measurement systems for both the final product and major subassemblies. The approval, installation and initial utilization of these measurement systems was for the reduction of dimensional variation. Management recognized that these measurement systems could also be used to establish a rapid response system. With such a system, problems occurring within the body shop could be contained and corrected within the body shop. A secondary objective of the local management was to more effectively utilize problem solving resources. Fewer people are now available for monitoring and evaluating the data from these measurement systems than during the initial phases of the variation reduction program.

1.1.2 Long Term Objectives - Divisional Driven

As the organization looked to the future of dimensional process control, two characteristics were identified. First, more data will be available on the processes and equipment that generate a final product characteristic. Second, process control responsibility may be more localized with individual tool owners initiating corrective actions on the basis of process data (Parsons 1995). These characteristics emphasize certain aspects of the objectives stated above. In terms of Deming's (1986) approach to new equipment, the utilization of current measurement systems must be maximized before more complex measurement systems can be successfully managed. With the general direction towards a more distributed process control system, the need for a disciplined approach is increased.

1.1.3 Academic Objectives

This project bridges the gap between academic research and industrial practice. Therefore, a primary objective of the thesis is to facilitate knowledge transfer between the worlds of academic research and industrial practice. Academic research benefits from the realism of the problem described and the challenges in the implementation of a control mechanism. Industry benefits through the presentation of academic research in the context of a known industrial process.

1.2 The Body Assembly Process

The body shop is the area of an assembly plant where sheet metal stampings and minor subassemblies are welded together to form the "body-in-white" (BIW). Incoming material is received from stamping suppliers, routed through subassembly tooling, then welded in a framing fixture. Additional sheet metal subassemblies such as doors and hoods are attached to the body. Final adjustments are made to the surface finish and fit of the body panels before the body proceeds to paint. Following the paint process, components and subassemblies are installed in or on the body until it completes the assembly process. This process is shown in Figure 1-1. The body shop is responsible for the key product characteristic of body panel "fit." Fit is expressed in terms of the size and shapes of gaps between panels and the flushness of adjacent panels.

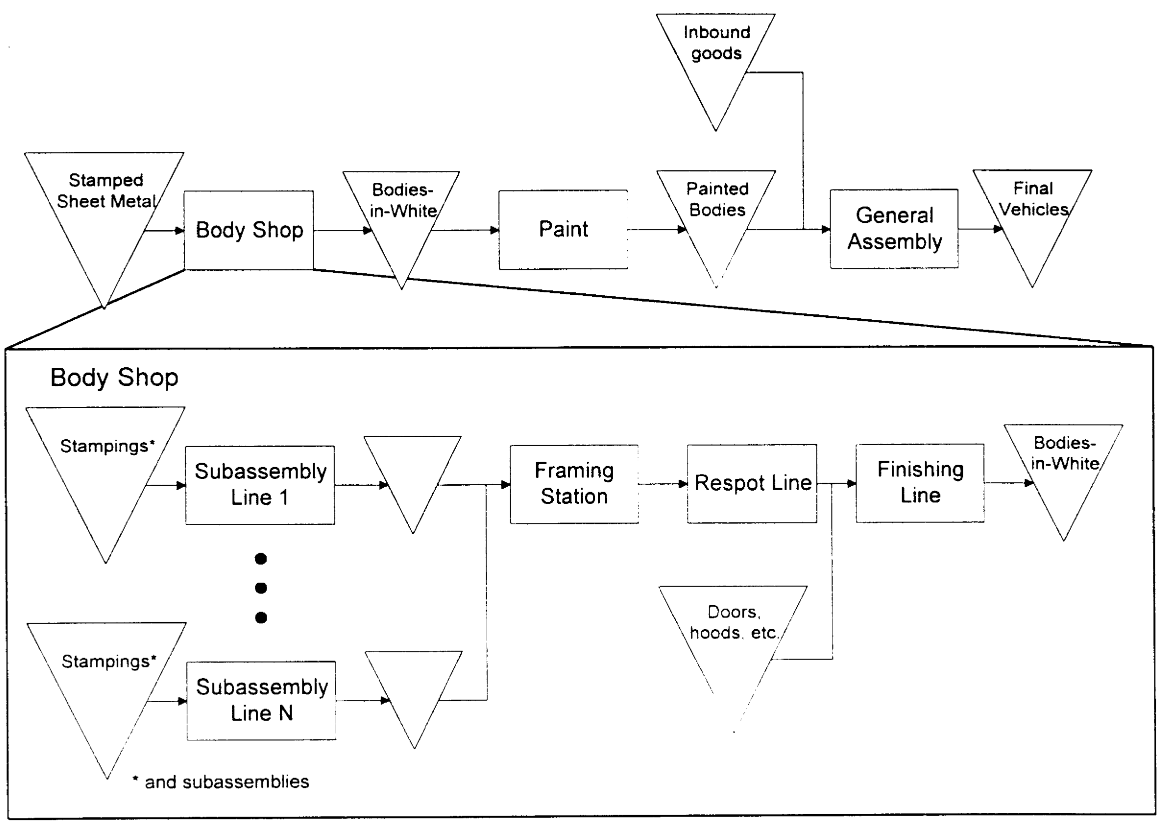

Figure 1-1: The automobile assembly process and the more detailed body shop assembly process. (Figure adopted from McGettigan 1992)

1.3 Process Control

The objectives of feedback process control apply at many levels for a given production process. In feedback control, the output of a process is used to adjust a process input such that the output achieves a specified objective. Improper implementation of feedback control can lead to situations that are unstable resulting in process output with higher variation than without the use of feedback control. Instabilities in a control system are often related to delays between the process output and the controlled input; this instability has been shown for the engineering problem of controlling a velocity servo mechanism (Hardt 1995). A second control characteristic that deteriorates performance is 'tampering' with a system that is already in a state of control. The classic example of the impact of tampering with a process is the funnel experiment[1]. Characteristics of a feedback control system are shown in Figure 1-2.

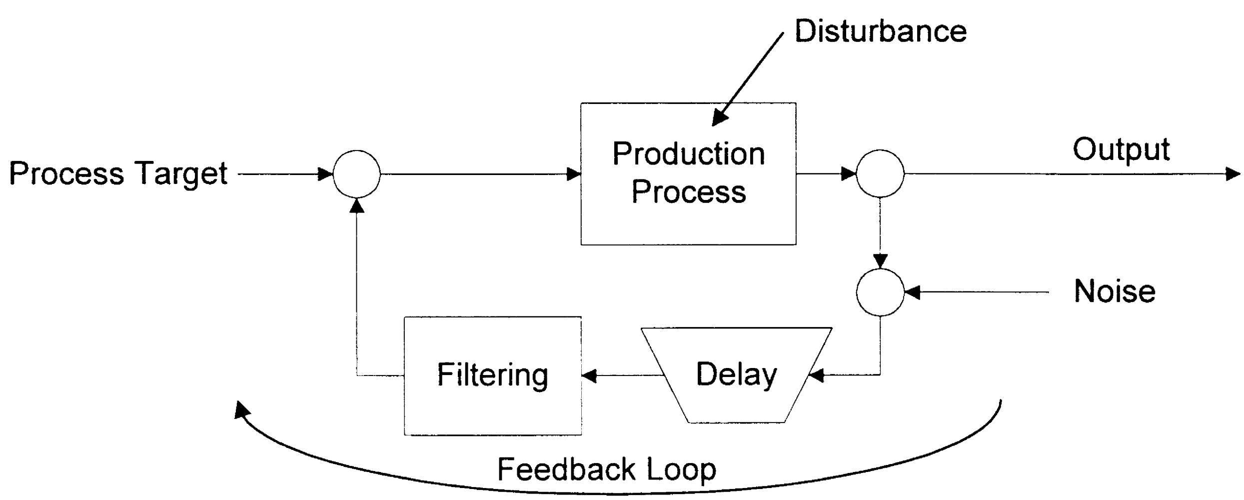

Figure 1-2: Process control diagram for a generic production process. Note that disturbances effect the process, noise is added to the feedback measurement, and the feedback is processed through delays and filters before it can be used to adjust the process input.

[1] The funnel experiment is an example that was presented by Deming (1986) to demonstrate that tampering with a process leads to higher variation. The experiment consists of a funnel mounted over a target. In the experiment 4 process control rules were used in the attempt to minimize deviations from the target. All strategies that attempted to compensate for observed deviations from the target increased the variation.

The objective of process control is to minimize the effect of the disturbance on the output. The first response is to identify and eliminate the disturbance; the longer term response is to modify the production process to be more robust to the potential disturbance, and in the highest level of control, feedback is used to counteract the disturbance to minimize changes in the output (Hardt, 1995). The disturbance elimination control approach is to identify the problem, analyze the problem, establish corrective action, and capture the learning from the event. Alternatively, the process can be made more robust to given disturbances in the environment. This optimization is where designed experiments (Taguchi, 1986) and planned observation are most effectively utilized (Exner, 1995). The third case is where a feedback control system is created such that the process input parameters are adjusted in response to changes in the process output. At the current stage of automobile manufacturing, the most common use of feedback systems is to identify disturbances effecting the production process. Corrective actions are then taken to eliminate that disturbance.

1.4 Research Approach

The research approach taken in this project focused on the shop floor. Understanding the data characteristics and information needs in the body shop was obtained through a variety of problem solving projects. These projects ranged from immediate problem solving efforts for which speed of detection was most critical to chronic problems where deep understanding of the entire production process and supply chain was required. Questions that were asked of these projects included "how could this problem have been detected more rapidly?" and "what information or analysis would have helped solve the problem more rapidly?"

An automated data analysis and notification system was developed and implemented based upon the initial identified needs. Additional opportunities and shortcomings were identified through experience with the initial system. The main survey of literature was postponed until after the needs of the body shop were understood. A second analysis method was then developed based upon the exponentially weighted moving average. Representative data sets exhibiting batch to batch variation as found in a body assembly process were generated to evaluate the sensitivity of the various approaches to a process with 'in-control' batch to batch variation. The detection capability of the algorithms were evaluated using data sets generated to represent characteristic process events.

1.5 Organization of the Thesis

The thesis begins with background of the problem in terms of the sources and characteristics of data in the body shop. The current approaches available through current practice and the academic literature are reviewed. The technical aspects of the process control approach are discussed, focusing on a specific search algorithm, an exponentially weighted moving average algorithm, and multivariate analysis methods. Algorithm performance is presented using simulated data sets. A proposal for management control that emphasizes a disciplined approach is presented. Conclusions and recommendations are found in the final section.

2. Background on the Problem

This section presents background on the problem of data based process control. An appreciation for feedback mechanisms in the body shop is developed to clarify the need for an automated processing algorithm. Final body shop output variation results from the combination of upstream process variations and final assembly variation. Statistical process control challenges arise from the characteristics of variation associated with process data. Current approaches found in practice and in the literature provide a starting point for the remaining analysis.

2.1 Feedback Mechanisms

This section examines many mechanisms for dimensional feedback in the body shop. General criteria for evaluating feedback mechanisms are presented. The specific sources of feedback in the body shop are described. The feedback sources are evaluated using the key criteria. Synergies between measurement systems and additional measurement system features are discussed. The data from these feedback mechanisms is monitored and interpreted by a process expert.

A process expert is a person with knowledge of and responsibility for the dimensional characteristics of the product. The process expert has responsibility for monitoring each of these feedback mechanisms and drawing conclusions about the status of the process. The large number of feedback mechanisms and the large amounts of data generated by these mechanisms create the need for the automated analysis methods presented in Section 3 and Section 4. The multivariate methods presented in Section 5 also assist in the translation of data into information useful to the process expert.

2.1.1 Criteria for Feedback Mechanisms

Dimensional process control of automobile body assembly uses many data sources. No single feedback mechanism can provide all the needed information on the status of the production process: however, using these mechanisms together can provide in-depth feedback on the status of the process. The contribution of these sources can be assessed based upon several criteria:

- Delay - Delays associated with a given feedback mechanism adversely effect the usefulness of that measurement for the control of manufacturing processes. First, delays between the occurrence of a problem and detection of the problem hinder the ability to link cause and effect. The absence of this link makes problem solving difficult. Additionally, using delayed measurements to look for changes in the production process results in a large number of vehicles or parts built in the suboptimal condition before problem identification.
- Accuracy - The accuracy of a measurement system must be understood to be a useful feedback mechanism. Accuracy is composed of bias and precision. (Doebelin, 1966) Problems of bias, or systematic errors, can often be overcome through more frequent calibration or through determination of the systemic cause. Problems of precision (or random errors or repeatability) can often be overcome through repeated measurements.
- Validity/Relevance - Some data sources provide data that is directly relevant to the areas requiring control while others may be available but unimportant. For example, data on the current for a given weld gun may be available, but if the relationship between this weld current and the dimensional characteristics of the vehicle is weak or unknown then the relevance of this data for dimensional control is low (although it may be highly relevant for other requirements such as weld strength). Relevance can be established through understanding of the detailed product design or through experience of mapping observed problems back to a characteristic of the data.

2.1.2 Sources of Dimensional Feedback

The sources of feedback available in the body shop are discussed below. While these sources are specific to the body shop, their characteristics are representative of measurement system alternatives available in other industries.

2.1.2.1 Coordinate Measurement Machines

A coordinate measurement machine makes precise dimensional measurements of an object. While the term coordinate measurement machine is generic, in body shop specific usage, a coordinate measurement machine (CMM) refers to an articulating arm that obtains dimensions by physically touching the product with a probe. CMMs are used in a variety of industries to measure dimensions. Available CMMs range from automated to flexible and from large to portable. The most fixed CMM is a large, permanent, automated setup where two probes characterize the entire body using a pre-programmed routine. The next level is a more flexible version of the same 2 probe setup. This setup is used for custom evaluations of the body or major subassemblies. A smaller setup can measure minor subassemblies in an automated or manual fashion. Portable CMMs can gather product or process measurements on the shop floor.

2.1.2.2 Optical Coordinate Measurement Systems

Optical coordinate measurement systems use lasers and optical sensors to rapidly measure dimensional characteristics. This technology enables the measurement of production output on every part produced. This high frequency measurement capability increases the understanding of variation. Optical measurement technology also enables measurement in the manufacturing environment, potentially minimizing the feedback delay for process control. This minimization of delay is only achieved by rapidly processing measurement data into information for the process expert.

2.1.2.3 Hard Checking Fixtures

Hard checking fixtures, located on the production floor, facilitate measurements of key dimensional characteristics. These fixtures have two primary characteristics. First, mounting surfaces and clamps hold the part as it will be attached to the body in a downstream operation. Second, the part is measured relative to a set of referenced dimensions. In most cases, the fixture design uses a standard measurement probe. This design feature facilitates automated data collection methods. These fixtures can also be used with a portable CMM.

2.1.2.4 Body Panel Gap and Flush Measurement

Special tools developed for measuring the key product characteristics of body panel gaps and flushness enabled the introduction of a statistical process monitoring program for these characteristics.

2.1.2.5 Operator Process Observation

Operators are in contact with the product and the process throughout the facility. From experience they come to know a great deal about what their parts or tools should look like at a given stage in the process. Formalization of the feedback and follow-up process represents a challenge regarding successful use of operator feedback.

2.1.2.6 End of Line Production Audit / Daily Body Shop Supervisors Review

At the end of the assembly process, auditors evaluate vehicles selected from daily production. These audits provide feedback on quality characteristics of the vehicle; one set of audited product characteristics is the "fit" of body panels. Fit refers to primarily to the visual appearance of the relationship between body panels or between body panels and other components. On a daily basis, the body shop production supervisors meet in the audit area to review any identified problem vehicle characteristics. They follow-up on these issues with the appropriate worker who may be unclear on the expectations or standard of production. Several shifts pass between body shop production and audit feedback because the vehicle must travel through paint, general assembly, and the audit procedure. This delay minimizes the apparent relationship between the cause and effect.

2.1.2.7 Quarterly Corporate Audits / Japanese Export Audit

A corporate audit team conducts a formal audit on a quarterly basis. This audit is an evaluation of vehicles awaiting shipment, and it identifies items that would clearly generate a customer complaint. These audits are one of the key metrics for the plant, with goals and status posted in many locations around the plant. The Japanese export audit, conducted by Japanese customer representatives, identifies virtually every minor and major deviation from the design target. These audits represent the standards of a key export market and clarify the magnitude of the quality improvement task.

2.1.2.8 Warranty / Dealer Meetings

Feedback is obtained from dealers through two mechanisms - warranty and dealer meetings. The warranty system identifies customer problems severe enough to justify returning to the dealer. The two major difficulties with using the warranty system as a feedback mechanism are the significant delays from production until feedback and the lack of precision with which warranty information is recorded. The relationship between the warranty item code selected and the actual root cause of the problem is not always clear. The strength of warranty as a feedback mechanism is that it represents a cost of correction that is responding to a true customer complaint. Meetings between dealers and the assembly plant management are held on a regular basis. These meetings give the dealers a chance to provide more direct feedback on issues that they observe in the field.

2.1.2.9 Customer Satisfaction Surveys

Since customer satisfaction is a primary goal of the process control system, data available from customers on their satisfaction is a highly relevant metric. The primary difficulty associated with using customer feedback is the delay required to get the information. Customer surveys can be used effectively in two ways, first as a check on the control process and second as a method for prioritizing long term problem solving efforts.

2.1.3 Evaluation of Dimensional Feedback Mechanisms

The key characteristics of the primary feedback mechanisms are presented in Table 2.1. This table provides a framework for comparing these different measurement systems. This comparison clarifies how these measurement systems complement one another by addressing different information needs within the body shop.

Table 2.1: Evaluation of the primary dimensional feedback mechanisms available within the body shop.

	Delay/Measurement Time	Accuracy	Validity/Relevance
Coordinate Measurement Machine	Body must be removed from production line measurement then takes 3-4 hours	Regarded as the standard.	500+ points dilutes impact of measured changes. Useful for specific questions such as "why?" and "how much?"
Optical Coordinate Measurement System	Body is measured in a special station of the production line shortly after critical dimensions are set	Adequately precise for most needs. However, higher frequency of measurement errors than with CMM.	Needs better understanding of cause-effect-impact relationships.
Observation by Production Operators	Operators loading parts directly into dimensional tooling can provide immediate feedback. Downstream operators can provide delayed feedback	Changes are perceived well, but absolute levels are difficult to define.	In a healthy work environment, this is very relevant feedback because actual changes in the tooling are observed or real impacts to the assembly process are identified.
Gap and Flush	Can identify changes to the process before bodies leave the body shop, but the root cause may lie far upstream.	High resolution measurement that has successfully passed various gauging standards.	Measurements taken at the first point in the process where final customer characteristics are directly observable.
End of line audit	~2 days after production in the body shop. Several vehicles evaluated each day.	Low resolution measurements, looking for problems - virtually an attribute data set	Examines the car as it goes to the customer - highly relevant.
Customer Satisfaction Surveys	3-4 month delay as a minimum required to allow actual customers to get real experience with the vehicle	Low resolution categories.	Most relevant, it information directly from the customer.

2.1.4 Synergies Between Measurement Systems

This breakdown of measurement system characteristics can show how different feedback sources work together as part of a process event identification system. It is often necessary to utilize information from more than one of these sources in evaluating a production problem. For example, in some cases a change observed through optical measurement may leave the engineer puzzled as to impact of the problem (questioning the relevance of the event). The relevence increases by looking at the body after installation of the doors and fenders. Additionally, through consideration of data from CMM, a more detailed view of the physical change is obtained (since many more locations on the part are measured). Another example is the coupling of a highly relevant measurement with a highly accurate measurement. Specifically, a visual observation of the poor fit of certain body panels - a highly relevant measurement, is often coupled with measurements from a coordinate measurement machine - a highly accurate measurement.

2.1.5 Measurement Contribution to Problem Solving

Along with criteria of a measurement system as a feedback mechanism, the contribution of a measurement system to problem solving must also be evaluated. Considerations for problem solving include:

- Sampling frequency - Having data on each part produced is valuable in problem solving because observable patterns of variation can help identify or eliminate potential root causes.
- Delay - Identification of root causes becomes more difficult with the passage of time.
- Multivariate - Changes (or lack of changes) in other parameters can narrow the scope of potential root causes. This is particularly useful with CMM data due to the large number of measurements taken on the body.
- Data tracking capabilities: Date, time, job sequence number (JSN), and tooling path information can also narrow the scope of potential root causes. Tooling path information identifies the tools that were used to manufacture a given part. This is of particular importance where multiple tools are used to produce the same part.

2.2 Sources of Variation

The sources of variation in the automobile body dimensions can be broken down in two methods. The first method discusses root cause identification for a particular case of variation. The second addresses the hierarchical nature of the automobile body manufacturing process.

2.2.1 Fundamental Sources of Variation

For any production process stage, there are a number of potential causes of process problems. One structure that formalizes the identification of these potential sources is the Ishikawa diagram, also known as the fishbone diagram. The form of the diagram evolves from the process of "asking the 5 whys." (Shiba 1993) In this process, the fishbone is constructed by adding branches as the list of potential effects and causes is traced back through the manufacturing system to a deeper set of causes. In manufacturing problem solving, a structured form of the Ishikawa diagram facilitates the expression of all potential root causes. This structure is shown in Figure 2-1; the main categories of fundamental root causes are: man, material, machine, and method. In recent years, maintenance and measurement have been added to the structured list (Clinton, 1995). These categories initiate the process of identifying root causes.

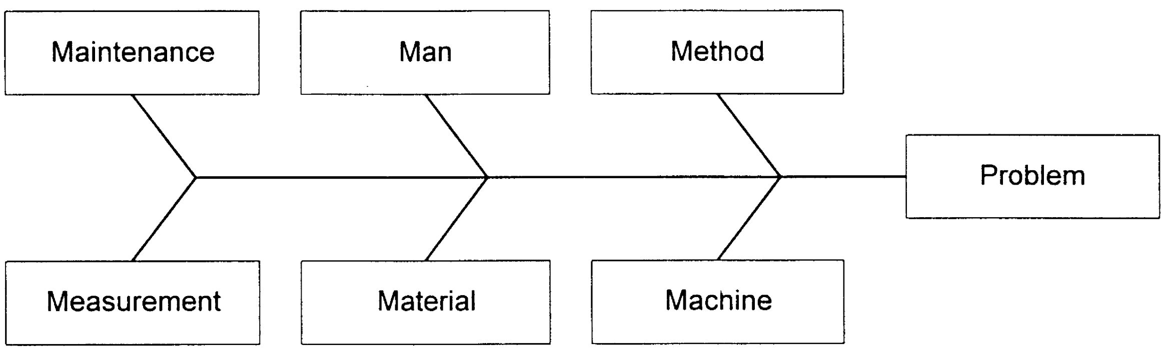

Figure 2-1: Basic form for Ishikawa diagram with the six primary causes of variation shown.

2.2.2 Sources of Variation in Automobile Body Assembly

The sources of variation in terms of the hierarchy of the manufacturing process was presented by McGettigan (1992). This categorization, shown in Figure 2-2, starts with the framed body variation and works back through the manufacturing process to variation in the raw steel, stamping presses, dimensional tooling, welding parameters etc.. Asterisks (*) in the chart indicate branches of the hierarchy that repeat at a lower level. For example, the branch starting with "Form Variation ***" is also a category under "Trim/Piece Variation" and "Flange/Reform Variation."

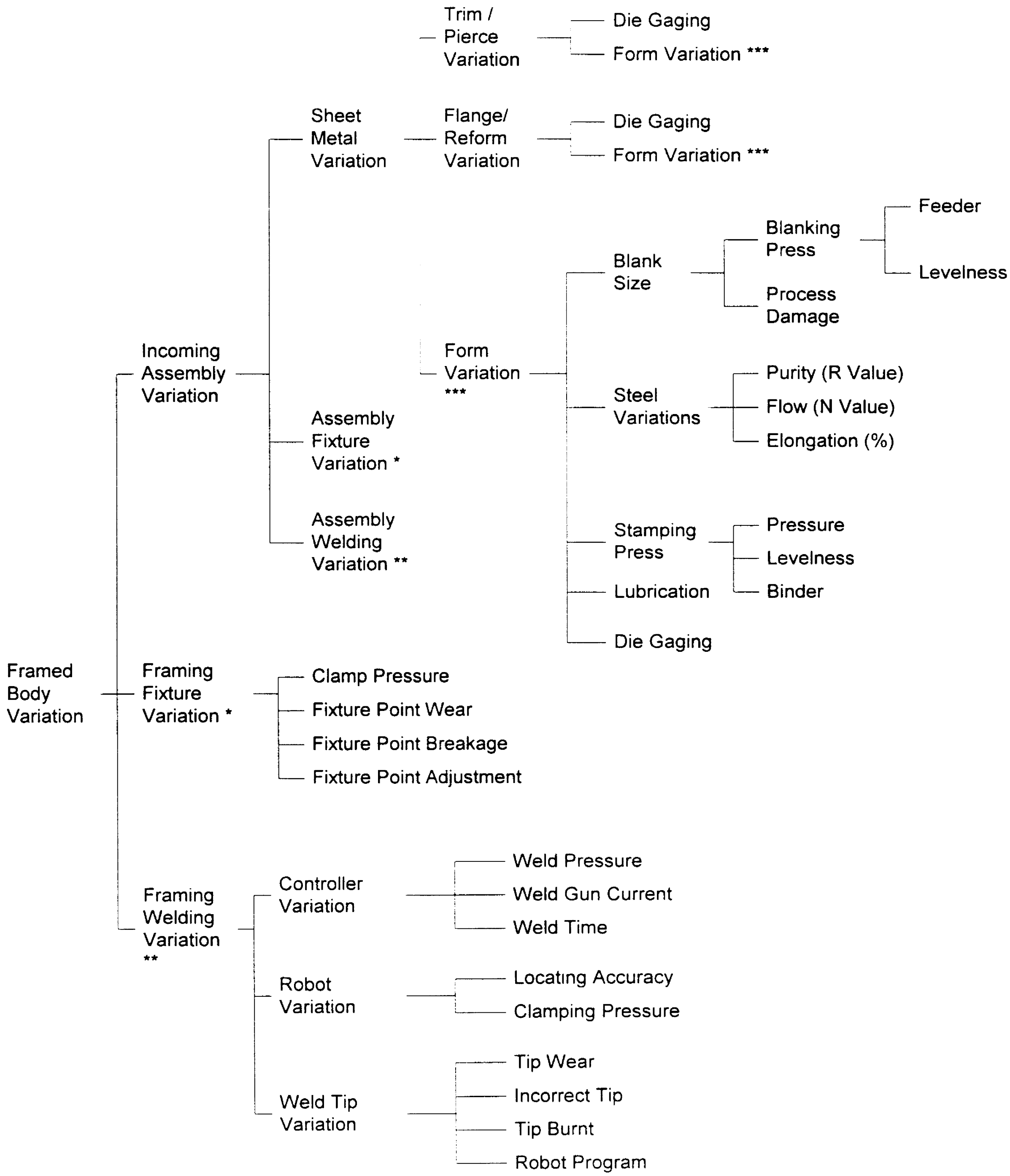

Figure 2-2: Sources of variation in body framing (McGettigan 1992).

2.3 Characteristics of Variation

2.3.1 Hierarchical Variation - Non-independent data

One observed characteristic of data in the body shop is time dependence introduced through the presence of upstream batch processes. The simplest representation of this characteristic is to simplify McGettigan's chart, reducing the sources of variation into a two stage process. The first stage is stamped sheet metal produced in batches and the second stage is assembly of that sheet metal using a tooling fixture and welding. In the first simplification, once dies are set up in a press, the resulting parts are identical, but there is random variation in the characteristics of each particular set up. In the second simplification, the variation from assembly to assembly is independent. Despite the randomness of both processes, the total output, defined as the sum of the batch value and the piece value, has considerable time dependence. This representation assumes that the parts from different batches have not been mixed. This characteristic appears in the bottom set of points in Figure 2-3.

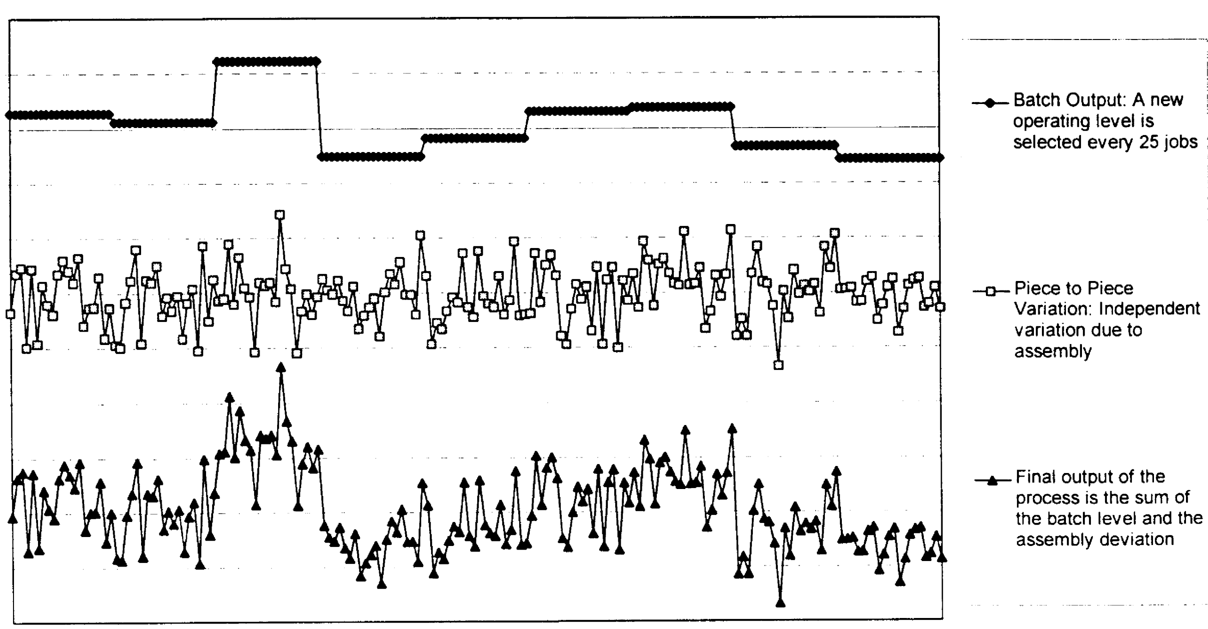

Figure 2-3: Creation of dependence in output due to the addition of batch process variation and independent piece to piece variation. Final = Batch + Piece.

The simulated output shown in Figure 2-3 includes patterns, but those patterns do not imply a process that is not in a state of statistical control. Referring to the teachings of Shewhart (1931):

> A phenomenon will be said to be controlled when, through the use of past experience, we can predict, at least within limits, how the phenomenon may be expected to vary in the future. Here it is understood that prediction within limits means that we can state, at least approximately, the probability that the observed phenomenon will fall within the given limits.

Shewhart's lesson clarifies the potential confusion between the need to achieve a state of control, where the production output comes from an independent, normal distribution, and the need to be able to predict the output of the process, at least within limits. Common cause[2] variation may impact the process in ways that create time dependence in downstream measurements.

One of the standard assumptions in many statistical analyses is that the data can be described by a process model consisting of a process mean and a random error as shown in Equation 2-1. The proposed process model relaxes the unchanging process mean assumption. As shown in Equation 2-2, the mean is a function of time. The specific model used in this analysis selects a mean from a normal distribution at a given point in time, and that value is maintained until another new mean is selected. Equation 2-3 expresses this model as the sum of a batch mean (x_{batch}) and a piece to piece variation (x_{piece}). Even in a process with batch variation, sampling can be performed such that the samples are independent. For example, in the above scenario, if samples were taken separated by a number of jobs larger than length of an individual batch run, then the samples would be independent (because each sample would come from a different batch).

$$Y = \mu + \varepsilon \qquad (2\text{-}1)$$

$$Y = \mu(t) + \varepsilon \qquad (2\text{-}2)$$

$$Y = x_{batch} + x_{piece} \qquad (2\text{-}3)$$

---

[2] Common causes are the drivers of variation that exist in the manufacturing process. They are contrasted with special causes that represent changes in the manufacturing process that lead to higher variation. It is the general objective of process monitoring strategies to be insensitive to common causes and sensitive to special causes.

The relationship between variation in the sample mean and variation within a given sample represents an important issue for statistical process control in the body shop. In the model that generated the data presented in Figure 2-3, the batch to batch (low frequency) variation is not related to the piece to piece (high frequency) variation. Equation 2-4 shows the total variance as a function of individual components of variation. The total variance $\left(\sigma^2_{\text{total}}\right)$ is equal to the sum of the low frequency variance $\left(\sigma^2_{\text{batch}}\right)$, the high frequency variance $\left(\sigma^2_{\text{piece}}\right)$, and the covariance of the high frequency and low frequency components of variation $\left(\rho_{\text{piece/batch}}\sigma_{\text{piece}}\sigma_{\text{batch}}\right)$ where $\rho_{\text{piece/batch}}$ is the correlation between high and low frequency variation (Hogg and Ledolter 1992). For the model that generated the data presented in Figure 2.3, the high frequency variation is unrelated to the low frequency variation; therefore, their variances are also uncorrelated. In this situation, where $\rho_{\text{piece/batch}} = 0$, the total variance is simply equal to the sum of the variances of the components of variation as shown in Equation 2-5.

$$\sigma^2_{\text{total}} = \sigma^2_{\text{batch}} + \sigma^2_{\text{piece}} + \rho_{\text{piece/batch}}\sigma_{\text{piece}}\sigma_{\text{batch}} \qquad \text{(2-4)}$$

Setting $\rho_{\text{piece/batch}} = 0$,

$$\sigma^2_{\text{total}} = \sigma^2_{\text{batch}} + \sigma^2_{\text{piece}} \qquad \text{(2-5)}$$

Evaluation of optical measurement data determined the correlation between the high frequency and low frequency variation. The data was first decomposed into subgroups to enable calculation of the variance of the mean for each sample $\left(S^2_{\text{batch}}\right)$ independently from the within sample variance $\left(S^2_{\text{piece}}\right)$. This decomposition was accomplished by taking a sample size of 20 measurements at an interval of 30 jobs. The total variance for the 1000 jobs $\left(S^2_{\text{total}}\right)$ is compared to the predicted total variance based upon Equation 2-5. Figure 2-4 shows the actual total variance versus the predicted total variance. The linear trend of slope = 1 and the tightness of the distribution around the model prediction line indicate that the covariance term in Equation 2-4 is small. The three major deviations from the model prediction are the result of outliers that occurred in the measurements. The conclusion of this analysis is that the variance of the sample mean is uncorrelated to the within sample variance. This conclusion implies that the within sample variance should not be used as the basis for statistical process control limits for sample means. This implication conflicts with classical control methods that are based upon the model shown in Equation 2-1 (Hogg and Ledolter 1992, DeVor 1992). This conclusion and the implication are true in cases where variation of the sample mean is not correlated to the within sample variation.

Figure 2-5 illustrates the error arising from estimating the standard deviation of the sample means using the average of the within sample standard deviations for body shop data. The prediction of the standard deviation for the sample mean based upon the assumption of independence can have an error three times the value of the prediction. This error leads to an underestimation of the variation of the sample mean that in turn leads to excessively narrow control limits for the sample mean. These narrow limits create a situation leading to frequent false alarms. Figure 2-6 establishes a baseline set of data that is used to calculate control limits for the simulated process with batch variation. Figure 2-7 shows an example of how these falsely narrow control limits generate false signals. In that example, 30 subgroups taken from the identical process that was used to establish the control limits resulted in 5 signals that the process was not in control. These false signals demonstrate the impact of falsely assuming independence.

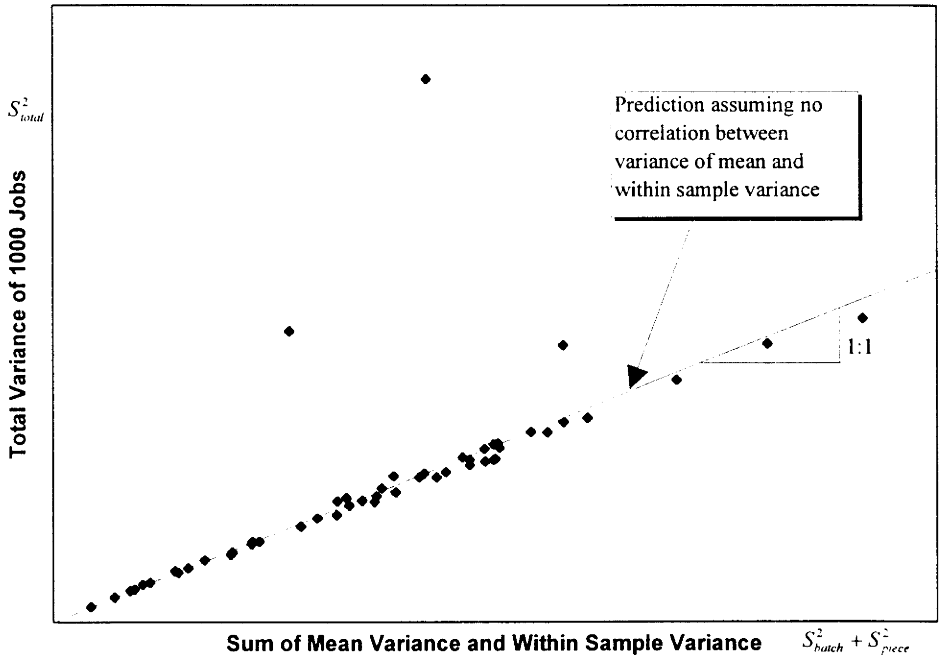

Figure 2-4: Actual Total Variance vs. Predicted Variance. The sum of the variance of the mean and the average within sample variance predicts the total variance of the data set. The three points that deviate from the predicted line result from outliers in the data set.

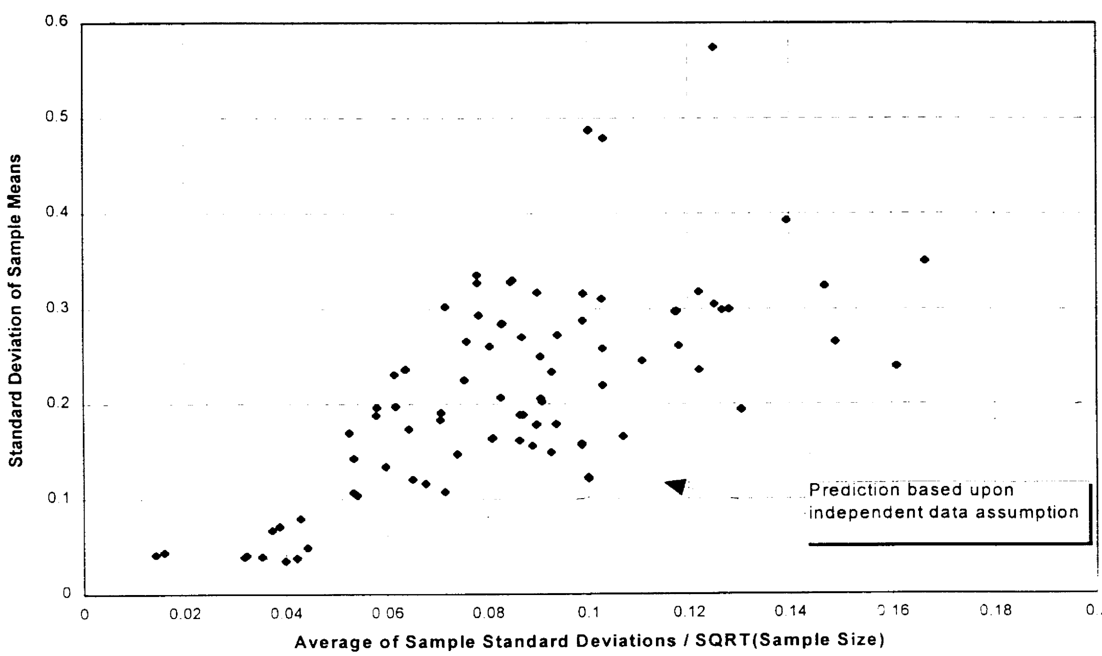

Figure 2-5: Standard deviation of sample means vs. average sample standard deviation / square root of the sample size. The independent data assumption leads

to a prediction for the variation of the sample mean that significantly underestimates the observed variation of the sample mean.

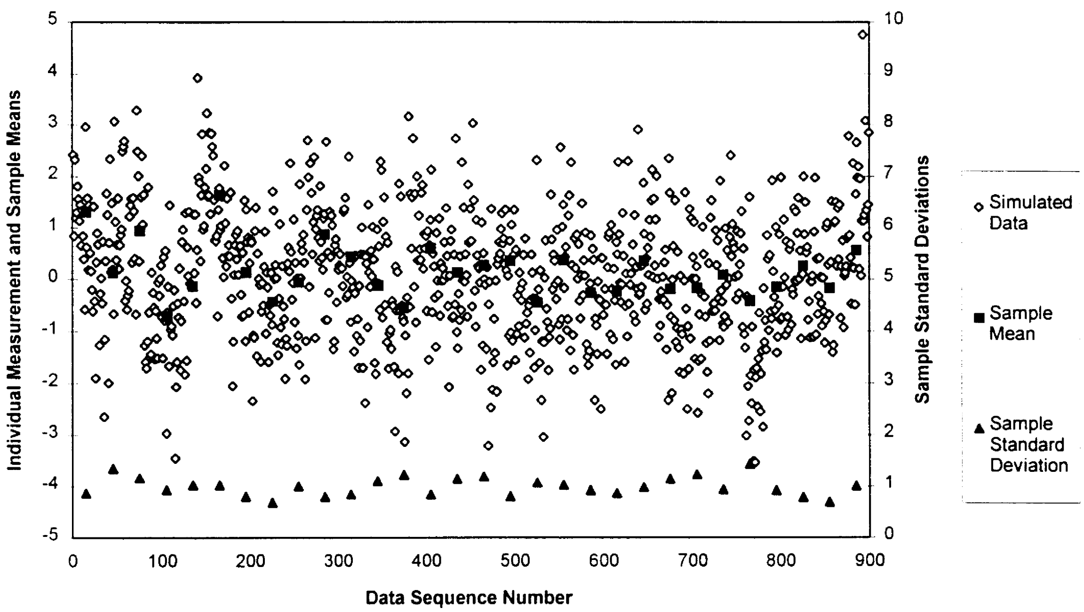

Figure 2-6: Simulated data used to generate control limits for the sample mean. 30 samples of data were taken with 15 measurements in each sample. The average and the standard deviation from each sample are shown. This data simulates a process with a batch length of 25 jobs and batch variation equal to half the piece to piece variation.

The within sample mean, $\bar{X}$, is calculated using Equation 2-6 for each of j samples with 15 measurements in each sample.

$$\bar{X}_j = \frac{\sum_{i=1}^{15} X_i}{15} \tag{2-6}$$

The within sample standard deviation, S_{X_i}, is calculated for each of j samples using Equation 2-7. Note that the denominator of Equation 7 is equal to n-1, where n is the number of measurements in each sample.

$$S_j = \sqrt{\frac{\sum_{i=1}^{15}\left(X_i - \overline{X}_j\right)^2}{14}} \tag{2-7}$$

The average of the 30 sample means, $\overline{\overline{X}}$, is calculated using Equation 2-8. This value is used as the centerline of the control chart. This term is also referred to as "X-Bar-Bar."

$$\overline{\overline{X}} = \frac{\sum_{j=1}^{30}\overline{X}_j}{30} = 0.160 \tag{2-8}$$

The average of the sample standard deviations, $\overline{S}_X$, is an estimate of the piece to piece variation. In traditional control chart methods, this value is assumed to estimate the complete variation of the process. This term is also referred to as "S-Bar-X."

$$\overline{S}_X = \frac{\sum_{j=1}^{30} S_{X_j}}{30} = 0.997 \tag{2-9}$$

The standard deviation of the sample means, $S_{\overline{X}}$, is a new parameter that is calculated in establishing control charts with processes that have underlying batch variation. Calculation of this parameter is shown below. This term is referred to as "S-X-Bar."

$$S_{\overline{X}} = \sqrt{\frac{\sum_{j=1}^{30}\left(\overline{X}_j - \overline{\overline{X}}\right)^2}{29}} = 0.54 \tag{2-10}$$

This value is not used in the example shown in Figure 2-7. Traditional control chart methods estimate this value based upon the average of the sample standard deviations divided by $\sqrt{n}$.

This calculation is shown in Equation 2-11, where the sample size, n=15. Note that this value for $S_{\overline{X}}$ is less than the variation of the sample mean that was calculated in Equation 2-10.

$$S_{\overline{X}} = \frac{\overline{S}_X}{\sqrt{n}} = \frac{.997}{\sqrt{15}} = 0.26 \qquad (2\text{-}11)$$

The upper and lower control limits for the sample mean are calculated using Equations 2-12 and 2-13 with the 0.26 estimate of $S_{\overline{X}}$ from Equation 2-11.

$$UCL = \overline{\overline{X}} + 3\frac{\overline{S}_X}{\sqrt{n}} = 0.93 \qquad (2\text{-}12)$$

$$LCL = \overline{\overline{X}} - 3\frac{\overline{S}_X}{\sqrt{n}} = -0.61 \qquad (2\text{-}13)$$

Figure 2-5 showed that Equation 2-11 underestimates the actual variation of the mean in the presence of batch variation. Figure 2-7 shows the impact of this underestimation on the generation of false alarms. 5 "out of control" points were identified from 30 samples taken from the identical process that was utilized to generate the control limits. If the direct estimate of the variation of the sample mean was used $\left(S_{\overline{X}} = 0.54\right)$, the control limits would have been set at +1.78 and -1.46 and no alarms would have occurred.

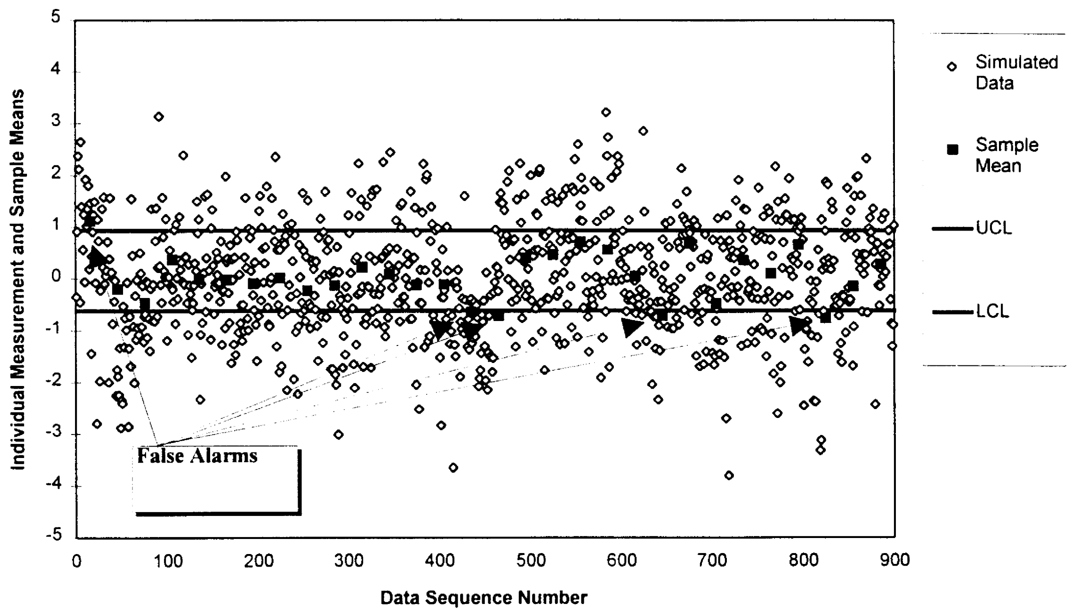

Figure 2-7: False alarms generated by an underestimation of the variation in the sample mean. These control limits were calculated using the average of the sample standard deviations to estimate the variation of the sample mean.

This analysis recommends that in the presence of underlying batch variation, the variation of the sample mean should be estimated directly. This is done by taking the standard deviation of the sample means taken during the baseline period. The estimate of variation in the sample mean achieved through the assumption of independence is unnecessary and leads to systematically narrow control limits in the presence of batch variation.

2.3.2 Outliers

An outlier is a measurement that falls outside a range predicted by a model of the production process. This measurement deviation may arise from either a measurement error or an actual manufacturing process deviation. Data in the body shop includes a significant number of outliers. In addition to uncertainty regarding the source of the outlier (process or measurement), the outlier may or may not represent a condition that represents a downstream problem (either for the customer or downstream assembly). While it is recognized that the objective must be the minimization of outliers, the process of achieving a state of minimal outliers requires developing a variable measure of outliers (instead of the attribute data of either an outlier is present or not present). This variable measure enables proper prioritization of problem solving efforts.

Appropriately high priority should be given to outlier problem solving when: (1) the magnitude of the outlier is large, (2) the frequency of outlier occurrence has increased, or (3) an outlier occurs in a measurement that typically does not see outliers.

2.3.3 Multiple Tooling - Non-normal distribution

In addition to the assumption of independence discussed in Section 2.3.1, an assumption of most statistical analysis for process control is that the data is "identically distributed." Identically distributed means that each measurement is taken randomly from the same population. A specific form of this distribution is typically assumed, the normal distribution. The normal distribution is shown in Figure 2-8. The normal distribution can be described completely by two parameters; the most common parameters used are the mean and standard deviation. The variation can also be expressed as a multiple of the standard deviation. The parameter 6σ, defined as six times the standard deviation includes 99.74% of the production output from a normally distributed process.

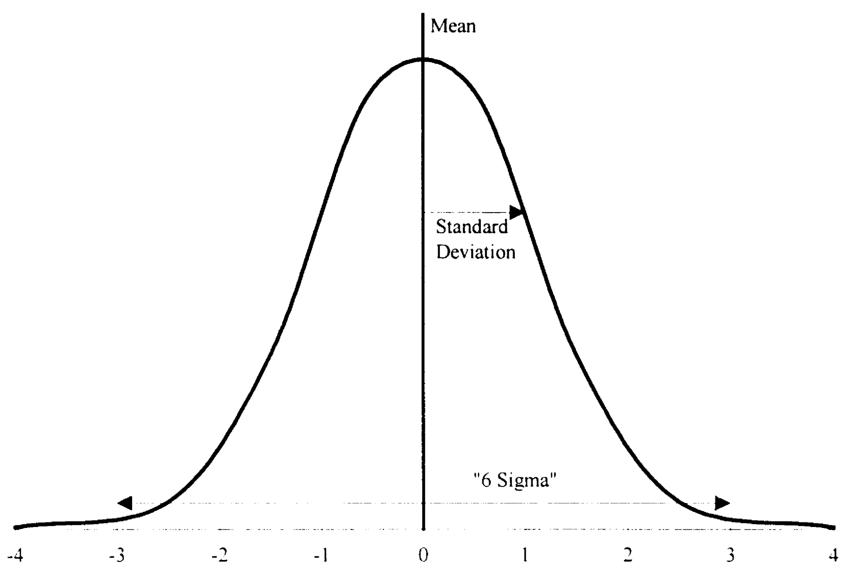

Figure 2-8: The normal distribution. A process subject to random errors can be modeled as a normal distribution. This distribution is described completely by the mean and standard deviation. The "6 Sigma" variation is a parameter that describes virtually the entire range of production output.

As can be seen in Figure 2-9 and Figure 2-10, not all processes follow a normal distribution. A particular case where processes can deviate from a normal distribution is the case of multiple tools operating in parallel. In this scenario, more than one tool or fixture is utilized to manufacture the same part. In these production scenarios, the mean of each particular tool may be slightly different from one fixture to the next. This difference in means can result in a pattern of measurements as shown in the run chart of Figure 2-9. This process results in the measurement distribution shown in Figure 2-10. This data set represents an extreme case of multiple tool mean differences. In this case, the difference is tolerated because the range of variation is well within the target specification range (adequately high process capability, even with this variation).

The normality of process data can be assessed using a statistical test that quantifies how closely the data set represents a normal distribution. This statistical test is called a χ^2 test ('chi squared'). Applying such a test to the data set shown in Figure 2-9 results in a χ^2 probability of 0.04 that the data came from a normal distribution; utilizing the full data set of 1000 points reduces the χ^2 probability to $1x30^{-37}$ as shown in Figure 2-10. This reduction is due to the larger number of measurements used to estimate normality. A histogram and the χ^2 test results for a set of normally distributed data are shown in Figure 2-11. This particular sample of data from a normal distribution generated a χ^2 value of 83%. The χ^2 test utilizes a probability threshold (α), such as 5%, and then compares the χ^2 test value to that threshold. If the χ^2 test value is less than the threshold (α), then it can be stated with $(1-\alpha)\%$ confidence that the data did not come from a normally distributed process.

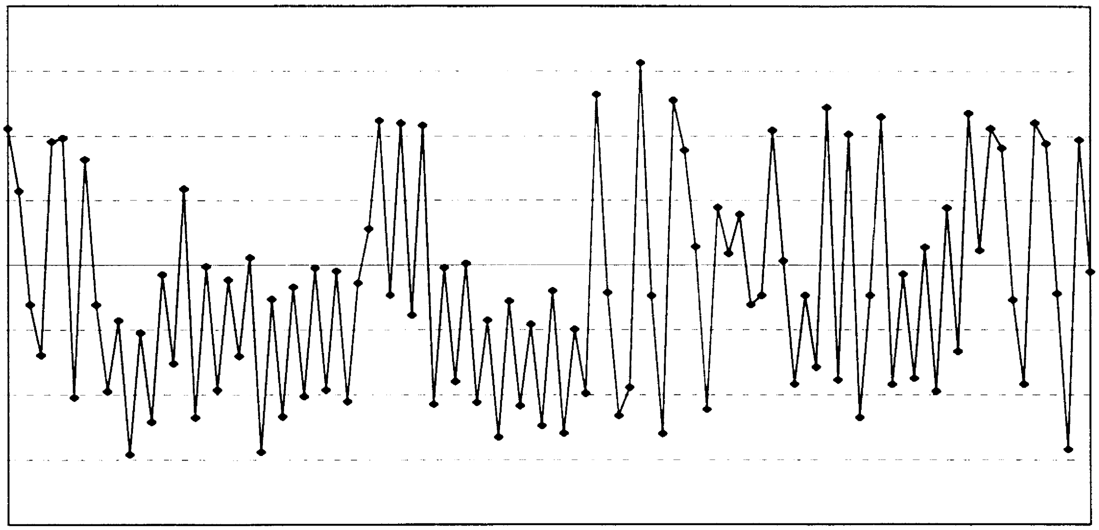

Figure 2-9: Run chart for a process with three tools operating in parallel. It can be seen that during certain periods of operation only two of the tools were in operation. A histogram of data from this process is shown in Figure 2-10.

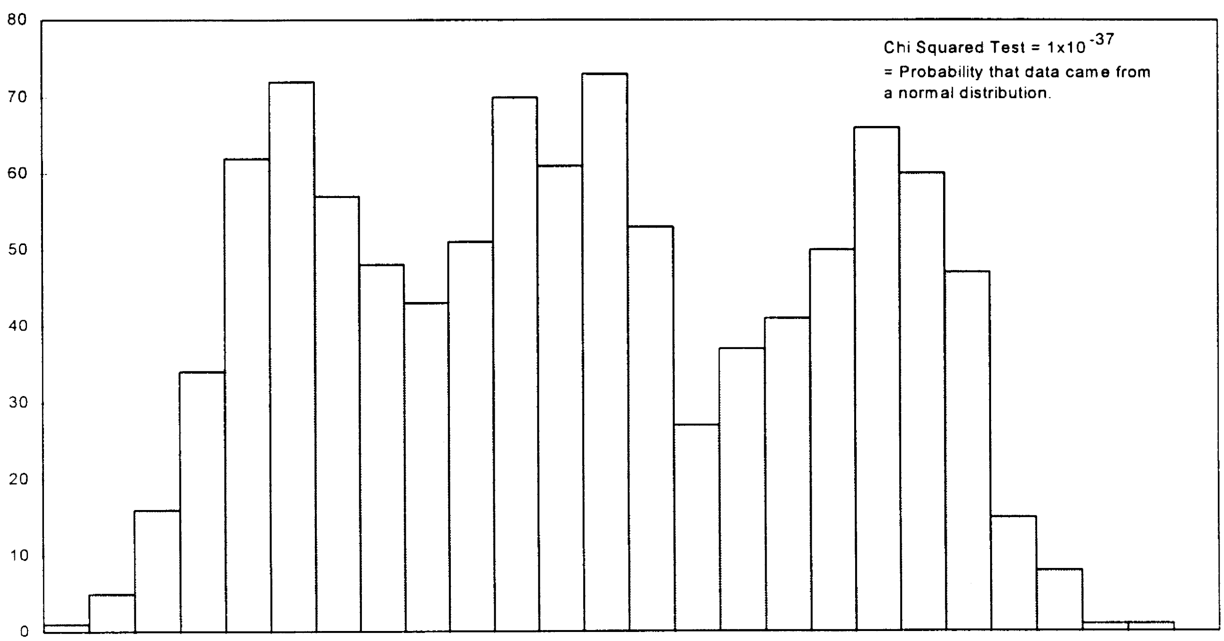

Figure 2-10: Histogram of measurements from process with multiple tools. For this particular process, the process variation for each machine is only a small fraction of the total tolerance, so even though their means are not aligned, all parts are well within specification.

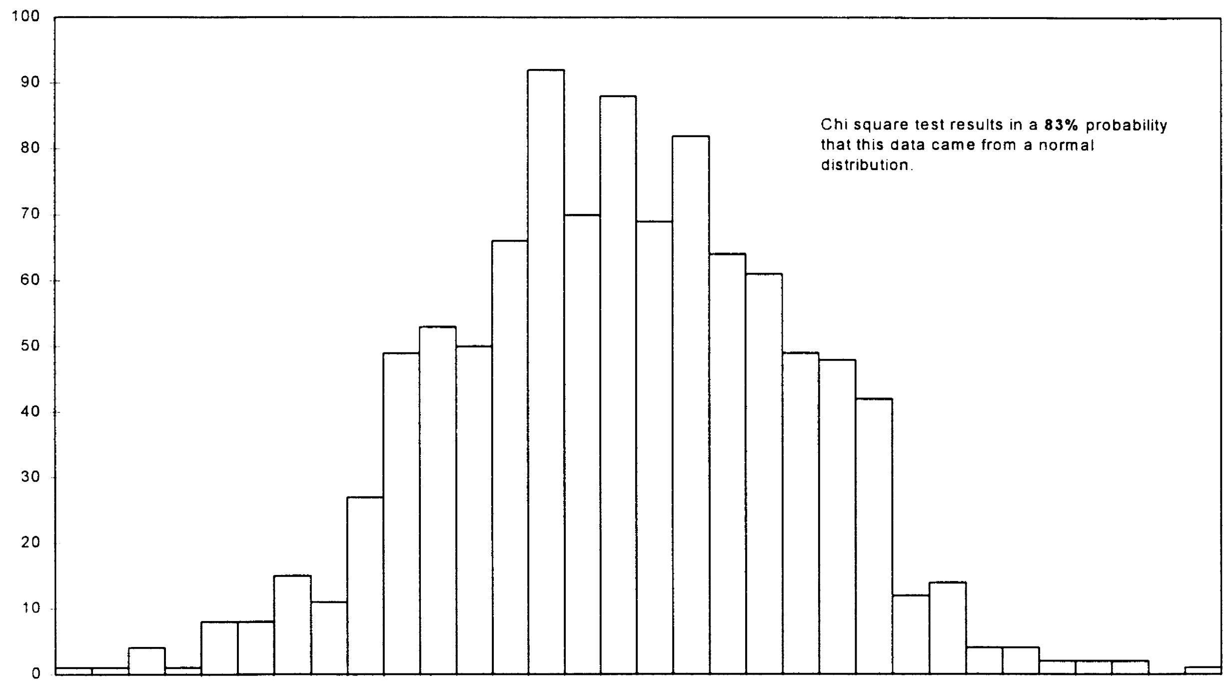

Figure 2-11: Histogram of data generated by a process described with a normal distribution.

2.4 Current Approaches

A variety of mechanisms to reduce incoming measurement data to information have been developed and/or used at the observed assembly plant. These mechanisms provide insight regarding the objectives of data analysis. They also identify characteristics of successful and unsuccessful data reduction approaches.

- Body-in-White CMM Report: (R. Houston, Fetz Engineering) - This report summarizes the set of CMM measurements that are generated on a BIW. This statistical analysis compares the most recent set of CMM data to two statistical baselines. The first baseline is calculated from the most recent 25 measurements, and the second baseline utilizes all measurements taken during the year. This report processes data for each dimension and classifies measurements by standard deviation band. Points outside $\pm 3\sigma$ limits are noted in a special column. The weaknesses of this method are that even the reduced data set is still very large, deviations are not prioritized, and large amounts of data are presented without an accessible reference to a tooling point. The low measurement frequency (approximately once per day) results in a more independent data set than the optical measurements taken on every body. This independence in combination with utilization of the last 25 measurements to estimate the current state of the process results in an effective monitoring strategy for body-in-white CMM measurements.

- Tooling point CMM Report - The tooling point report summarizes CMM data for key BIW control points. Specialized reports are generated on a daily basis with statistical analysis and pictorials. (R. Houston) This report addresses one weakness of the BIW CMM report, in that pictorials of the body indicate clearly where the measurement is located. A second strength of this report is that a run chart of recent measurements is also shown to facilitate interpretation by the process expert. The main weakness here is the lack of a summary or priority list. A cover sheet with a prioritized ranking of points that are outside control limits would enhance these reports.
- Zone deviation / penalty assessment (P. Franks / J. Carlson). This report was developed by one of the tooling engineers and the skilled trades operator of the coordinate measurement machine. One strength of this report is that it was developed by the people who utilize the information to make changes to the process inputs. This report uses a dead zone around the target followed by a penalty for each incremental distance outside the dead zone. This is very similar in concept to the quality loss function. These penalties for individual measurements are then combined into penalties for areas of the body and then finally into a rating for the entire body. Combining the penalty assessment and area ratings from this report with the pictorials, historical data comparisons and run charts from the tooling point CMM report would result in an effective report for body shop tooling engineers.
- Standard SPC software. Several standard SPC software packages are available. These packages process data from a variety of sources, generate control charts and identify if a given incoming measurement represents an out of control condition, according to standard control chart rules. The major weakness foreseen with this tool is the inability to survey all the dimensions being monitored for prioritization of deviations in the process. The second weakness arises from the assumption of independence and the false alarms that the assumption may lead to.

- Pareto charts of variation and the Continuous Improvement Indicator (CII). A key aspect of the case study approach to variation reduction in the body shop is the generation of a Pareto diagram of variation expressed in terms of the 6σ variation of dimensional parameters. The objective for variation reduction efforts being conducted in the industry is the "2mm Body." This competitive objective states that 95% of the measured points on an automobile body should have a 6σ range of measurements less than 2mm. Performance in terms of this objective is characterized by the Continuous Improvement Indicator (CII). The variation for each dimension is tracked, updated and posted on a daily basis. This report was highly effective when variation was being reduced on a daily basis by providing visual tracking of progress. The variation has reached a near steady state due to both diminishing returns and reduced resources. The reporting of variation levels is broken down by body style and measurement station resulting in a major report that is generated on a daily basis. These reports generate a large amount of paper and they inspire relatively little action. These full length reports would be more appropriately converted to a weekly report primarily for the variation reduction teams to review in their meetings.
- Daily entry and posting of Statistical Process Control (SPC) charts. SPC charts are created for body panel fit measurements taken manually after the doors, fenders, hood and decklid are installed. These charts are created manually on the production line. The data is also entered into the computer for processing and printouts. A few of these charts have been used very actively to make adjustments to the process; most however, do not generate a course of action when an out of control condition is indicated. A disciplined reaction plan should be followed when the SPC chart indicates a change in the process.
- Control limits on optical measurement data. (J. Clinton) In cases where a problem has been identified, production halting control limits on parameters measured with the optical coordinate measurement system have been implemented. This method shows that in practice, when the cost of a problem is known, it is justified to shut down the production line in response to data.
- Biweekly review of sheet metal build concerns. (M. Lenosky) This is a management control process where a list of issues are tracked by the assembly plant and are addressed by the

stamped sheet metal supplier. The periodic demonstration of upper management support for this process has helped sustain progress towards quality improvement.

- Variation Reduction Process. A variation reduction process is in place within the plant. The process consists of variation reduction teams that work to solve dimensional variation problems, a variation reduction coordinator who serves as both a problem solving resource and a coordinator of efforts across the plant and up through management, and a steering committee that works to reinforce the long range objectives of variation reduction. Weekly meetings are held for each major area of the body shop. These meetings bring together tooling design engineers, manufacturing engineers, production/maintenance supervisors, and hourly process coordinators; visiting members of the team included students from the University of Michigan. These teams attack variation reduction using a case study methodology. Locations of highest variation are identified, root causes are identified, and corrective actions taken. This process was more effective with a full time variation reduction coordinator.
- Quality Engineering Improvement Teams. These teams attack the chronic problems in the build of the car. They focus on confirmed customer dissatisfiers. Since the resolution of these problems is more difficult and takes longer, it is appropriate to utilize customer feedback to help prioritize these efforts (otherwise, customer feedback is generally too delayed to be useful for control of the process). One strength of these teams is their ability to work across organizational boundaries, bringing together tooling, design, maintenance and production to solve customer focused problems.

2.5 Approaches Found in the Literature

One objective of methods from recent literature is the attempt to apply statistical process control methods to processes that are in a "state of control," yet do not have independent data. These underlying patters are typically associated with time dependence of a process. One aspect of time dependence arises when a significant contributor to overall variation has a period to its variation that is longer than the sampling frequency. Examples of time dependence come from a variety of processes: chemical process concentration readings (Alwan and Roberts, 1988), furnace temperatures (Stone and Taylor, 1995), and semiconductor processing (Sachs et.al., 1995).

2.5.1 Time Series Analysis

Time series analysis examines the characteristics of data as a function of time. A widely referenced book on time series analysis was written by Box and Jenkins (1970). The exponentially weighted moving average (EWMA) for process control was developed by Hunter (1986). A related paper was developed by MacGregor and Harris (1993) that explained the calculation of the exponentially weighted moving variance (EWMV). The use of time series analysis for SPC in automobile assembly was examined by Kendall Key (1991); an autoregressive integrated moving average (ARIMA) model was used to eliminate time dependence in the process data. A discussion of the use of time series methods in process control was made in discussing the Run by Run Controller (Sachs et. al., 1995). This paper addressed the issues of underlying batch changes in the context of the semiconductor industry, yet it has similar applications in automobile assembly.

2.5.2 Run by Run Controller

The Run by Run controller was proposed by Sachs et. al. (1995) to address the hierarchical nature of variation in a production process. In their case, the hierarchy of the process had a significant impact on the characteristics of variation. They examined batch to batch variation in the semiconductor industry. The variation addressed for semiconductor processing is similar in terms of data dependence to automobile body assembly variation. Their controller uses statistical methods to calculate process input variables to reduce final output variation.

2.5.3 Outlier Detection and Treatment

In the introduction to their book Outliers in Statistical Data (Barnett and Lewis 1994), an outlier is defined as "an observation (or subset of observations) which appears to be inconsistent with the remainder of that set of data." They continue on to discuss the crucial nature of the phase "appears to be inconsistent." A main challenge in the consideration of outliers is whether an extreme observation is considered to have come from the same underlying process or whether it represents a 'contaminant' where that data has come from some other distribution. Their text discusses a wide range of techniques and approaches to the problems of outliers in statistical data.

Several examinations of outliers have been conducted for body shop data. York (1995) used boxplots and subjective evaluation to remove outliers from the body shop data set. Roan (1993) compared a measurement to data taken before and after the measurement to determine if a point represented an outlier. Derksen (1996) has examined the time and space patterns of outliers occurring in body shop data.

2.5.4 Multivariate Statistical Methods

Multivariate statistical methods examine all of the measured parameters together and make statements about the status of the process as a whole. Principal component analysis (PCA) is an approach to the reduction of large amounts of data into a manageable amount of information. This approach reduces the number of parameters required to describe the major contributors of the variation. PCA identifies linear combinations of the parameters being measured such that each combination, or principal component, is uncorrelated with the other combinations. A simple example of PCA applied to body assembly data was performed by Roan (1993). Additional examples can be found in multivariate analysis textbooks such as Applied Multivariate Statistical Analysis (Johnson and Wichern 1988.). A related approach is to filter out known physically induced error before analysis of the data, such as removing the error associated with the presentation of the part in the measurement station (York 1995). Multivariate statistics can also be used in process control by monitoring a statistic that more effectively checks for "out-of-control" conditions in parameters that are correlated with each other (MacGregor and Kourti, 1995). This method reduces a large number of measured parameters to a single multivariate control chart. PCA and multivariate SPC are discussed in more detail in Section 5.

2.5.5 Management Approaches

Several concepts in the manufacturing management literature are relevant to variation reduction. The first approach emphasized in Kaizen (Imai 1986) is that the process must be continually improved. The second recommendation of Imai is that management rewards should be focused on the process followed, not on the results achieved. The Toyota Production System emphasizes, among other things, the establishment and evaluation of quality at each manufacturing stage.

Both approaches emphasize the importance of people in the improvement process. Deming (1986) emphasizes the need to focus on the system, treating the causes - not just the symptoms. In Total Quality Management (TQM), a similar argument is made for asking “Why?” five times in the problem solving process to reach deeper into a problem, leading to true understandi· f the root cause. Also in TQM, the commitment of top management is viewed as a key initi: ep to quality (Shiba 1993).

2.6 Quality Loss

The concept of quality loss was introduced by Taguchi (1986) to quantify the principle that lower quality is achieved by inspecting product output to be within a specification limit than is achieved through a process with low variation centered on the design target. This concept is illustrated in Figure 2-12.

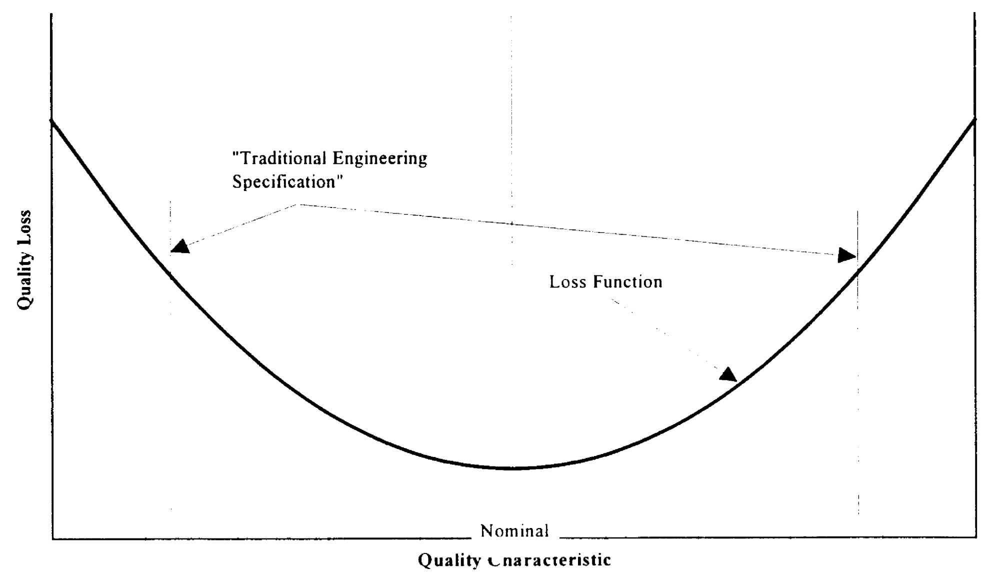

Figure 2-12: Quality loss shown as an increasing function of the distance from nominal. Under this view, being near the specification limit is almost as bad as being outside the limit.

This approach addresses other aspects of quality that can be found in the realistic understan ıg of the manufacturing environment. First, in most cases, parts just outside the specification limit are not significantly worse than those just inside a specification limit. Second, processes operating centered on the design target exhibit higher quality than those that are "within specification" but are centered closer to one limit. Third, parts further outside the specification limit are worse than the parts just slightly outside the specification limit.

Examples of the continuous deterioration of quality near specification limits are readily available in practice. Consider the simple example of attaching two parts using a screw. The deterioration of quality might progress as follows:

- Both parts perfectly on target - both holes aligned as assembly arrives at the operator.
- Slightly off - operator must lightly hold part in place while screw is driven
- More off - operator must apply significant force to hold part in place while screw is driven.
- Rework required - hole must be enlarged to permit insertion of the screw.
- Scrap - there is no way to allow insertion of the screw. Part must be scrapped.

This escalation of the cost of quality is focused on the internal costs incurred. Four categories of cost were outlined by DeVor (1992):

- Prevention Costs - maintaining a quality control system
- Appraisal Costs - maintaining a quality assurance system
- Internal Failures - manufacturing losses such as scrap and rework
- External Failures - warranty, repair, customer and product service

2.7 Choosing an Analysis Approach - Multivariate vs. Time Series

Given the range of available analysis methods, the appropriate situations for univariate (single parameter at a time with independent data assumed), multivariate (examining the output of many parameters together), and time series analysis (examining the pattern of data over time) must be determined. Measurement systems can be broken down along two axes: sampling rate and detail level as shown in Figure 2-13. The data sampling rate is the frequency of measurement; for example, a measurement taken once per shift (CMM) has a low data sampling rate but optical measurements, taken on every BIW, have a high sampling rate. The data sampling rate could also be stated in terms of the level of autocorrelation in the data with respect to time, where autocorrelation is the correlation between a data set and the same data set offset in time. The detail level of the data is the number of measurements taken on a single part at a single time. For example, a CMM check that generates 40 measurements on a single subassembly would have a higher detail level than an optical measurement check that measures 10 characteristics on the same subassembly. The detail level of the data could also be based upon the correlation of the data with other characteristics being measured. For each area, a corresponding body shop measurement system has been identified. Advancing measurement technology moves to the upper right of the chart. In the case of optical measurements, the primary challenge is time dependence of the data; therefore, efforts were focused on time series methods.

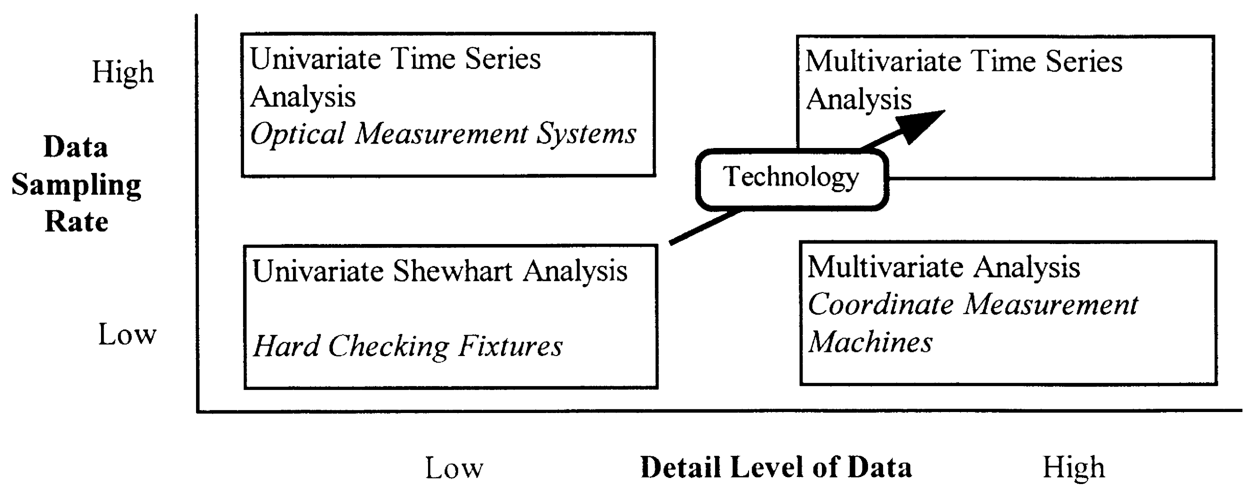

Figure 2-13: Primary focus for analysis methods as a function of the detail level of the data and the data sampling rate.

2.8 Technical Objective and Conclusion

The technical objective is to develop an automated statistical processing algorithm that rapidly detects process events, supports rapid problem solving through supplemental data characterizations, and supports overall variation reduction efforts by informing process experts of unusual patterns or characteristics of the data. Additionally, the algorithm must be insensitive to characteristics of the data that do not represent special causes. It was shown that in the presence of batch variation, an assumption of independence leads to falsely narrow control limits. In the presence of batch variation, the variance of the sample mean should be calculated directly. The methods in Section 3, 4, and 5 have been developed focusing on the optical coordinate measurement systems, but the approaches can be applied to other sources of data.

3. Specific Search Algorithm

The objectives of the specific search algorithm are to minimize the time to detection for large process events, minimize false alarms in the presence of underlying batch variation, and to specifically detect different types of process events. The specific search algorithm has several characteristics that differentiate it from traditional statistical process control approaches. First, specific statistical tests determine if a certain type of process event has occurred. Second, the tests utilize different sample sizes to improve performance relative to the traditional boundary of sensitivity (minimum size detectable event) versus detection speed (time from event to signal). Third, the algorithm compares a detected process event to a statistical description of the process established during a baseline period to assess the severity of the process event. Fourth, this baseline characterization relaxes the assumption of independent data and allows for the presence of "in-control" batch to batch variation. The specific search algorithm addresses mean shifts, variation changes, and outliers in real time. Slower changes in the mean and in the shape of the distribution are also monitored, but a less frequent interval is recommended for these parameters. The overall flow of data into information for the process expert is shown in Figure 3-1. The organization of this section follows Figure 3-1 from the top to the bottom, addressing event detection, prioritization, and information for each of the main event categories.

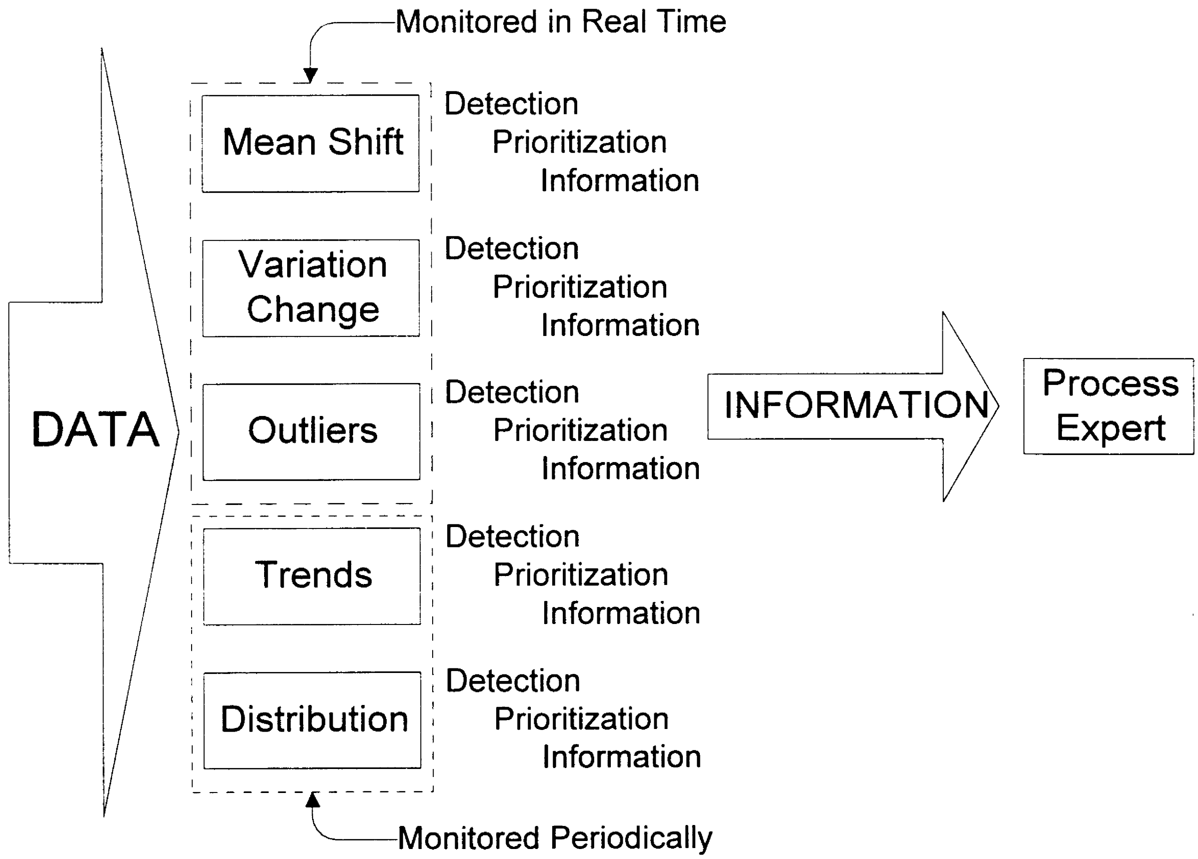

Figure 3-1: Specific statistical tests process data into information for the process expert. Some of these tests are conducted in real time while others are conducted on a periodic basis. Each category is subdivided into detection, prioritization, and information phases.

There are two reasons why it is desirable to categorize process events as shown in Table 3.1. First, the different categories will often correspond to different types of process events; therefore, categorization should accelerate the problem solving process. Second, the different categories associate with different reaction plans. Reaction plans are discussed in more detail in Section 7. The categorization methods presented here are formal to enable automation, but informal classification is part of the existing case study methodology in practice in the plant. Inclusion of outliers as an equal category in this process is deliberate. Except for Roan (1993), the approaches found in the literature either assume that the data does not contain outliers or that the objective of the analysis is to find outliers. This approach takes a middle course, treating outliers as another type of process event that must be detected, prioritized and resolved.

Table 3.1: Process events and reaction plans for different data patterns.

Title	Types of Possible Process Events	Characteristics of Reaction Plan
Mean shift	New run week of stamped parts, locator breakage, pressure lost to a clamp	Major shift: stop production, find and correct. Minor shift: track impact to see if one operating point is better than the other.
Mean trending	Weld tip wear, other wear and thermal conditions	Is this a self correcting condition? Can the process be made less sensitive to this cycle?
Variation change	Loose, broken, worn, or misadjusted clamp.	Inspect clamps for tightness.
Outlier - minor	Weld slag build up in tool, part interference, part misalignment, pallet locator off target or missing.	Inspect vehicle for severity assessment and clues to root cause.
Outlier - major	Measurement error, dirt or marks on body, missing hole, visible deformation	Categorize into: 1. Major deformation: scrap 2. Missing hole: rework 3. Dirt/Marks: OK
Secondary Distribution	Non-centered sets of multiple tools. Intermixed parts from different run weeks. Intermittent clamping problems	Examine data patterns for additional clues, match with process knowledge.

A set of statistical parameters, calculated from a baseline data set, describes the expected variation of a process. Due to the underlying batch variation that creates dependence in the data, it is necessary to utilize more than the mean and standard deviation to characterize the variation of the process. This assessment of the variation recognizes that the underlying drivers of high frequency and low frequency variation are not necessarily equal for all production dimensions. As discussed in Section 2, traditional control chart methods assume that the only variation in the sample mean is due only to the use of sample of data to estimate the mean. This method relaxes that assumption such that the actual mean (not just the estimate) is allowed to vary within a range. In this method, 30 samples of data are taken from the baseline data set; each sample includes 30 individual measurements. The normal variation of the process is characterized in terms of the following parameters:

$\overline{\overline{X}}$: Overall average of the process (See Equation 2-8)

$S_{\overline{X}}$: Standard deviation of the means for each sample (See Equation 2-10)

$\overline{S}_X$: Average of the within sample standard deviations (See Equation 2-9)

For an independent data set with adequate sample size, the $S_{\overline{X}}$ and $\overline{S}_X$ should be highly correlated and should follow the relationship $S_{\overline{X}} = \frac{\overline{S}_X}{\sqrt{n}}$ where n is the sample size. As was shown in Section 2, in the presence of batch variation, this relationship does not adequately predict the expected variation of the sample mean.

3.1 Mean Shift

The rapid detection of mean shifts was the most important scenario identified by personnel in the body shop. The reasons cited fell mostly into two categories. First, an undetected or delayed detection of a change in the process mean that effects product quality or assembly can result in a large backlog of parts or bodies that need to be reworked or scrapped. Second, rapid identification of the mean shift facilitates rapid identification of the root cause. In addition to the effect of starting sooner, information regarding the event disappears with the progression of time.

3.1.1 Detection

The objective is to minimize the time elapsed from when a mean shift occurs in the process until mean shift detection by the algorithm. The conflicting objective is to minimize the probability of detecting a mean shift when no mean shift occurred. This objective is intended to avoid wasted efforts on false alarms. The possible combinations of the actual presence or absence of a process event and the presence or absence of a detection signal are shown in Table 3.2. The detection of mean shifts is based upon a comparison of the data taken since a given point in time with data taken from a period just prior to that given point in time. The process is described in the flowchart in Figure 3-2, and the corresponding characteristics are shown in the run charts in Figure 3-3.

Table 3.2: Matrix of the event detection signal vs. the actual presence of a process event. The upper left and lower right regions represent the desired performance of a process monitoring algorithm. The upper right and lower left represent errors in the detection process.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Detection Signal Given</td></tr>
<tr><td>YES</td><td>NO</td></tr>
<tr><td rowspan="2">Actual Event Present?</td><td>YES</td><td>Correct Detection</td><td>Missed Event
Type II Error
β Risk</td></tr>
<tr><td>NO</td><td>False Signal
Type I Error
α Risk</td><td>Correct Rejection</td></tr>
</table>

The statistical test is based upon a comparison of the sample taken just before and just after a hypothesized mean shift. The test must reflect the small sample size after the hypothesized mean shift; therefore, the Student's t distribution must be used instead of the normal distribution. The basic statistical test is defined as:

H_o: $\mu_{new} = \mu_{old}$ Any difference in observed means can be explained by statistical chance

H_1: $\mu_{new} \neq \mu_{old}$ The difference in the data can not be explained by statistical chance

A two sample t-test is used to determine if a change in the mean has occurred at a given point in time. The variance before and after the mean shift is assumed to be similar. This assumption allows the pooling of the variance using data from both before and after the hypothesized mean shift. S_P^2 , the pooled variance, is a weighted average of the variance from each of the two samples and is calculated as shown in Equation 3-1.

$$S_P^2 = \frac{(n_{OLD} - 1)S_{OLD}^2 + (n_{NEW} - 1)S_{NEW}^2}{n_{OLD} + n_{NEW} - 2} \qquad (3\text{-}1)$$

where,

n_{OLD} = number of measurements used from before the hypothesized mean shift (set to 30)

n_{NEW} = number of measurements used since the hypothesized mean shift (varies from 3 to 30)

S^2_{OLD} = variance of the measurements taken before the hypothesized mean shift

S^2_{NEW} = variance of the measurements taken since the hypothesized mean shift

The test statistic (T_{MS}) is calculated as shown in Equation 3-2.

$$T_{MS} = \frac{\overline{X}_{OLD} - \overline{X}_{NEW}}{\sqrt{S^2_P\left(\frac{1}{n_{OLD}} + \frac{1}{n_{NEW}}\right)}} \tag{3-2}$$

where,

$\overline{X}_{OLD}$ = average of measurements taken before the hypothesized mean shift

$\overline{X}_{NEW}$ = average of measurements taken since the hypothesized mean shift

The hypothesis test is performed by comparing the test statistic T_{MS} to the Student's t distribution. H_0 is rejected and H_1 is accepted if:

$$|T_{MS}| \geq t\left(\alpha/2; n_{OLD} + n_{NEW} - 2\right) \tag{3-3}$$

where α is the probability threshold for the statistical test, n_{OLD} is the number of measurements in the sample taken before the hypothesized mean shift (set equal to 30 in the implementation), and n_{NEW} is the number of measurements taken since the hypothesized mean shift.

This approach is then applied to a flowchart (Figure 3-2) such that the above test is conducted at different points in time working backwards from the most recent measurement as shown in Figure 3-3. This range (n=3 to 30) is used because it generally takes longer to detect a small mean shift than a large mean shift. By selecting a single small n, smaller mean shifts may be missed, and by selecting a single large n, large mean shifts will not be detected as rapidly. These additional tests conducted on each new data point resulting from the iteration of the test over the range for n=3 to 30 requires an adjustment to the actual α probability used in the t-test. The actual α probability threshold is bounded by α on the low end (if the additional tests do not impact the probability) and $1-(1-\alpha)^{28}$ on the high end if the tests were independent (additional tests increase the probability of declaring an event). The exponent of 28 results from the 28 tests that are conducted as n goes from 3 to 30.

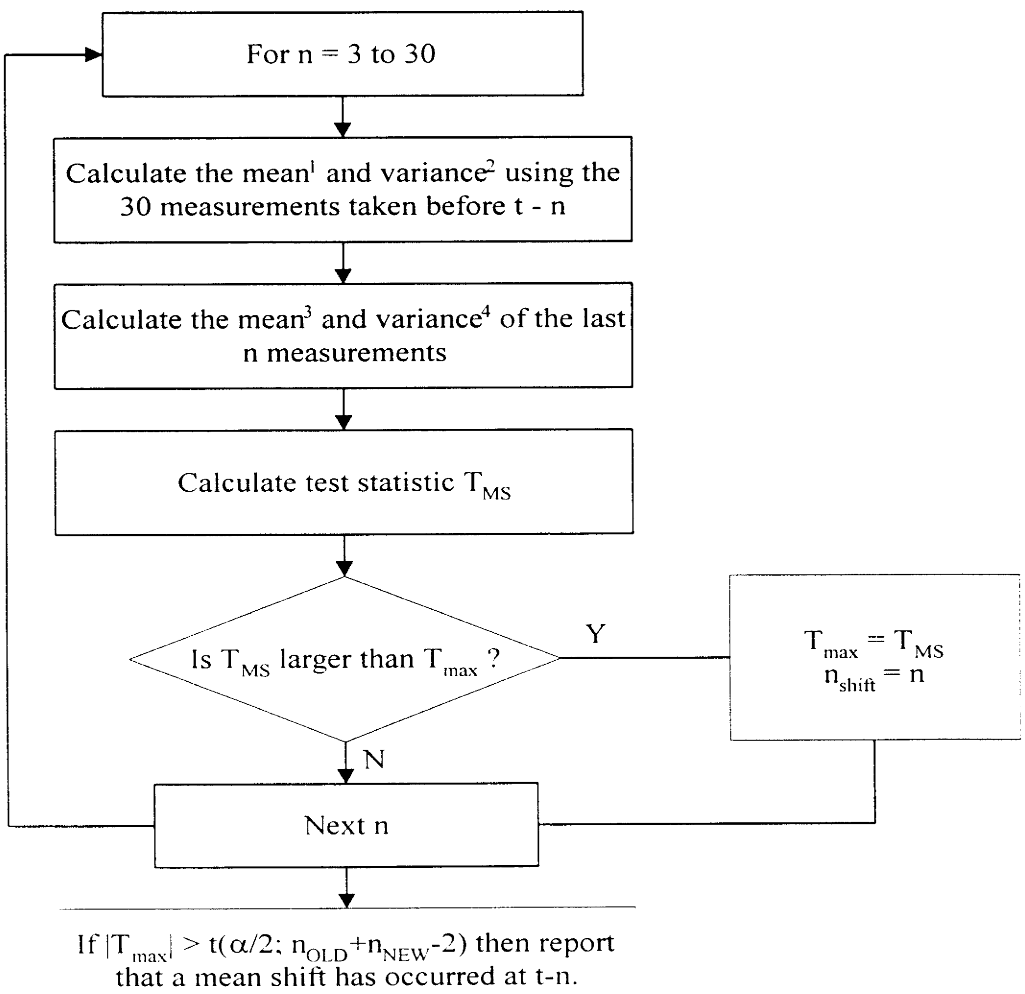

Figure 3-2: Flowchart for the mean shift detection algorithm.

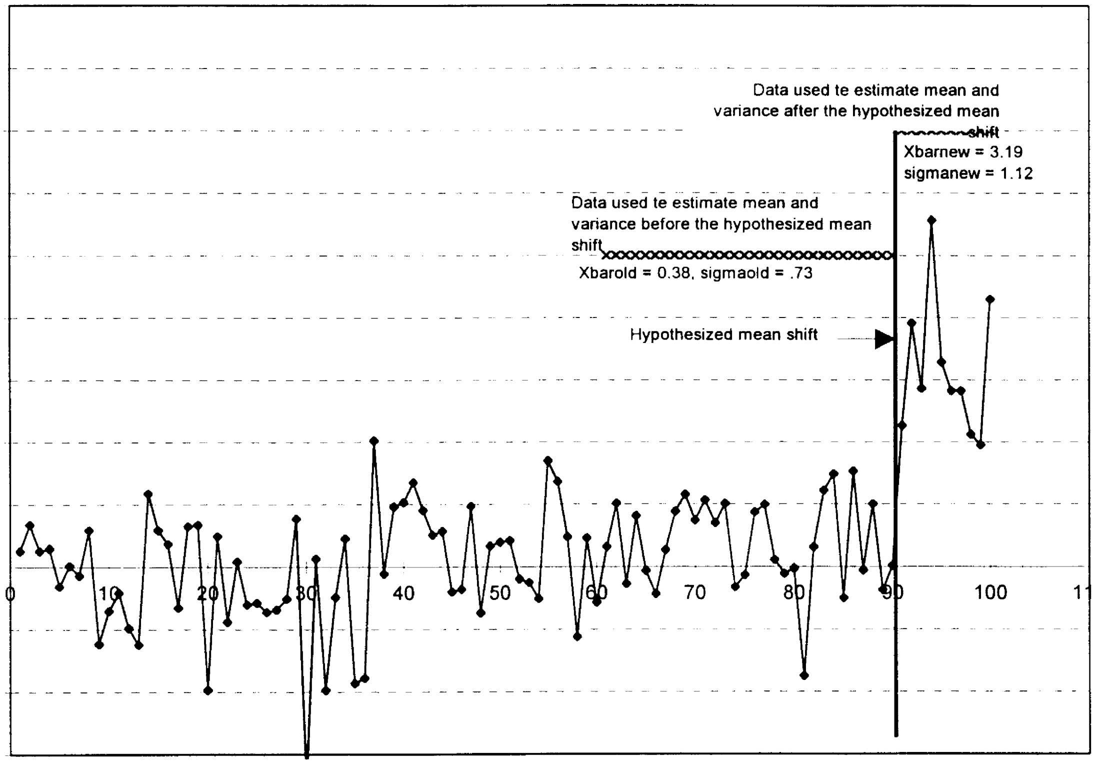

Figure 3-3: The run chart for a process event with a mean shift of $+3\sigma$ is shown. The process mean and variation are indicated before and after the mean shift. The case shown is for n=10. In this case, n corresponds exactly to the time when the mean shift occurred. This is the point where the test statistic will reach a maximum.

A major issue in mean shift detection is speed or consistency of detection versus the probability or frequency of false signals. Calibration of the algorithm is done to appropriately balance the cost of missed and/or delayed signals with the cost of investigating false signals. The key calibration parameter is the threshold for the t-test, α; for example, α can be increased to detect smaller shifts at the expense of a higher frequency of false signals. In addition to calibration of the detection algorithm, the prioritization process acts as an additional filter to avoid excessive costs of false signals. This prioritization is discussed in the following section.

3.1.2 Prioritization

The prioritization of a detected mean shift utilizes a comparison of the process event to statistics generated from the baseline data set. Two factors are used in the prioritization process. The first factor assesses how large the mean shift was relative to expected variation of the process mean. The second factor assesses how far the new level of the mean is from the expected center of the production process. The overall average of the mean during the baseline period ($\overline{\overline{X}}$) quantifies the expected center of the production process. The sample standard deviation of the sample means from the baseline data set ($S_{\bar{X}}$) quantifies the expected variation of the mean.

Qualitatively, the following strategies are used for prioritization:

- A large mean shift is more severe than a small mean shift. (Shift Size Severity)
- A mean shift resulting in an operating point outside the expected operating range is more severe than a mean shift that results in an operating point within the expected operating range. (New Mean Severity)

The prioritization process leads to a decision of whether or not to stop production during the problem solving effort. An example of the initial reaction versus the prioritization factors is shown in Figure 3-4. The reaction map is divided into three zones. The zone to the upper right represents major changes to the production output such that the expected value of additional production is negative (costs associated with scrap, rework, and customer satisfaction outweigh the savings due to the possibility of continued efficient production under the condition that downstream processes and the final customer are not impacted). The lower left zone represents the region where production continues normally without specifically informing the process expert of a change. The limit for this zone is influenced by the relative cost of investigating false signals. These limits can be established through an economic analysis such as the method described by Montgomery et. al. (1995). The remaining region is the domain of the process expert. Events falling into this range provide a mechanism for learning about the production process. Events in this range have either experienced a significant change, or are operating close to the edge of the expected operating range. Both situations provide an opportunity to conduct natural experiments. Feedback from downstream effects and investigation into upstream causes can accelerate process understanding. As understanding of cause-observation-impact is increased, variation can be reduced by eliminating the significant causes. The two axes of Figure 3-4 are the two factors that influence prioritization:

$$\text{Shift Size Severity} \equiv \frac{\overline{X}_{NEW} - \overline{X}_{OLD}}{S_{\overline{X}}} \tag{3-4}$$

$$\text{New Mean Severity} \equiv \frac{\overline{X}_{NEW} - \overline{\overline{X}}}{S_{\overline{X}}} \tag{3-5}$$

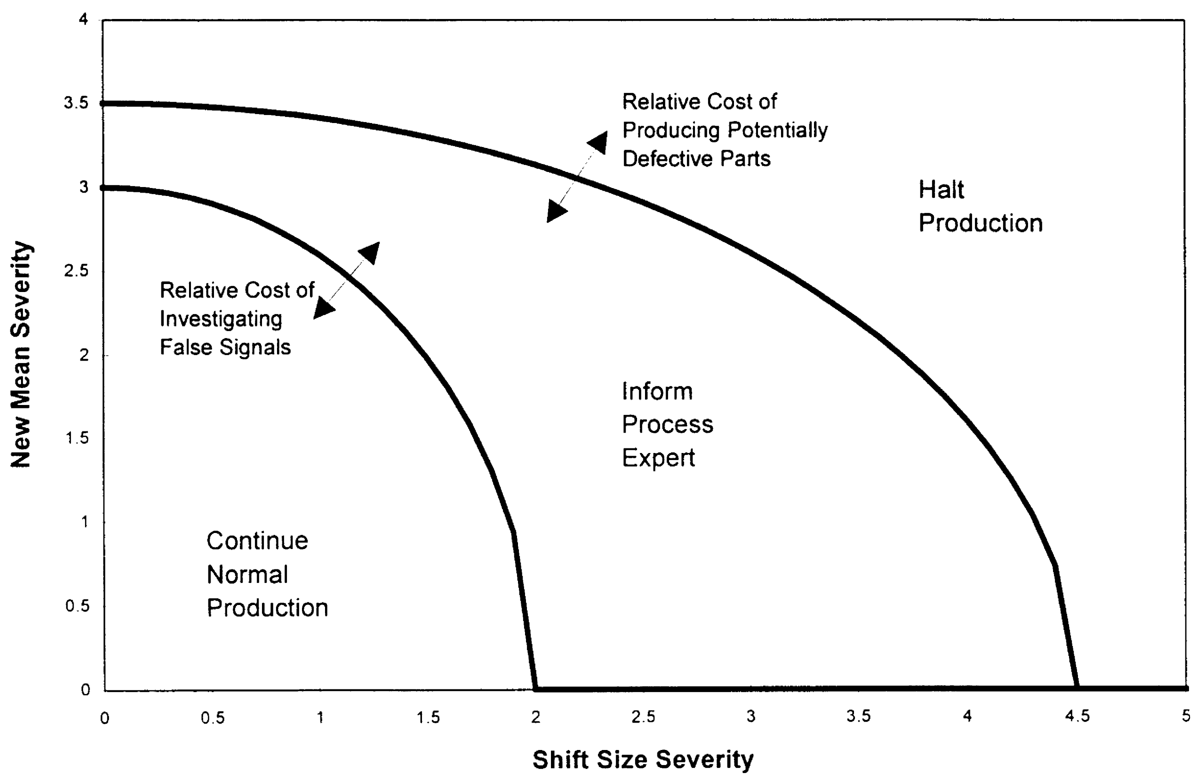

Figure 3-4: Initial reaction map. Severe events will halt production and less severe events will only inform the process expert. Contributors to the definition of these thresholds are indicated. The large 'inform' region facilitates natural experiments.

3.1.3 Information

The next objective of the automated processing algorithm is to provide supplemental information about the process event to assist in rapid problem solving. Based upon discussions with problem solvers in the body shop and through experience working with these problem solvers, the focus has been placed on reporting characteristics of the data rather than on providing a recommended course of action. The latter focus would have led in the direction of expert systems, pattern recognition, and engineering models of variation. The chosen focus emphasizes extraction of supplemental information and unusual patterns in the data that may be associated with the detected process event. Information for problem solving can be broken down into primary and derivative information. Primary information is taken directly from the observed data. Derivative information is an interpretation of the primary information based upon process expertise. Some aspects of derivative information could be automated, but the value of such an effort has not been established. In the case of mean shifts, the primary and derivative information is shown in Table 3.3.

Table 3.3: Mean shift primary and secondary information

Primary Information (extracted directly from data)	**Derivative Information** (following interpretation by process expert)
Time of occurrence	Time since start of shift (or last break)
Job Sequence Number (JSN)	Jobs since start of shift (or last break)
Measurement Location	History of events for that point Downstream process implications Relevant tooling points Parts involved
Operating Point Before Shift	
Operating Point After Shift	
Baseline Variation of Mean	
Baseline Variation of Individuals	
Run chart of last 100 measurements	Unusual patterns or subpopulations
Concurrent changes in other data	Potential causes that effecting multiple points

3.2 Variation Change

The rapid detection of changes in variation is an important aspect of variation reduction and process control for two reasons. First, upstream variation will cause economic losses to either downstream processes or the final customer through larger deviations from the target (Taguchi, 1986). Second, it is easier to determine the root cause of a change in variation if the problem can be identified and investigated in real time.

3.2.1 Detection

The detection of variation changes involves comparison of data sets taken immediately before and immediately after a potential change in the variation. To obtain an accurate assessment of variation and changes to variation, it is necessary to examine a larger sample than for detecting mean shifts. The detection of a change in variation is based upon a hypothesis test using the F distribution.

The null hypothesis: H_0 is that the true variance since the potential change is the same as the true variance before the potential change and that any differences in the observed sample variances are the result of statistical chance.

$H_0 : \sigma^2_{new} = \sigma^2_{old}$: Any difference in the observed variance can be explained by statistical chance.

The alternate Hypothesis: H_1 is that the true variance since the potential change is greater than the true variance before the potential change.

$H_1 : \sigma^2_{new} > \sigma^2_{old}$: The difference in observed variance can not be explained by statistical chance.

A test statistic is calculated from the measured data. This test statistic, T_{VC}, is the ratio of the variance since the hypothesized variation change to the variance since the hypothesized change.

$$T_{VC} = \frac{S^2_{new}}{S^2_{old}} \qquad (3\text{-}6)$$

A statistical test for comparing measured sample variances, called the F-Test, is used to determine if H_0 should be rejected and H_1 should be accepted as shown in Equation 3-7.

$$T_{VC} \geq F(\alpha; n_{new} - 1, n_{old} - 1) \tag{3-7}$$

where S^2_{new} is the variance since the hypothesized variation change, S^2_{old} is the variance during the period just before the hypothesized variation change, α is the probability threshold for the statistical test, n_{OLD} is the number of measurements in the sample taken before the hypothesized mean shift (set equal to 30 in the implementation), and n_{NEW} is the number of measurements taken since the hypothesized mean shift.

As in the case of mean shift detection, the test will be conducted over different time horizons. Values for n_{NEW} of 20 and 50 jobs is used in the implementation.

3.2.2 Prioritization

The prioritization will once again utilize information obtained from a baseline period. In this case, the *F* test is conducted against variance established during the baseline period. Variation changes that are significant, but do not represent a significant change relative to the baseline variation will be reported to the process expert, but will not trigger a production halting reaction plan. If the change represents a significant change from the baseline variation, a production halting reaction plan will be initiated. This difference is due to the scenario that if a source of typical variation is eliminated for a period of time and the variation is unusually low, an increase in variation will be triggered when that source is brought back on-line. The appropriate reaction for that scenario is to inform the process expert of this change so that the impact of this particular source on variation can be understood. After elimination of that source of variation, the baseline can then be reestablished with the new lower level of variation. The statistical test is defined as follows, where $\overline{S}^2_X$ is the average within sample variance from the baseline data set.

$$\frac{S^2_{new}}{\overline{S}^2_X} \geq F(\alpha; n_{new} - 1, n_{baseline} - 1) \tag{3-8}$$

where $n_{baseline}$ = number of baseline samples • measurements per sample

3.2.3 Information

The information that is extracted and supplied to the process expert in the case of variation changes includes the time and JSN when the change took place, the magnitude of the change in variation, characteristics of the variation, and changes in any other closely related variables. The objective of supplying additional information is to accelerate establishment of root cause and corrective action. The combination of a run chart and a histogram is usually adequate to support the process expert in definition of the variation event. Additionally, parameters that are correlated with the parameter of high variation are also reported.

3.3 Outliers

Outliers represent a special category of process events that complicates the effort to establish process control. The issue of outliers has been addressed significantly in the literature, but with the exception of Roan (1993), most efforts have focused on one of two extremes. In the first extreme, outliers represent the focus of the analysis where improved outlier detection algorithms are proposed. In the second extreme, outlier detection is approached such that outliers need to be identified so that they can be removed from a data set prior to other forms of analysis. In the observed body shop, the distinction in importance between outliers and other forms of variation is not clear. It is the objective of this analysis methodology to treat outliers and other forms of variation in an integrated manner.

Another characteristic of outliers in the body shop is that outliers can originate in either the production process or in the measurement system. In this particular environment, outliers resulting from the measurement itself usually create outliers with larger magnitude than process outliers. Possible causes of measurement outliers include: dirt on the part, markings on the part, dirt on the camera etc. Measurement errors tend to result in larger deviations than are physically possible. A threshold to distinguish between measurement errors and process outliers can be effective. The same causes that create measurement outliers create missing measurements. A routine mechanism is required to address measurement errors as well as process outliers. If a measurement error occurs, it remains necessary to confirm that the measurement was not in error due to a very large deviation in the process. A true deviation large enough to be declared a measurement error should be observable with the naked eye. If such an event occurs, the measurement error threshold should be increased.

Defining outliers as a deviation from the current operating point in excess of the current level of variation is generally a good rule. However, in the current operating environment, this still leads to a higher outlier frequency than can be addressed by the process expert. This high frequency creates a need to prioritize outlier events to facilitate problem solving for process improvement.

3.3.1 Detection

The detection of an outlier is based upon an process of comparing a data point to its expected value based upon surrounding data. The detection is broken down into two phases. First the data point is compared to the mean and variation before the data point using the $\overline{X}_{OLD}$ and S_{OLD} as in the mean shift detection. If the data point is outside the expected range based on that criteria, the data point is compared to the data taken just before and just after the hypothesized outlier. Once again, an iterative process is utilized to optimize the tradeoff between detection speed and the minimum size detectable event.

The test statistic utilizes the average and sample standard deviations calculated for evaluation of the mean shifts. The test statistic is defined in Equation 3-9.

$$T_{OTL-1} = \frac{\left|x_n - \overline{X}_{OLD}\right|}{S_{OLD}} \qquad (3\text{-}9)$$

For the second level of analysis, the mean and sample standard deviation of the data taken since the hypothesized outlier and an equivalent number of data points taken just before the hypothesized outlier are calculated and used to compute a second test statistic. The mean of the points taken immediately before and after the hypothesized outlier is calculated according to Equation 3-10.

$$\overline{X}_{OTL} = \frac{\sum_{i=1}^{n-1} x_i + \sum_{i=n+1}^{2n-1} x_i}{2n-2} \quad (3\text{-}10)$$

The sample variance of the same set of points is calculated using Equation 3-11.

$$S_{OTL}^2 = \frac{\sum_{i=1}^{n-1}\left(x_n - \overline{X}_{OTL}\right)^2 + \sum_{i=n+1}^{2n-1}\left(x_n - \overline{X}_{OTL}\right)^2}{(2n-2)-1} \quad (3\text{-}11)$$

The second test statistic is then calculated using Equation 3-12.

$$T_{OTL-2} = \frac{\left|x_n - \overline{X}_{OTL}\right|}{S_{OTL}} \quad (3\text{-}12)$$

The first test statistic follows a Student's t-distribution with 29 degrees of freedom (which is very close to a normal distribution due to the high number of degrees of freedom), and the second test statistic also follows a t-distribution with 2n-3 degrees of freedom. The t-distribution is then used to calculate the probability that the point in question represents an outlier. Note that Equation 3-13 is usually solved for T_{OTL-1} and used as a constant.

$$p_{OTL-1} = 1 - t(T_{OTL-1}, 29) \quad (3\text{-}13)$$

$$p_{OTL-2} = 1 - t(T_{OTL-2}, 2n-3) \quad (3\text{-}14)$$

A probability threshold is selected to achieve an appropriate tradeoff between Type I and Type II error. The threshold should be detected to obtain an appropriate tradeoff between false alarms and missed detection. If the probability from the t-distribution is greater than the threshold, then an outlier is declared.

This process is conducted for a range of values for *n*. This is done to optimize the tradeoff between detection speed and the minimum size outlier that can be detected.

An example of the detection process using the sequence of data 1.2, 0.9, 3.1, 0.8, 1.1 with n=3 is presented in Equations 3-15 through 3-18.

$$\overline{X}_{OTL} = \frac{(1.2+0.9)+(0.8+1.1)}{2\cdot 3-2} = 1.0 \qquad (3\text{-}15)$$

$$S^2_{OTL} = \frac{(1.2-1.0)^2+(0.9-1.0)^2+(0.8-1.0)^2+(1.1-1.0)^2}{(2\cdot 3-2)-1} = 0.033 \qquad (3\text{-}16)$$

$$T_{OTL-2} = \frac{|3.1-1.0|}{\sqrt{0.033}} = 11.5 \qquad (3\text{-}17)$$

$$p_{OTL} = 1 - t(T_{OTL-2}, 2n-3) = 0.9986 \qquad (3\text{-}18)$$

3.3.2 Prioritization

The first factor in the outlier prioritization process is the magnitude of the outlier, where the larger the deviation from the normal process, the higher the priority. The second factor in outlier event prioritization is the frequency of outlier occurrence. This combined approach allows the process expert to react to the process when either a severe outlier has occurred or when the frequency of outliers increases.

A standard process must be established for following up on individual outliers. One option for this would have the dimensional information fed forward to a subsequent station in the body shop, so that an operator there can make special note if the dimension in question appears acceptable from a measurement error standpoint. The body can then be marked to alert downstream operators who must attach parts to that surface or hole and to facilitate follow-up by the process expert.

A question that may be asked is: "are not all outliers unacceptable and demanding of rework?" Some outliers may be tolerable in the short run, may provide advanced warning for more major problems and may lead to a better understanding of the process. First, in the properly certified process, it may be likely that a process outlier condition remains well within specification. This scenario is demonstrated in Figure 3-5. Second, the focus should be on the process of identifying and correcting the true root cause of outliers and establishing prevention for the future. This method serves to identify natural experiments, where existing variation of the process creates the opportunity to learn about issues that are typically only explored through formal experiments.

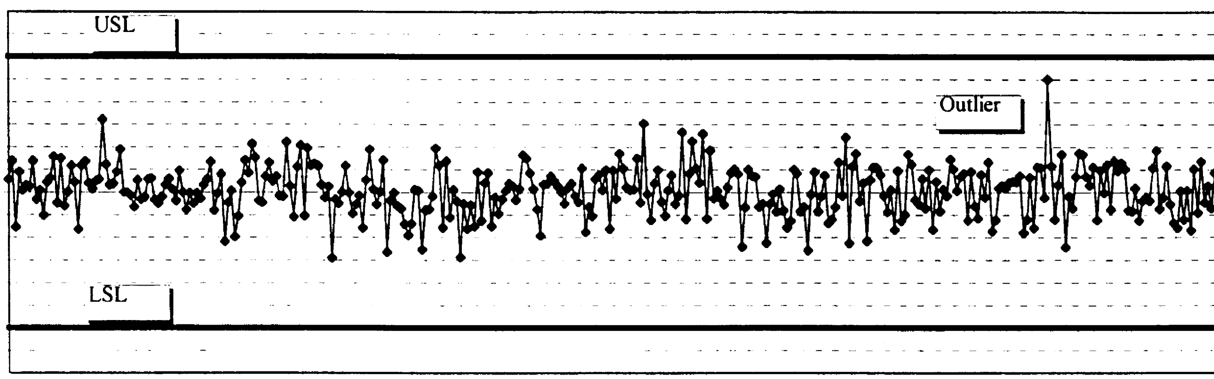

Figure 3-5: An outlier that occurs in a process with an otherwise high CpK is an example of a situation where other than the marginal quality loss, the outlier can be taken as an opportunity to learn more about the robustness of the process or as a signal for potentially more severe problems that are about to occur. (simulated data).

3.3.3 Information

The information provided in conjunction with a detected outlier is intended to assist in determining the true root cause and to place this particular outlier in the context in which it occurred. It is useful to examine some of the typical causes of process outliers. These causes include:

- Dunnage - particularly the top or bottom part in a stack
- Inventory - a part from a previous batch may have been inserted
- Initialization - a certain machine may have a problem with the first part or two produced
- Operation - a certain operation may not have been performed on a single job
- Incorrect part - a wrong part may have been inserted into the system
- Multiple fixtures - one problem fixture out of many may appear as an outlier in final line
- Interactions - a combination of minor deviations combines to create an outlier condition.

3.4 Trend

Trends offer a particularly interesting type of variation to monitor and control. Trends often find their roots in physical characteristics of the process. Additionally, in many cases it is difficult to distinguish the difference between a trend, a mean shift and random patterns in the data. Selecting an appropriate time horizon for evaluating a trend component proved difficult. Since the trend component represents the slope of the mean, and the slope is associated with a derivative of the signal, it was difficult to obtain a meaningful signal for the slope. Additionally, the parameters that typically could generate a slope in the output usually have independent control mechanisms acting to correct themselves, such as steppers on welding units (as weld tips wear, the current is automatically increased to maintain quality welds). This led to a decision to not specifically model the trend component of the variation; instead, the deviation of the process mean from its' baseline target is reported to identify any process changes that affected the mean of the process but were sufficiently gradual to avoid triggering the mean shift hypothesis test. The actual parameter that is tracked is the ratio of the deviation of the process mean from the baseline mean to the standard deviation of the mean determined from the baseline as seen in Equation 3-19.

$$T_{TRD} = \frac{\left|\overline{X}_{new} - \overline{\overline{X}}_{baseline}\right|}{S_{\overline{X}}} \qquad (3\text{-}19)$$

If the value of the trend parameter is larger than a threshold value, then a trend condition could be said to exist. This parameter also effectively prioritizes the condition such that larger deviations have a larger trend parameter. The sample size used to calculate $\overline{X}_{new}$ should be the same size as the subgroups used in the baseline analysis. Additionally, this procedure acts as a follow-up mechanism such that if mean shifts are not corrected, they will appear in the trend parameter. It is not necessary to monitor this parameter in real time; it would be adequate to report this parameter once or twice per shift. The measured parameters are reported in rank order of their deviation from the baseline target according to the magnitude of T_{TRD}. If this deviation is larger than a threshold values, then an investigation should be initiated.

3.5 Secondary Distribution / Normality

The distribution of a set of measurements also provides insight to the status of operations. The distribution can be examined through a histogram that can often identify when multiple tools have separated from their targets. An additional use of the histogram is to better understand the cause of outlier measurements. An assessment of the frequency of occurrence for points deviating from the target can often be combined with knowledge of the tooling and material flows to identify a potential root cause.

The histogram is a highly visual analysis method, but the volume of measurements prevents a visual assessment of every measurement condition. Therefore, a statistical method is required to make a preliminary assessment of the "interest" of the histogram. The method that is available for this process is the Chi-square test. This test can be used to take a sample of data, divide it into bins associated with a given range, and compare the number of samples in each bin to the number that would be expected given a specified distribution. The distribution selected for comparison in this case would usually be a normal distribution.

Since this is primarily a diagnostic evaluation, it is not necessary to monitor this in real time; once per shift should be more than adequate. A larger sample size is required for this test than for the other tests to achieve consistent results. The results of the test can be used directly, or they can be standardized relative to the baseline in order to look for changes in the normality of a given process (otherwise, the same multiple tooling condition may always appear at the top of the priority list).

3.6 Specific Search Algorithm Summary

The specific search algorithm consists of a series of statistical tests conducted in an iterative manner to achieve rapid detection of major process events and eventual detection of smaller magnitude process events. The algorithm provides a prioritization mechanism based upon the magnitude of the process event and the new operating point of the process, relative to the process characterized from a baseline period. Information obtained in the process of identifying and prioritizing the process event is used as an initial set of information to assist in the problem solving process.

Mean shift detection is based upon a 2 sample t-test for the difference in means conducted with the hypothesized transition point ranging from 3 to 30 points in the past. Variation change detection is based upon an F-test comparing the most recent data with data taken just prior to a hypothesized event. Outlier detection is based upon the comparison of an individual measurement to data both before and after the measurement. Trend detection is executed on a less frequent basis and is intended to identify points that have either shifted slowly away from their baseline process mean or have experienced an uncorrected process mean change. The shape of the distribution is also evaluated on a less frequent basis and is intended to identify unusual patterns in the data that represent opportunities for variation reduction.

Prioritization is intended to establish three ranges of events: major events for which rapid halting of the production process is justified, minor events that facilitate learning through the use of natural experiments, and insignificant events that are part of the typical variation of the process and do not represent an unusual operating point. Prioritization of the mean shift event incorporates the magnitude of the mean shift, the new estimate of the process mean, and the expected variation of the process mean. Prioritization of the variation change event uses a comparison of the new level of variation to the variation during a baseline period in addition to the change in the variation obtained during event detection. Prioritization of outliers is based upon both the magnitude of the deviation from the surrounding data and expected frequency of outlier occurrence based upon the baseline sample.

Parameters used in the detection and prioritization process are reported as a starting point for the problem solving process. This information includes the time and job sequence number (JSN) associated with the process event. Additionally, when an event is detected, the correlation between the point experiencing the event and other measurements from the same measurement station is reported to provide additional problem solving information.

4. Exponentially Weighted Moving Average

The use of the exponentially weighted moving average (EWMA) for control charts was first reported in a paper by Roberts (1959). Despite the history of the EWMA in the literature, it was seldom employed by quality control engineers prior to 1986 (Hunter 1986). Hunter identified strengths of the EWMA, "the EWMA chart is easy to plot, easy to interpret, and its control limits are easy to obtain." The EWMA was supplemented in 1993 by MacGregor and Harris in their paper on the exponentially weighted moving variance (EWMV).

4.1 High Frequency vs. Low Frequency Variation

One of the main objectives of processing the data using either subgroups or a filter is to separate the high frequency variation (piece to piece) from lower frequency variation (mean shifts, cycles and trends). This separation is particularly important in the case of the body shop where lower frequency variation is significant. In traditional statistical control methods, a sampling strategy is used to both minimize measurement costs and achieve samples that are independent. This independence requirement is one of the reasons why SPC samples are typically taken '5 parts in row: once per shift.' One weakness of these traditional methods is that in order to meet the statistical independence requirements, it is necessary to discard a large fraction of the data. Additionally, as was shown in Section 2 (Figure 2.5), the variance of the sample mean can not be completely predicted by the within sample variance and the sample size when the process includes underlying variation of the mean.

The moving average control chart is an alternative to control charts that assume independence. This estimated value of the process mean is then subtracted from the most recent piece of data, leaving a residual value. With the proper selection of the moving average, this residual achieves independence with respect to time. Traditional SPC methods can then be applied to these residuals. Separate control limits can be applied to estimates of the process mean and the process variance. Textbook statistical limits developed for use with moving average charts assume an underlying distribution that is independent with respect to time (DeVor 1992). It was shown in Section 2 that this is not the case with body shop process data. Therefore, an alternative method for determining control limits is also proposed. Figure 4-1 shows the decomposition of an actual set of raw data into the estimate of the process mean, an estimate of the process variation, and a residual value. The characteristics of variation in the mean are different from the variation of the individual measurements. Additionally, the residuals are independent with respect to time.

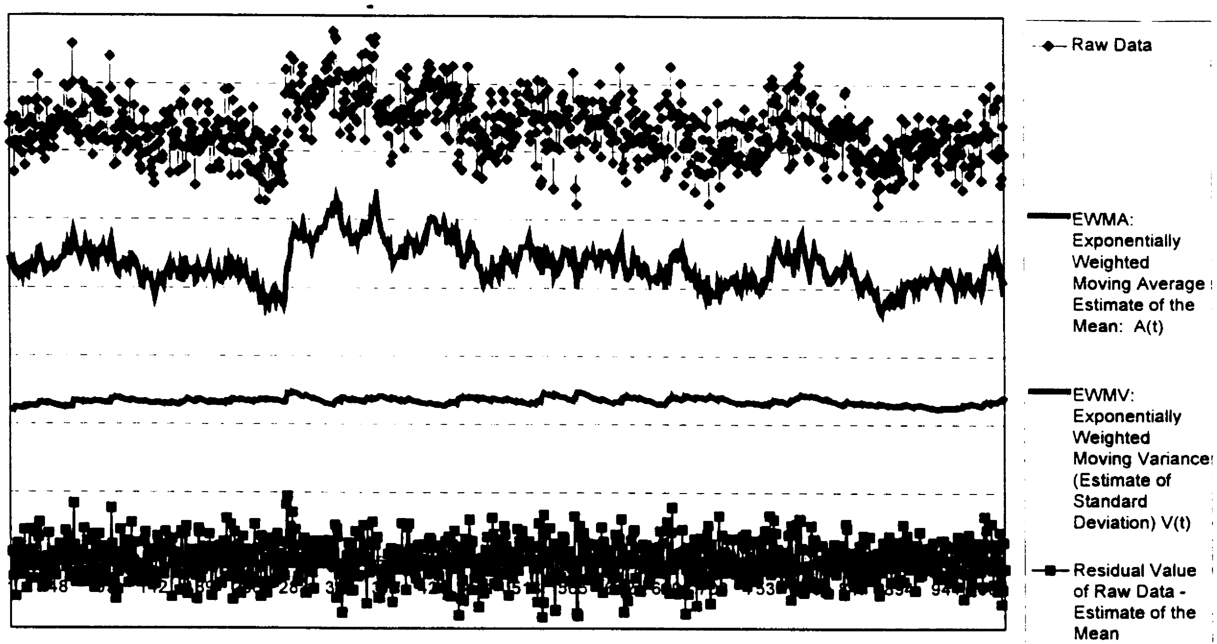

Figure 4-1: Breakdown of data using the EWMA algorithm. The raw data is shown at the top, the EWMA is shown next. The exponentially weighted moving deviation is shown next (magnitude is measured from the dotted line just below). The residuals are shown at the bottom.

4.2 General Approach to the Exponentially Weighted Moving Average

The exponentially weighted moving average is a special type of moving average that can be compared to a first order filter that separates high frequency input from low frequency input. One way to begin thinking about the exponentially weighted moving average is to start with a standard moving average. With a standard moving average, the current operating point of a process is estimated by taking the average of the last n measurements of the process. For example, the last 10 measurements can be used to estimate the mean. As new measurements are taken, the most recent measurement is included in the average and the measurement taken furthest in the past is discarded. In this case, the most recent 10 measurements are weighted equally with a factor of 0.1 and measurements taken prior to that have no effect on the estimate.

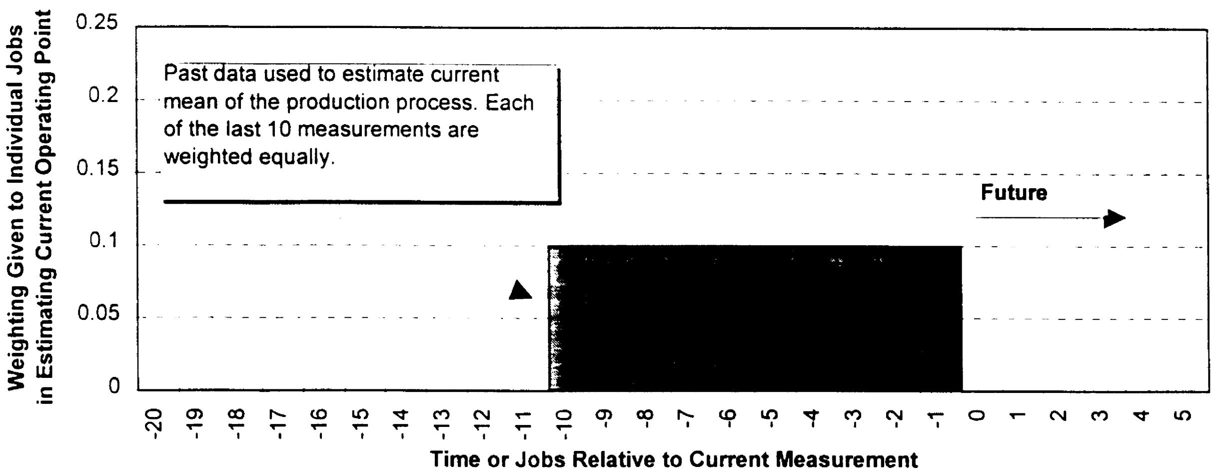

Figure 4-2: Individual measurement weightings for a standard 10 point moving average.

A potentially better estimate of the current operating point given a set of data, would give more weight to the most recent measurements than it would to the more distant measurements. As a first step, it could be said 'the influence of the most recent 5 measurements should be twice as high as the next most distant 5 measurements.' The exponentially weighted moving average distributes weights for all the measurements that have been taken such that this objective of higher weighting for more recent measurements is accomplished.

The exponentially weighted moving average is characterized by its weighting parameter r. A higher weighting factor gives a higher relative weighting to more recent measurements than a lower weighting factor would. The sum of weighting factors for all past measurements totals 1. The individual weighting factors associated with a given weighting parameter are shown in the charts below. Figure 4-3 is for $r = .05$ that spreads the weightings over many measurements, this weighting will remove high and medium frequency variations but will be slower to show a change in the mean of the process (Figure 4-4). Figure 4-5 shows the weighting factors associated with $r = .25$; this weighting will show changes in the mean of the process faster, but will retain some of the high frequency variation in its estimate of the process mean (See Figure 4-6). The weighting of an individual measurement is given by:

$$W_i = r(1-r)^i \quad \text{(i = number of jobs into the past)} \tag{4-1}$$

The sum of the weighted measurements provides an estimate of the process mean, A_t.

$$A_t = W_0 \cdot x_t + W_1 \cdot x_{t-1} + W_2 \cdot x_{t-2} + \cdots \tag{4-2}$$

The estimate can also be calculated on a continuous basis using the previous estimate, the new measurement, and the weighting parameter.

$$A_t = r \cdot x_t + (1-r)A_{t-1} \tag{4-3}$$

This estimation process is analogous to estimating the current mean of a process by taking the average of measurements from a sample as is done in standard control chart techniques. DeVor (1992) cites a relationship (Sweet, 1986) that is often used to relate the weighting factor r to the Shewhart sample size n.

$$r = \frac{2}{n+1} \tag{4-4}$$

For example, using Equation 4-4, a sample size of 9 would have similar characteristics to an r of 0.2 and a sample size of 3 would be similar to an $r = 0.5$.

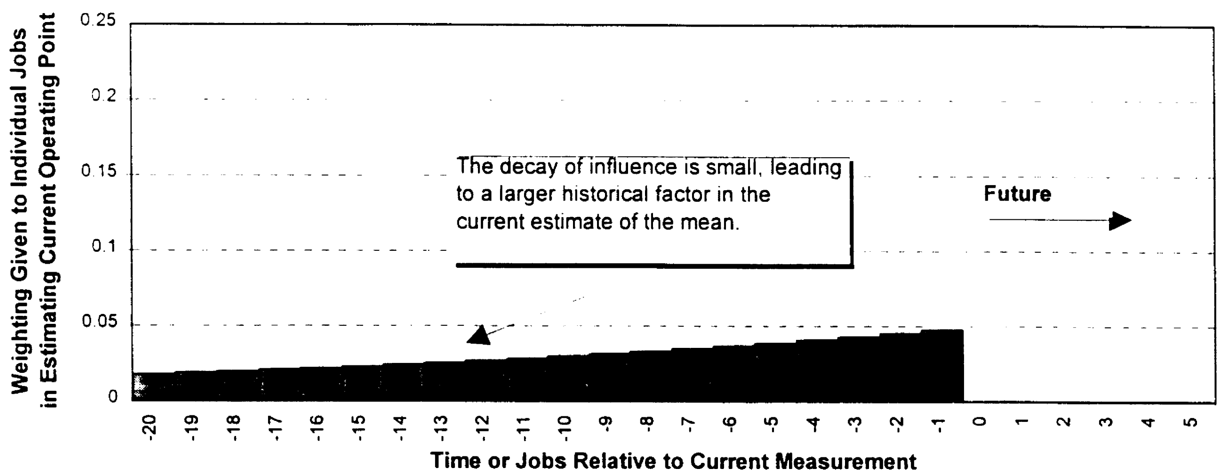

Figure 4-3: Exponential weighting of individual measurements for $r = .05$

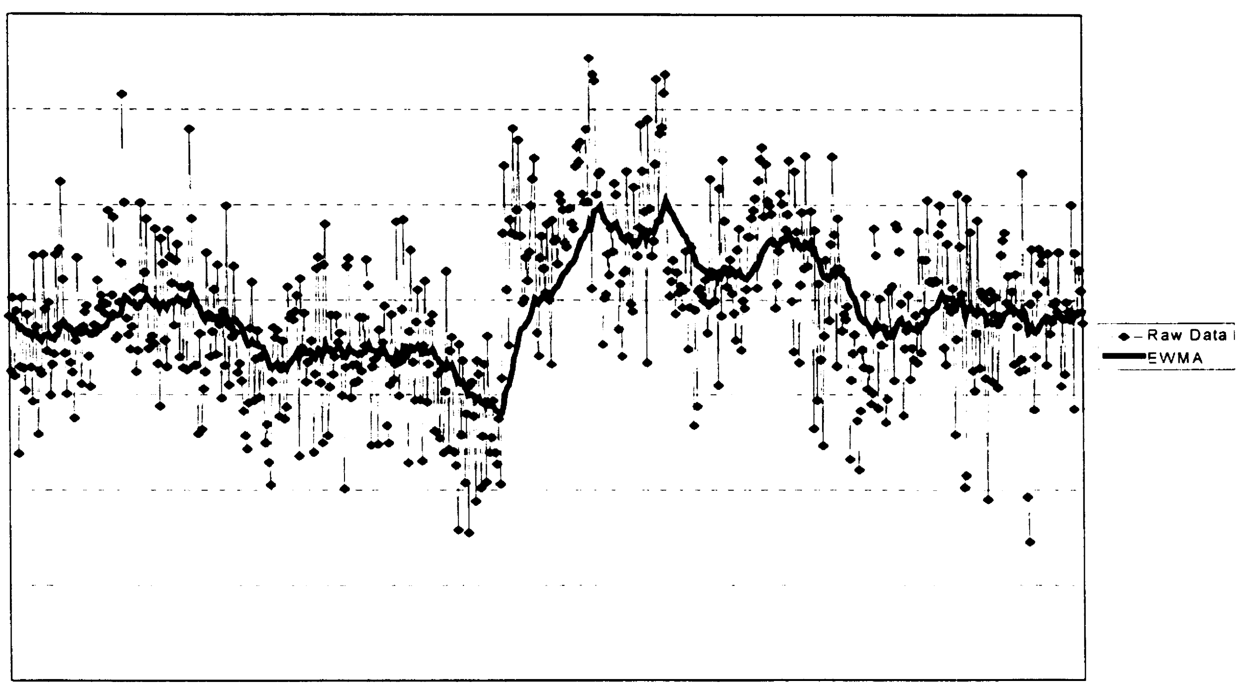

Figure 4-4: Filtering of data using EWMA with $r = .05$. Note that the filtered signal is damped and delayed from the original data.

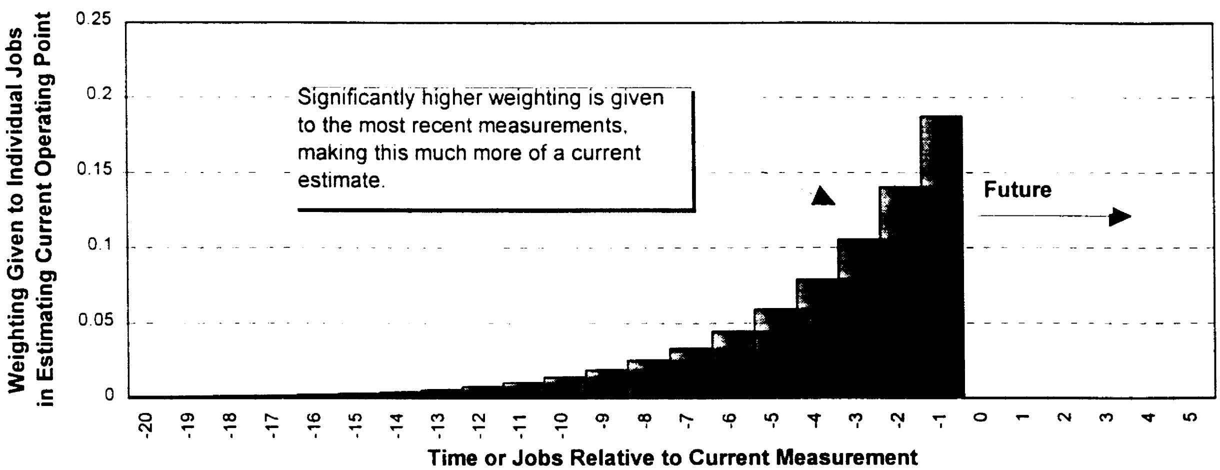

Figure 4-5: Exponential weighting of individual measurements for $r = .25$

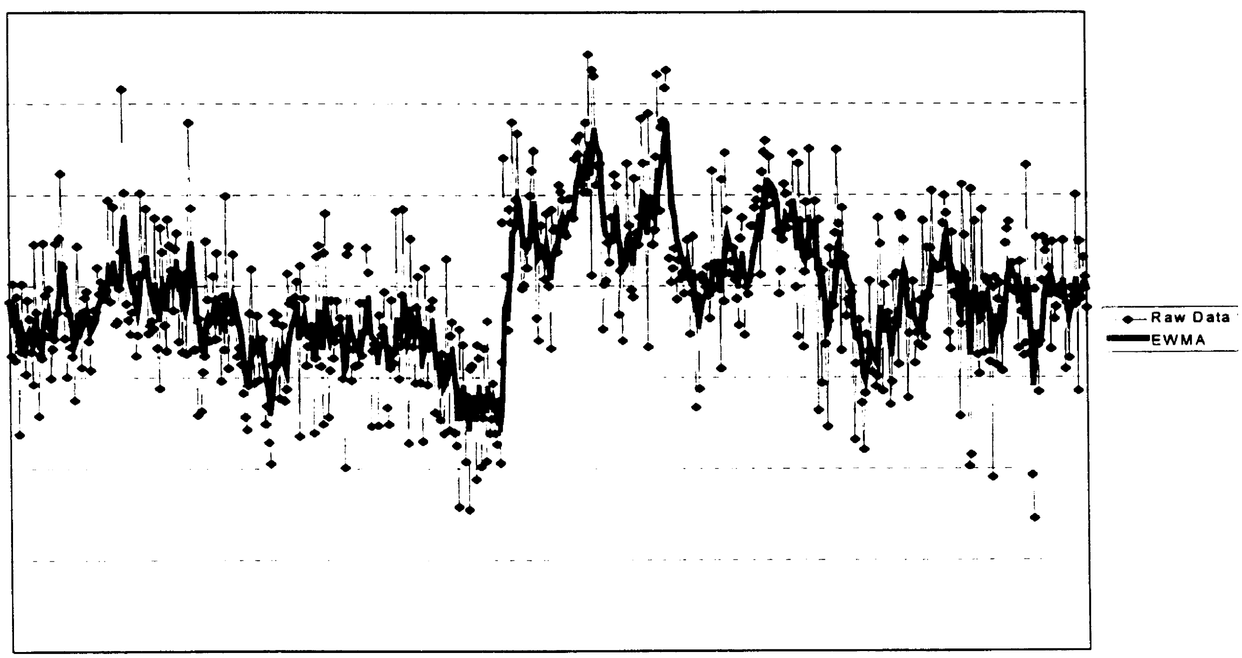

Figure 4-6: Filtering of data using EWMA with $r = .25$. EWMA estimate tracks changes more closely, but also includes high frequency variation.

Hunter (1986) introduced the EWMA by comparing it to the Shewhart, CUSUM, and moving average weighting methods. He noted that with r=1, the EWMA represents a Shewhart chart and as r approaches 0, the weightings resemble the CUSUM method. He concludes that "the choice of r can be left to the judgment of the quality control analyst." However, Hunter does go on to suggest that r be chosen to minimize the squared errors of the deviation. Selection of the weighting parameter r should address two objectives: (1) minimize autocorrelation of the residuals and (2) estimation of the process mean should be independent of the piece to piece variation inherent in the process. Based upon a typical body shop data set, a value for r of 0.20 was selected.

The exponentially weighted variance (EWMV) is similar to the EWMA in that the estimate of the process parameter is based upon a weighted average of past data. The difference is that the variance is being monitored instead of the mean. The equation for the EWMV is:

$$S_t^2 = r(x_t - \hat{\mu}_t)^2 + (1-r)S_{t-1}^2 \qquad (4\text{-}5)$$

where $\hat{\mu}_t$ is the estimate of the process mean at time t. This estimate is determined using the EWMA calculated through the previous measurement, A_{t-1}.

Attribute data can also be processed through an exponentially weighted filtering process. The objective of processing this type of data through a weighted average filter is to obtain an estimate of the frequency of occurrence for a given attribute. In this case, the process is used to examine the frequency of outlier occurrence.

4.3 Exponentially Weighted Moving Average Algorithm

The proposed statistical model utilizes continually updated estimates for the level of the mean and variation around the mean. The mean is estimated using the EWMA. The EWMV provides the estimate of the process variance. The EWMA and EWMV of prior data create a forecast for the next observation (Hunter, 1986). The algorithm consists of four steps: forecast, outlier check, parameter estimation, and parameter check. It is not necessary to utilize the same weighting parameter, r, for mean estimation, variance estimation, and outlier frequency estimation. Therefore, the following weighting parameters are defined:

r_M : to estimate the process mean

r_V : to estimate the process variation

r_L : to estimate the outlier frequency

The first step predicts values for mean and variation based upon data obtained up to and including the previous measurement. The estimates of the mean and variation using data through the previous measurement, A_{t-1} and V_{t-1}, are performed at the end of the previous iteration in Equations 4-9 and 4-10 (note that ^ indicates predicted value).

$$\hat{V}_t = V_{t-1} \tag{4-6}$$

$$\hat{A}_t = A_{t-1} \tag{4-7}$$

The second step compares the newest measurement, x_t, to the expected range for x_t based upon the current estimate of the process mean and variation.

If $\hat{A}_t - z \cdot \hat{V}_t < x_t < \hat{A}_t + z \cdot \hat{V}_t$ then x_t is not an outlier.

Otherwise, x_t represents an outlier. If x_t is outside the process range or data is missing, set the measurement outlier flag, m_t, = 1. If x_t is within the process range (not a measurement error), calculate the outlier severity:

$$\text{OUTSEV} = \frac{|x_t - A_{t-1}|}{V_{t-1}} - z + 1 \tag{4-8}$$

The third step updates values for mean and variation parameters. If x_t is not an outlier, then the parameters are updated based upon the new data. Note that the variation parameter V_t is an estimate of the standard deviation; therefore, it is calculated as the square root of the EWMV (S^2) that was discussed earlier.

$$V_t = \sqrt{r_V(x_t - A_{t-1})^2 + (1 - r_V)V_{t-1}^2} \tag{4-9}$$

$$A_t = r_M \cdot x_t + (1 - r_M)A_{t-1} \tag{4-10}$$

The outlier severity (OUTSEV) is then processed through an exponentially weighted filter, creating the parameter L. The objective of this filter is to send a signal when either a severe outlier has occurred or the frequency of outliers has become large.

$$L_t = r_L \cdot \text{OUTSEV} + (1 - r_L)L_{t-1} \tag{4-11}$$

The measurement error frequency is calculated. This parameter can be monitored to provide feedback for maintenance and improvement of the measurement system.

$$LM_t = r_L \cdot m_t + (1 - r_L)LM_{t-1} \tag{4-12}$$

4.4 Establishing Control Limits for Monitored Parameters

The above algorithm addresses how the most recent measurement will be evaluated to determine if it represents an unexpected condition. In addition to evaluating the most recent measurement, the process must be monitored for changes that occur over time (trending mean) or simply take longer to appear statistically (variation changes). Therefore, the statistical parameters utilized above can be monitored. Control limits for these parameters must be established. Theoretical limits can be calculated if the underlying process is independent and identically distributed (DeVor 1992), but if that were the case, traditional control charts would have been adequate. A system for developing control limits for the mean and variation based upon the evolution of a process from the initial measurements going forward is described in the following paragraphs.

4.4.1 Control Limits for the Estimate of the Mean

Control limits for the level of the mean (A) are established by first determining the expected center of the production process output and second determining the expected amount of variation of the mean about that target. The first step averages data determine the center of the proces The data used can either be from a baseline sample or can be continually updated. The second step estimates the variation of the mean. This estimation can be done in either of two ways. The first method assumes that the data is independent and calculates the expected variation of the mean based upon the deviation of individual measurements. This method is useful for establishing early control limits for the average. The second method takes periodic samples of the difference between the EWMA and the overall average of the process. This second method captures the variation of the mean directly, and when those samples are taken such that they are independent, accurate control limits can be established. The methods for calculating the control limits are outlined below.

The centerline of control chart ($\overline{A}$) is the average of all non-outlier data taken through T-1. Alternatively, the average of independent samples can be used to calculate the centerline.

An estimate of the variance of the process, σ^2 , can be made based upon the sum of the squared errors obtained from a baseline sample as shown in Equation 4-13.

$$\hat{\sigma}^2 = \sum_{t=1}^{T} \frac{e_t^2}{T-1} \qquad (4\text{-}13)$$

$$e_t = x_t - A_{t-1} \qquad (4\text{-}14)$$

T measurements are taken during the baseline period, e_t is the difference between the actual measurement at time t and the EWMA estimate of the mean just prior to the measurement.

By assuming independent data. the expected variance of the EWMA can then be calculated:

$$E\left(\sigma^2_{\mathrm{EWMA}}\right) = \left[\frac{r}{2-r}\right]\hat{\sigma}^2 \tag{4-15}$$

The expected standard deviation of the EWMA is:

$$\hat{\sigma}_{\mathrm{EWMA}} = \sqrt{\frac{r}{2-r}}\sigma \tag{4-16}$$

As sufficient data is generated, an estimate for σ_{EWMA} that does not rely on the independence assumption can be generated. In this case, $\hat{\sigma}_{\mathrm{EWMA}}$ is based upon deviations between the estimated average at a given time (A_t) and the centerline ($\overline{A}$). These sampled deviations are calculated at a sufficiently large interval to provide relatively independent deviations. In equation 4-17, w is the size of the interval, n is the current measurement, and therefore, n/w is the number of samples to be used in the estimate of the variance of the EWMA and $A(kw)$ is the value of A at $t=kw$. Figure 4-7 shows how the samples are taken at intervals in time; in practice, these samples would be separated by a greater amount of time, and more samples would be used.

$$\hat{\sigma}^2_{\mathrm{EWMA}} = \sum_{k=1}^{n/w} \frac{\left(A(kw) - \overline{A}\right)^2}{n/w - 1} \tag{4-17}$$

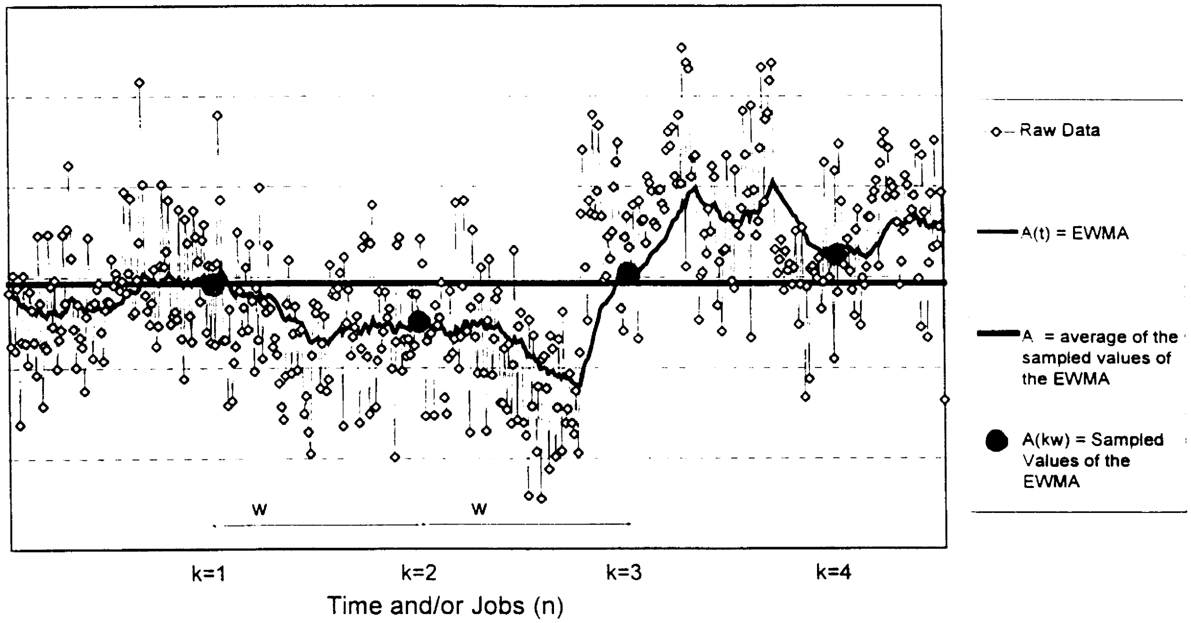

Figure 4-7: Example of the sampling process used in the estimation of σ_{EWMA}.

$\hat{\sigma}_{EWMA}$ is set to the maximum of $\hat{\sigma}_{EWMA}$ calculated directly from the sum of the squared deviations of the EWMA from the overall centerline and $\hat{\sigma}_{EWMA}$ calculated from the sum of squared individual measurement errors during the baseline period, assuming independence. Control limits are calculated using Equations 4-18 and 4-19 where z is selected to obtain the appropriate tradeoff between Type I and Type II errors (usually between 3 and 4).

$$UCL_A = \overline{A} + z\hat{\sigma}_{EWMA} \tag{4-18}$$

$$LCL_A = \overline{A} - z\hat{\sigma}_{EWMA} \tag{4-19}$$

A method for economically optimizing the EWMA detection parameters is presented by Montgomery et. al. (1995). The detailed optimization is an opportunity for future work, but the essence of the method is that the costs associated with problem solving efforts conducted on false signals must be balanced against the savings in quality loss obtained through event detection and problem correction.

4.4.2 Control Limits for the Estimate of Variation

Control limits for the level of variation (V) are established by first determining the expected level of variation and then by calculating the expected range for the variation estimate. The centerline of the control chart is $\overline{V}$. $\overline{V}$ is calculated by taking the average of a large number of samples of V_t taken during a baseline period. The samples are taken at intervals such that the samples are independent.

The upper and lower control limits are calculated based upon the variation of the process and the coefficients C_7 and C_8.

$$LCL_V = \overline{V} - C_7 \cdot \overline{V} \tag{4-20}$$

$$UCL_V = \overline{V} + C_8 \cdot \overline{V} \tag{4-21}$$

Values of C_7 and C_8 are shown in Table 4.1 for r_M=0.2 and r_V=0.05 for both an independent process and an autocorrelated process (ϕ=0.9), these values are taken from MacGregor and Harris (1993) and utilize approximations developed by Box.

Table 4.1: The coefficients used in the calculation of control limits for the variation as estimated from the EWMV.

		Independent Process	Autocorrelated Process with $\phi = 0.90$ and $\frac{\sigma^2_{piece}}{\sigma^2_{total}} = 0.5$
$\alpha = 0.05$	C_7	0.80	0.68
	C_8	1.29	1.08
$\alpha = 0.01$	C_7	0.73	0.63
	C_8	1.37	1.14

In regards to monitoring the outlier frequency, L_t is monitored, and if this value exceeds a control limit, then a process outlier signal is sent. The control limit is based upon a baseline data set.

When an outlier is detected, a separate monitoring process can be initiated such that additional data is monitored. Specific tests can be performed to determine if the outlier that was detected represents the beginning of a mean shift, the beginning of a variation change, or is truly a process outlier. The methods that could be used in this evaluation are essentially the same as those used in the specific search algorithms discussed in Section 3.

4.5 Exponentially Weighted Moving Average Summary

The exponentially weighted moving average and variance can be used to estimate the current operating state of the process in terms of the mean and variance (or standard deviation). Based upon these estimates, an expectation can be developed for an incoming measurement. If this measurement is outside the expected range, the measurement can be considered an outlier. If the measurement is not an outlier, then the estimates of the process mean and variation are updated with the new data; otherwise, the previous estimates are carried forward. The level of the mean, the level of variation and the frequency of outliers are monitored relative to control limits to look for changes in the production process. Control limits can be established for the eman can be established that do not rely upon an assumption of independence.

5. Multivariate Analysis Approaches

5.1 Principal Component Analysis

Principal component analysis (PCA) can be used to explain the variability of a system using a small number of linear combinations of the original variables. The general objectives of PCA are data reduction and interpretation.

The results of a PCA can be used to reduce a large set of measurement data into several key factors that explain a large fraction of the variation. This capability addresses one of the objectives of the 6 sigma prioritization process currently used in practice - focusing problem solving efforts on a few problems that represent the largest portion of the variation. As stated by Jackson (1980), "parsimony, defined as 'economy in the use of means to an end,' is the name of the game in principal components."

5.1.1 Strengths of Principal Component Analysis

The first strength of PCA is that the identified components are uncorrelated with each other. This means that if one underlying problem is causing a pattern of higher variation in a certain combination of measurements, with PCA all of this variation will be combined into a single principal component. Without PCA, this process of discovering which parameters of high variation are related is conducted informally through observation of process run charts, understanding of the likely possibilities, and occasionally the use of correlation between various measurements.

An example of the first four principal components obtained from a set of body shop optical measurement data is shown in Figure 5-1. The values to the left of the labels indicate the magnitude of contribution of that measurement to the given principal component. 53 measured parameters were utilized in the analysis with 150 measurements for each parameter.

- 1st Component

Principal Component	
-0.308	LRDD[Y]
0.279	BLD[Y]
-0.256	BLC[Y]
-0.255	LFDD[Y]
0.232	DOD[Y]
0.225	RRDF[Y]
-0.223	DOC[Y]
0.219	RRDE[Y]
-0.211	LRDF[Y]
-0.208	DOA[Y]
0.207	DOB[Y]
-0.196	LRDE[Y]
0.189	DOF[Y]
-0.186	DOE[Y]

- 2nd Component

Principal Component	
-0.376	MCC[Y]
0.293	MCD[Y]
0.262	DOE[Y]
0.246	MCC[Z]
-0.229	DOF[Y]
-0.221	BLA[Z]
-0.199	DOA[Z]
-0.185	DOB[Y]
0.185	BLB[X]
-0.184	DOC[Z]

- 3rd Component

Principal Component	
0.384	BLA[Z]
0.361	DOA[Z]
0.349	DOC[Z]
-0.321	LRDF[X]
0.231	BLB[Z]
0.218	DOB[Z]
0.195	DOA[Y]
-0.193	WSD[X]
-0.184	DOF[Y]

- 4th Component

Principal Component	
0.422	LRDF[Y
-0.288	LFDD[
0.281	DOB[Z
-0.258	MCC[Z
0.223	DOA[Z
0.204	LFDA[X]
0.197	RRDE[X]
0.195	RRDF[X]
0.189	DOC[Z]

Figure 5-1: The first four principal components explain the largest amount of variation in the body shop data set. The top contributors for each component are shown. The numbers to the left of the labels indicate that measurements contribution to the principal component.

The second strength of PCA is that the output is automatically prioritized. The first principal component is the linear combination of parameters that explains the maximum amount of variance. If the first principal component represents a correctable condition, then correction of that condition should have a bigger impact on overall variation than correction of any other condition. The clarity that is provided by PCA can be shown by examining the Pareto charts of the top 20 contributors to variation using (1) the magnitude of the principal components and (2) the magnitude of 6σ variation. The choice of priorities is much clearer in the case of PCA as shown in Figure 5-2.

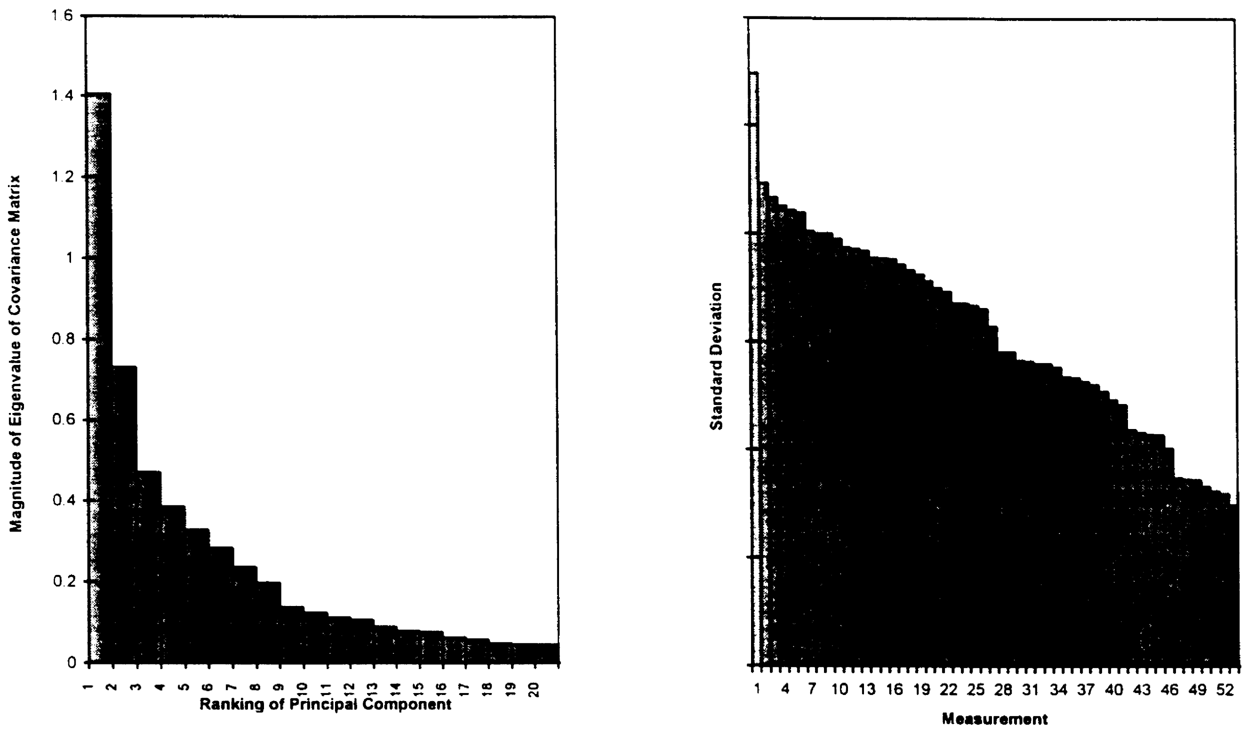

Figure 5-2: Pareto chart for PCA and 6σ variation. The principal components provide a much more appropriate mechanism for prioritization of problem solving activities. The chart on the right is very similar to a normal distribution plotted in descending order.

The third strength of PCA is in the area of interpretation. The coefficients used in the linear combinations that represent principal components indicate magnitude and direction of movement. An interpretation of first principal component would be:

- 1st Component

Principal Component	
-0.308	LRDD[Y]
0.279	BLD[Y]
-0.256	BLC[Y]
-0.255	LFDD[Y]
0.232	DOD[Y]
0.225	RRDF[Y]
-0.223	DOC[Y]
0.219	RRDE[Y]
-0.211	LRDF[Y]
-0.208	DOA[Y]
0.207	DOB[Y]
-0.196	LRDE[Y]
0.189	DOF[Y]
-0.186	DOE[Y]

All of the measurement points identified in the first principal component are for in/out variation of the top back of the vehicle. The first observation is that points on the left of the body are moving inward (-) while the points on the right side are moving out (+). The second observation is that points higher on the body are varying more on this component than points lower on the body.

5.1.2 Principal Component Analysis - Theory

The theory of PCA evolved from the objectives outlined at the beginning of this section. In-depth discussion of the theory and methods can be found in textbooks on multivariate statistics, for example "Applied Multivariate Statistical Analysis" by R. Johnson and D. Wichern (1988). An additional example as applied to an automobile body dimensional issue can be found in Roan (1993). The examples provided in the text and in Roan's thesis deal with only two to five measured parameters, whereas the example above included 53 parameters. The theoretical concepts as described by Johnson and Wichern:

> Algebraically, principal components are particular linear combinations of the p random variables $X_1, X_2, \ldots, X_p$. Geometrically, these linear combinations represent the selection of a new coordinate system obtained by rotating the original system with $X_1, X_2, \ldots, X_p$ as the coordinate axes. The new axes represent the directions with maximum variability and provide a simpler and more parsimonious description of the covariance structure.

The linear combinations that are achieved (Y1, Y2, ... , Yp) are the uncorrelated linear combinations whose variances are as large as possible, these are by definition the principal components. The first principal component is the linear combination with maximum variance. Additional principal components also maximize variance, but with the additional constraint that they are uncorrelated to all previous principal components. A key result derived in the text is that the principal components are uncorrelated and have variances equal to the eigenvalues of the covariance matrix. A second key result is that the sum of these eigenvalues is equal to the total population variance. An implication of these results is that taking the eigenvalue associated with a given principal component divided by the sum of the eigenvalues gives the fraction of the total variance that is explained by that principal component. These are the values that are used in the Pareto diagram shown in Figure 5-2.

5.1.3 Principal Component Analysis - A Practical Guide

The method to perform a Principal Component Analysis (PCA) on a large data set in practice is presented in this section. The tools that make the process easier include a spreadsheet program (such as Excel) and an matrix analysis tool (such as Matlab).

1. Open raw data text file in spreadsheet
2. Check for and eliminate outliers - using formal or informal method
3. Eliminate all rows that include missing or eliminated data
4. Eliminate all auxiliary information columns and empty columns
5. Save as an spreadsheet file (filename.xls)
6. Eliminate header information
7. Save as a comma delimited text file (filename.csv)
8. Close the text file.
9. Open the text file as a matrix in Matlab (M=csvread('filename.csv'))
10. Calculate the covariance matrix (A=cov(M))
11. Calculate the eigenvectors and eigenvalues of the covariance matrix ([v,d]=eig(A))
12. Save the eigenvector matrix as a comma delimited text file (csvwrite('evector.csv',v))
13. Save the eigenvalue matrix as a comma delimited text file (csvwrite('evalue.csv',d))
14. Open the two output files and the spreadsheet file.
15. The first principal component will be found in the right hand column
16. Copy this column to a blank area of the spreadsheet
17. Convert the values in this new column to their absolute values
18. Copy and transpose the header information so it is next to this column
19. Select the range of values and headers
20. Sort the selection so that the values are in decreasing order
21. The top factors that affect the first principal component will now be at the top of the column
22. Items 16-21 can be repeated for additional components.

5.2 Multivariate Statistical Process Control

In certain manufacturing situations, monitoring the control status of multiple parameters can provide a higher resolution of event detection. The method discussed here is in the area of multivariate Shewhart charts. These multivariate control charts are based upon Hotelling's statistic that measures the directed distance to a given target. The large dot in the hypothetical example shown in Figure 5-3 shows how both X1 and X2 can be within their respective control limits, yet the actual situation is that of an outlier. This condition is of particular of concern when the actual customer requirement is defined by the relationship of X2 to X1.

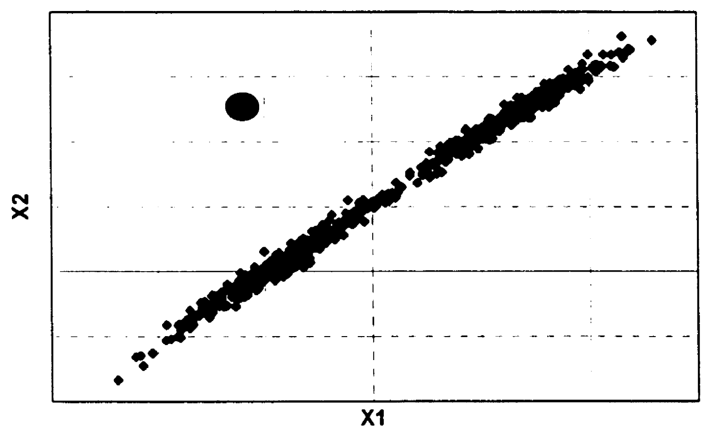

Figure 5-3: Hypothetical situation where a multivariate detection method would have detected an outlier that would not have been detected by univariate methods.

The general methodology is to quantify the natural relationship between the variables using the covariance matrix. Control limits are then developed in the form of a region in space around the natural relationship. The mathematics define this relationship precisely, and in the case of two variables, the region is an ellipse.

Estimation of the "in-control" covariance matrix (**S**) where n is the number of measurements used to calculate the covariance matrix and y is a vector of q parameters being measured for each job. (Note: T is the transpose of the vector). The vector $\bar{y}$ also has q elements, where each element is the average of the n measurements taken for that element's corresponding parameter.

$$\mathbf{S} = (n-1)^{-1}\sum_{i=1}^{n}(y_i - \bar{y})(y_i - \bar{y})^T \tag{5-1}$$

As new measurements are taken. Hotelling's T^2 statistic can be calculated where τ is a vector with the target operating points for each parameter of the process. For control of the process, τ can be replaced with $\bar{y}$.

$$T^2 = (y - \tau)^T \mathbf{S}^{-1}(y - \tau) \tag{5-2}$$

The control limit is then calculated using:

$$T^2_{UCL} = \frac{(n-1)(n+1)q}{n(n-q)} F_\alpha(q, n-q) \tag{5-3}$$

where $F_\alpha(q, n-q)$ is the upper 100*α% critical point of the F-distribution with q and n-q degrees of freedom.

An example is presented below of a pattern of data with an outlier and the resulting T^2 control chart. In this particular case, a univariate chart would have been sufficient to detect the outlying point.

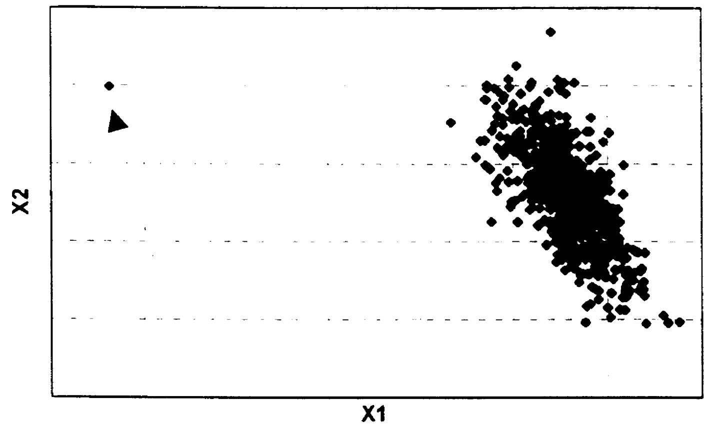

Figure 5-4: This was the most clear case of a multivariate outlier detection situation. However, this particular condition would have been detected with univariate detection performed on the X1 variable.

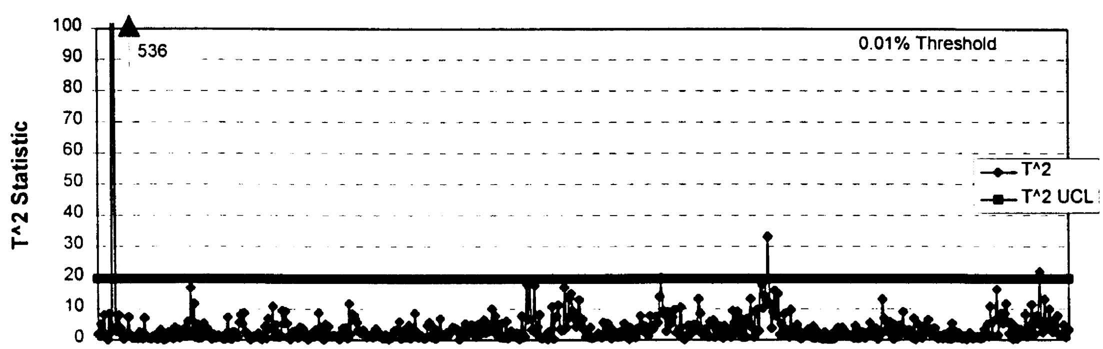

Figure 5-5: An example of Hotelling's T^2 statistic plotted against time. The statistic clearly separated the outlier from the data.

6. Performance of the Algorithms for Detection and False Signals

Algorithm performance is evaluated in this section. Statistical simulation was utilized for comparison of algorithm performance. The performance discussion addresses several key characteristics:

- Consistency of detecting relatively large process events.
- Speed at which large events are detected.
- Avoidance of false signals in the presence of batch variation.
- Deterioration of detection capability in the presence of underlying batch variation.

Performance of the various algorithms is evaluated using the probabilities of Type I error (false signals) and Type II error (failure to detect). The performance of each algorithm can be evaluated visually as shown in Figure 6-1. In the figure, the probability of declaring a process event within a given time is plotted against the magnitude of a process event. This presentation method can be useful for examining the tradeoff between Type I errors and Type II errors. A time limit for event detection of 50 jobs is used in the algorithm evaluation. The time to detection is also shown in Figure 6-1. The reported time to detection is the average time to detection for the detected events.

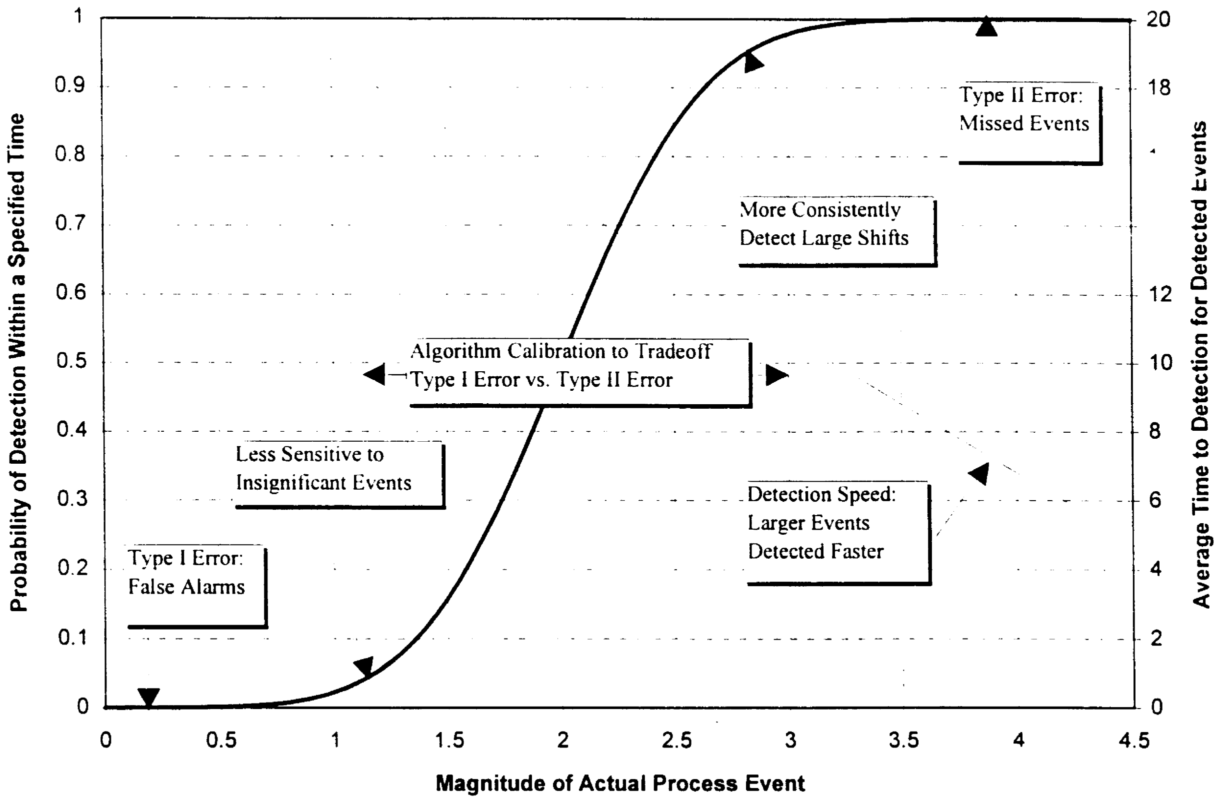

Figure 6-1: Generic representation of algorithm sensitivity to process events of increasing magnitude. Several characteristics of the representation are indicated.

6.1 Simulation Scenarios

6.1.1 False Alarm Sensitivity Scenarios

The first set of performance scenarios evaluate the probability of false alarms (Type I error). The first scenario, shown in Figure 6-2, is for the standard case of independent, normal variation. The second scenario, shown in Figure 6-3, includes both batch to batch variation and the independent piece to piece variation. A batch to batch variation (σ_{batch}) equal to ½ the piece to piece variation ($\sigma_{piece\ to\ piece}$) was added to the independent piece to piece variation. The performance objective is that if batch variation is present during the baseline establishment period, then this variation pattern should not trigger a process event signal during the monitoring period. Performance of false alarm sensitivity is evaluated using the probability of detection when the magnitude of an actual event is zero.

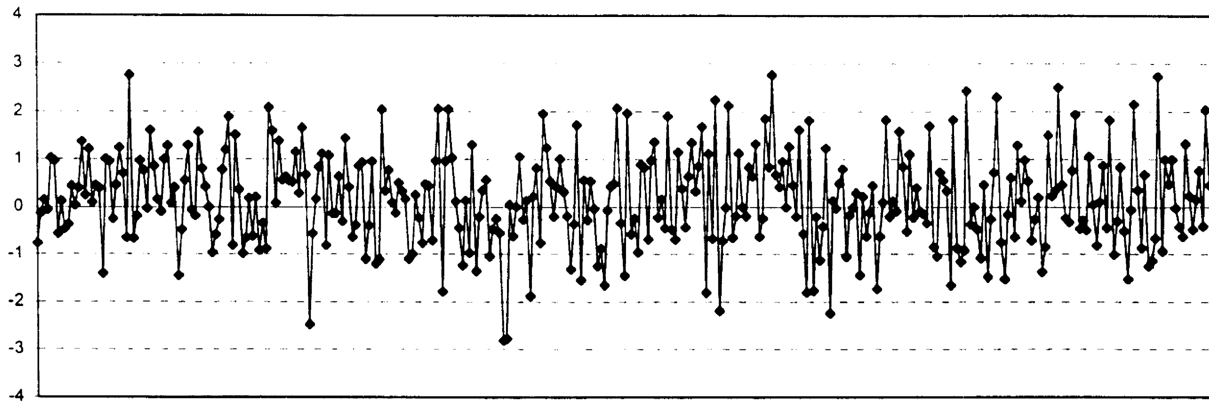

Figure 6-2: Type I error sensitivity scenario with no batch to batch variation.

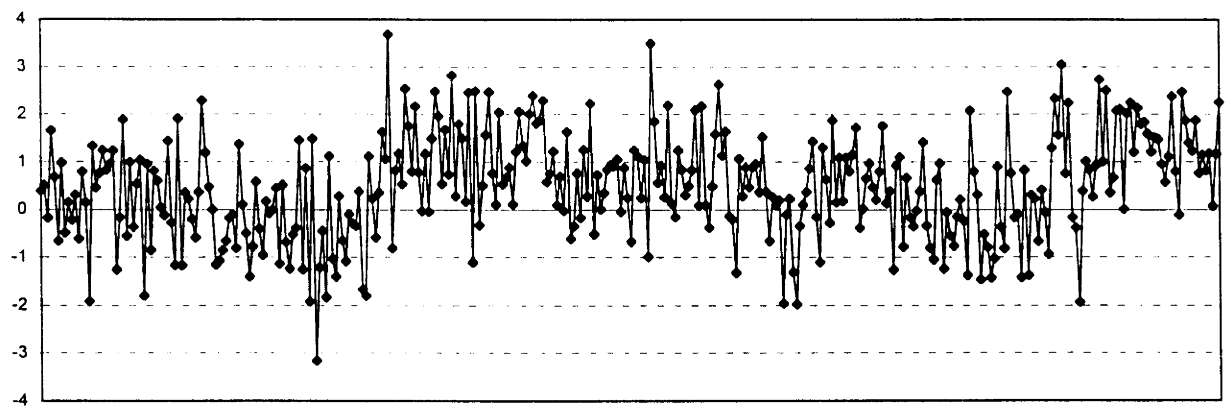

Figure 6-3: Type I error sensitivity scenario with batch to batch variation

6.1.2 Detection Scenarios

The second set of scenarios evaluates the detection performance of the algorithm. The first detection scenario is for a mean shift. In this case, a mean shift is introduced to the process at a given point in time. Mean shifts ranging up to 3.5 $\sigma_{\text{piece to piece}}$ are introduced to the system. The magnitude of the mean shift is defined as a multiple of the standard deviation of the piece to piece variation. These scenarios are run with and without underlying batch variation. The primary performance objective is to detect large events consistently. The secondary performance objective is to detect these large events as quickly as possible. In this production environment, the eventual detection of small mean shifts is not a major objective of the processing algorithm.

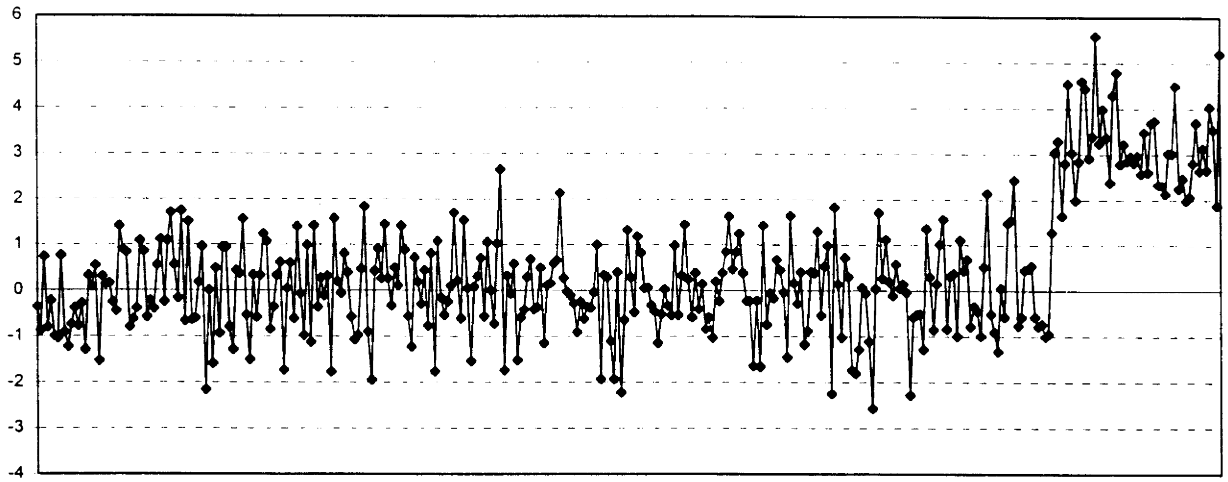

Figure 6-4: Mean shift detection scenario for a 3σ shift (no batch variation).

The second detection scenario is for a change in variation. In this case, the piece to piece variation of the process is increased by various levels, up to maximum of 300% of the baseline piece to piece variation ($\sigma_{\text{piece to piece}}$). Therefore, in the most severe scenario, the variation will be 4 times the original variation (100% + 300%). The magnitude of the variation change process event is defined as the ratio of the piece to piece variation after the event to the piece to piece variation before the event, expressed as a percentage.

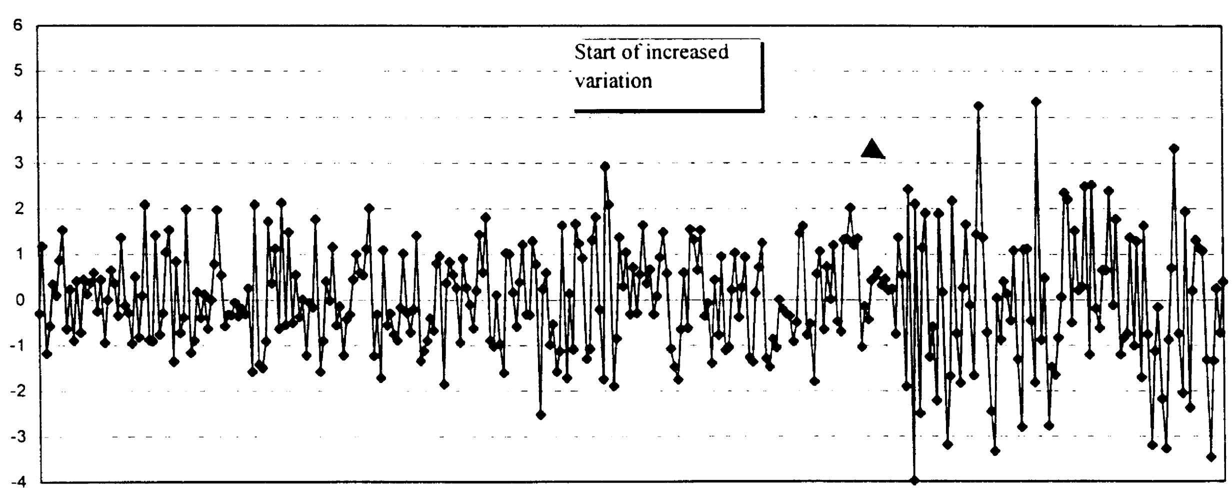

Figure 6-5: Variation detection scenario with a variation increase of 50% shown. The magnitude of the piece to piece variation = 150% of the original variation.

The third detection scenario is for the detection of an outlier. The event to be detected is an outlier of magnitude ranging up to 8 $\sigma_{\text{piece to piece}}$ from the mean of the process as shown in Figure 6-6. In the case of background batch variation, the outlier is placed at the specified distance from the mean of the batch. In the performance evaluation, each outlier is introduced in a separate run. The multiple outliers shown in Figure 6-6 are to illustrate the relative magnitudes of the process events that are being tested.

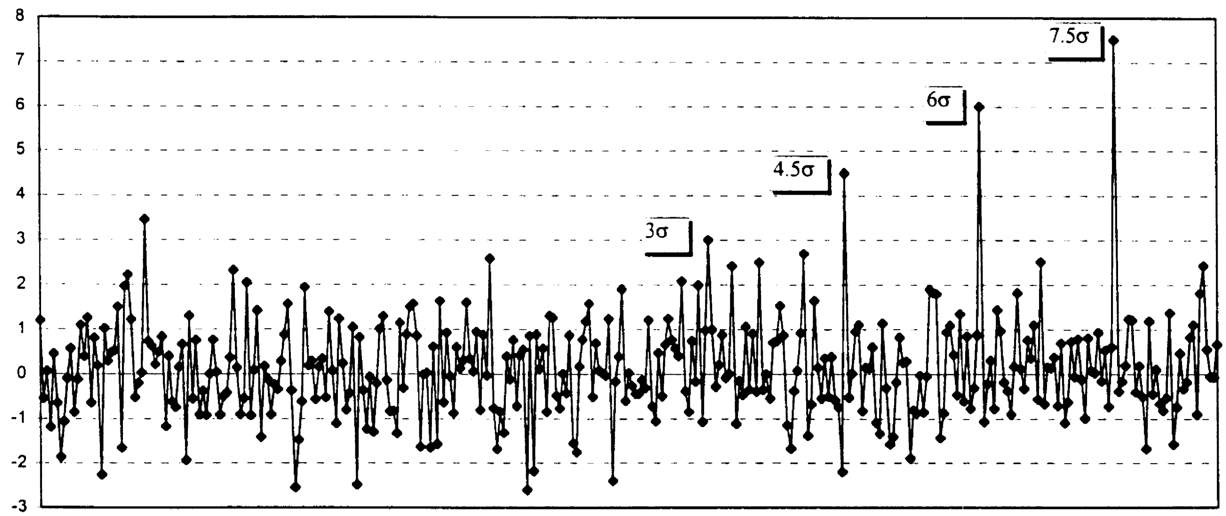

Figure 6-6: Example detection scenario for outliers at various distances from the mean of the process.

6.2 Performance Under Simulated Conditions

6.2.1 Specific Search Algorithm

The performance of the specific search algorithm is shown in Figure 6-7 and Figure 6-8. The specific search algorithm is insensitive to normal variation of the process, even if that variation includes batch to batch variation (shown in the broken line). The specific search algorithm successfully detects large mean shifts (> 2 $\sigma_{\text{piece to piece}}$) with high probability. The speed of detection is shown as the thin line in Figure 6-7. The algorithm successfully detects large mean shifts rapidly while taking more time to detect smaller mean shifts. A 3 standard deviation shift in the mean takes an average of 10.5 jobs to be detected.

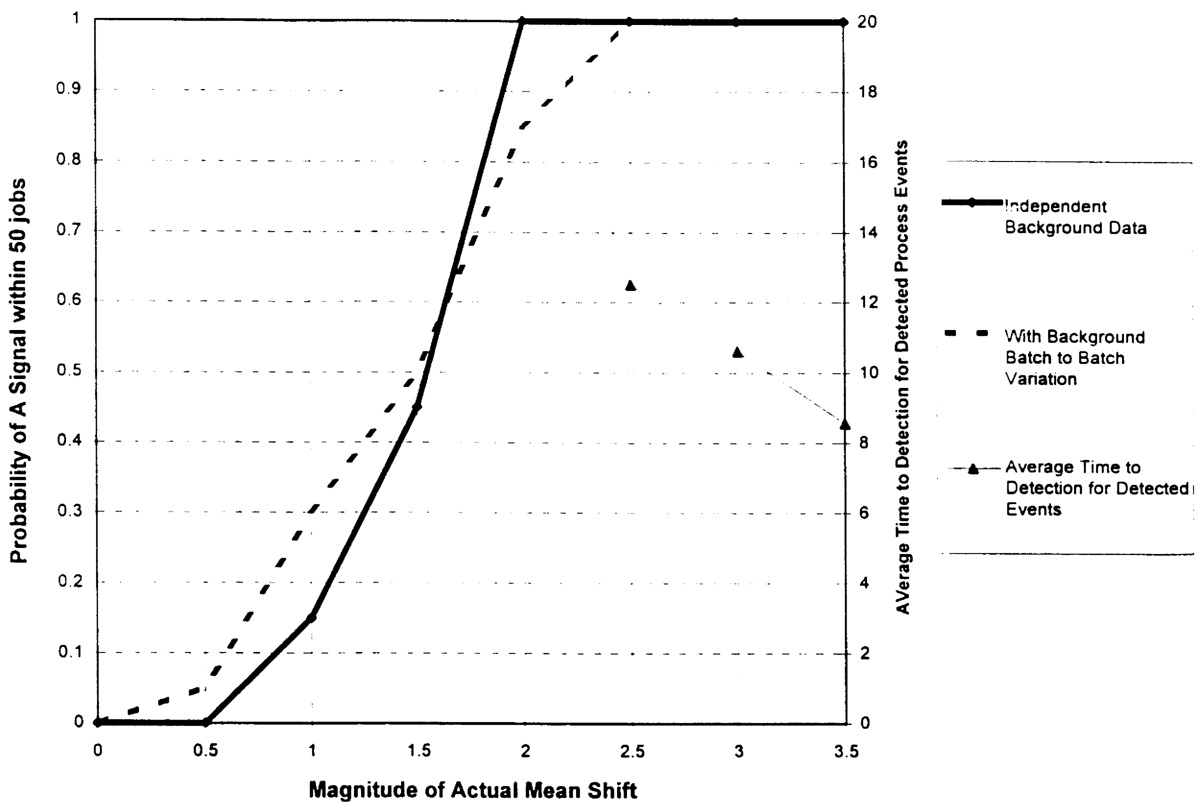

Figure 6-7: Mean shift performance of Specific Search algorithm.

In Figure 6-8, the probability of detecting an event versus the magnitude of the variation after the change is shown. The solid line represents performance when there is no batch variation in the underlying process. The broken line represents the probability of signaling an event when there is underlying batch to batch variation. The thin line represents the average time to detection for detected process events. The time to detection for a variation increase to 300% of the original variation is 14 jobs. It can be see from Figure 6-8 that the presence of batch variation slightly increases the likelihood of a signal at all variation change levels except for the case of no change. The algorithm is robust to batch variation as shown by the low probability of detection in the absence of a true event.

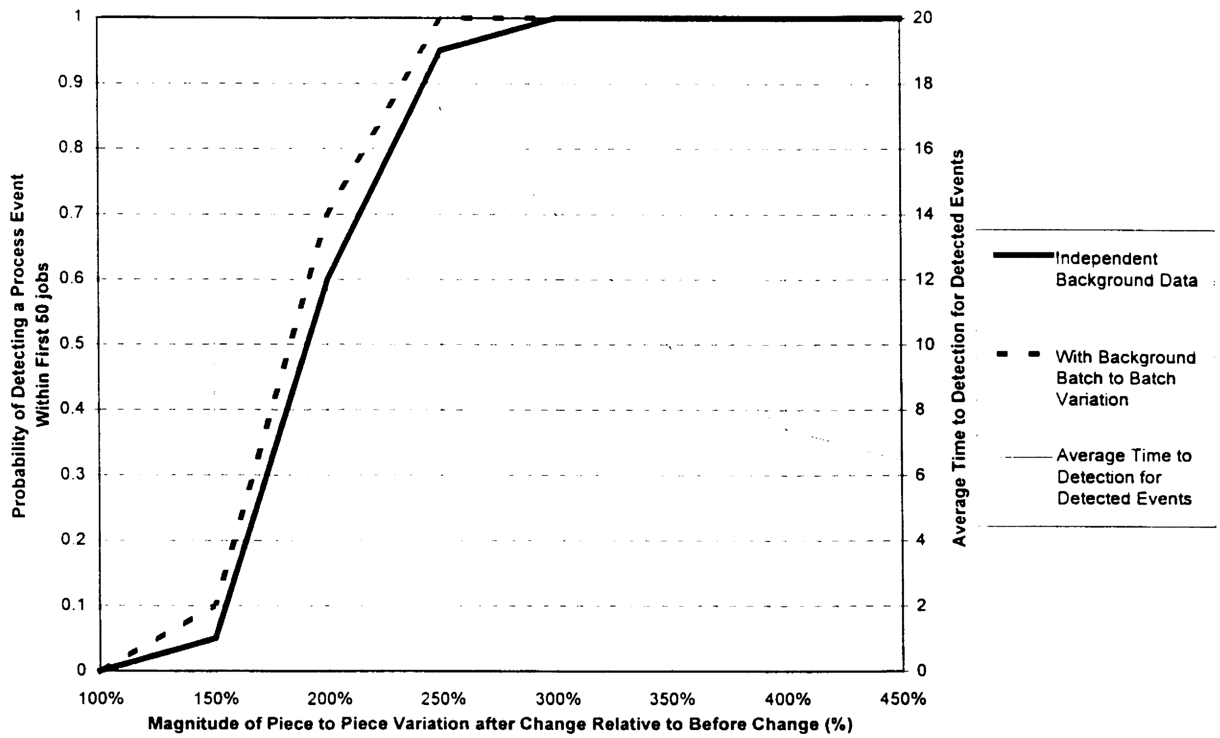

Figure 6-8: Variation change detection performance of the Specific Search algorithm.

6.2.2 Exponentially Weighted Moving Average Algorithm

The exponentially weighted moving average algorithm successfully detects large process events. The algorithm correctly sends no signal even when the underlying process includes batch to batch variation. The algorithm is also successful in the objective of rapidly detecting large changes in the process.

The mean shift detection performance of the EWMA algorithm is shown in Figure 6-9. It is shown that in the presence of independent data, even moderate sized mean shifts ($\geq 1.5\ \sigma$) are detected consistently within 50 jobs. Also, in the presence of independent data, the speed of detection is very rapid, less than five jobs for mean shifts larger than 2σ. The algorithm correctly sends no signal in the absence of a true mean shift. This characteristic demonstrates the insensitivity of the algorithm to underlying batch variation. The final characteristic to be taken from the simulation output is that in the presence of batch variation, the detection capability of the algorithm deteriorates. This deterioration is to be the expected by-product of minimizing sensitivity to batch variation.

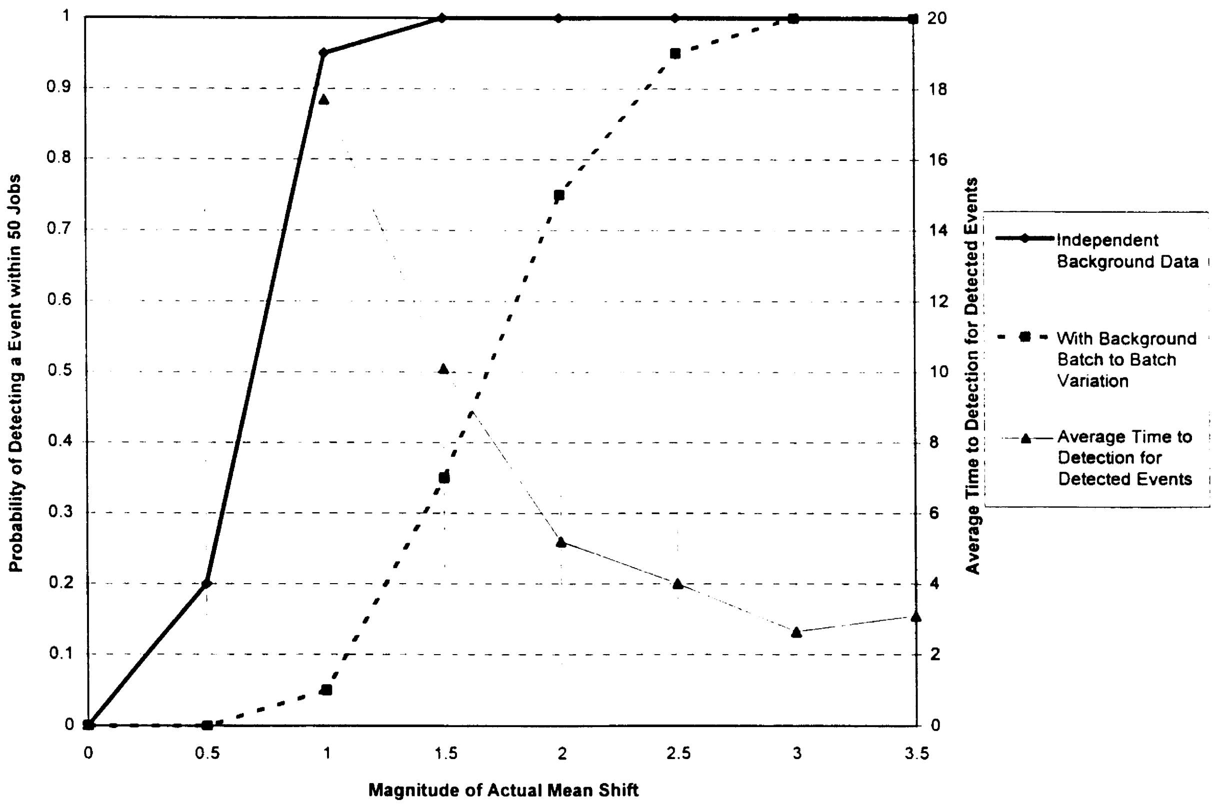

Figure 6-9: Mean shift detection performance for the EWMA algorithm (simulation results)

The performance of the EWMA algorithm for detecting changes in variation is shown in Figure 6-10. Variation changes that result in a final variation larger than 250% of the original variation are consistently detected within 50 jobs. Large changes in variation (resulting in final variation > 300% of original variation) are detected very rapidly, in less than 10 jobs. The algorithm has some deterioration of detection capability in the presence of underlying batch variation, but as discussed in the case of mean shifts, this is to be expected.

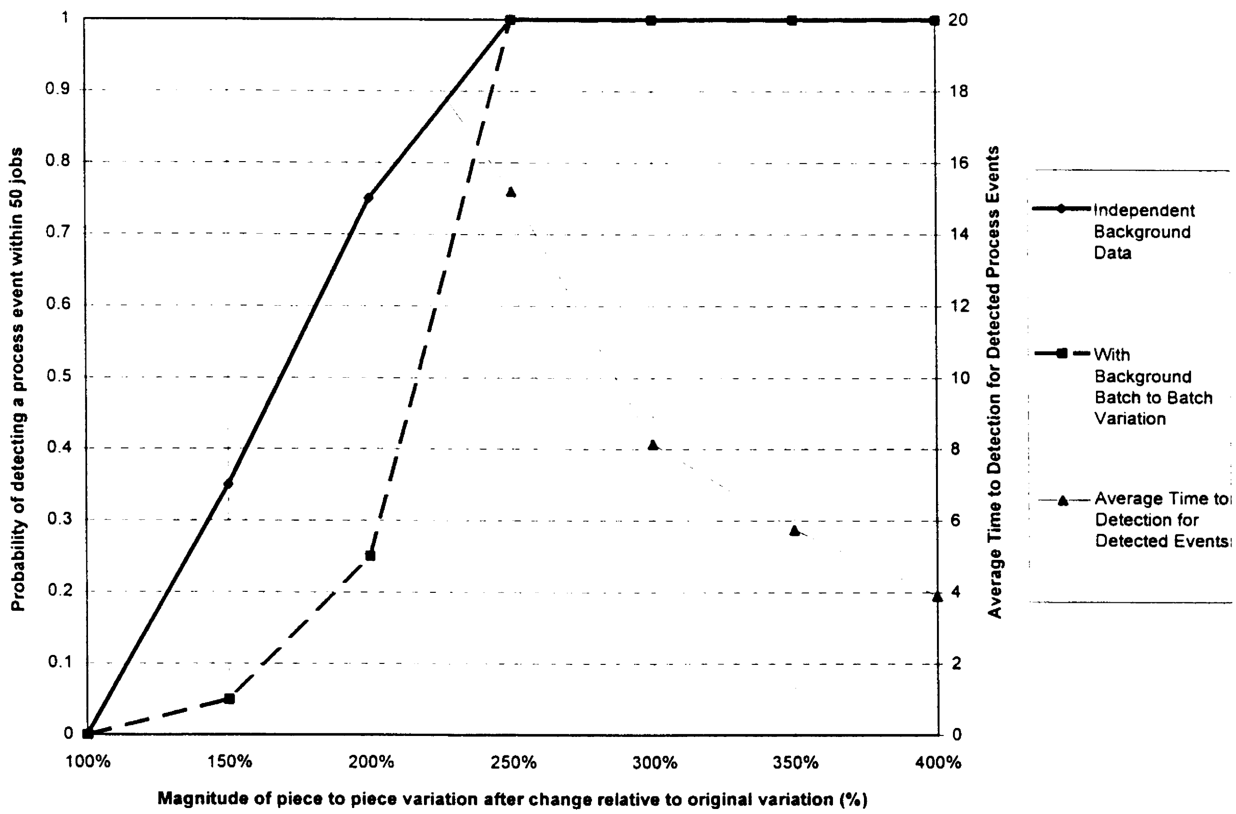

Figure 6-10: Variation change detection performance for the EWMA algorithm.

The performance of the EWMA algorithm for detecting outliers is shown in Figure 6-11. The algorithm correctly detects large magnitude outliers while rejecting small magnitude outliers. The actual level at which the high probability of detection occurs is a function of the calibration of the algorithm. All outliers that were detected were detected at the time when the outlier occurred.

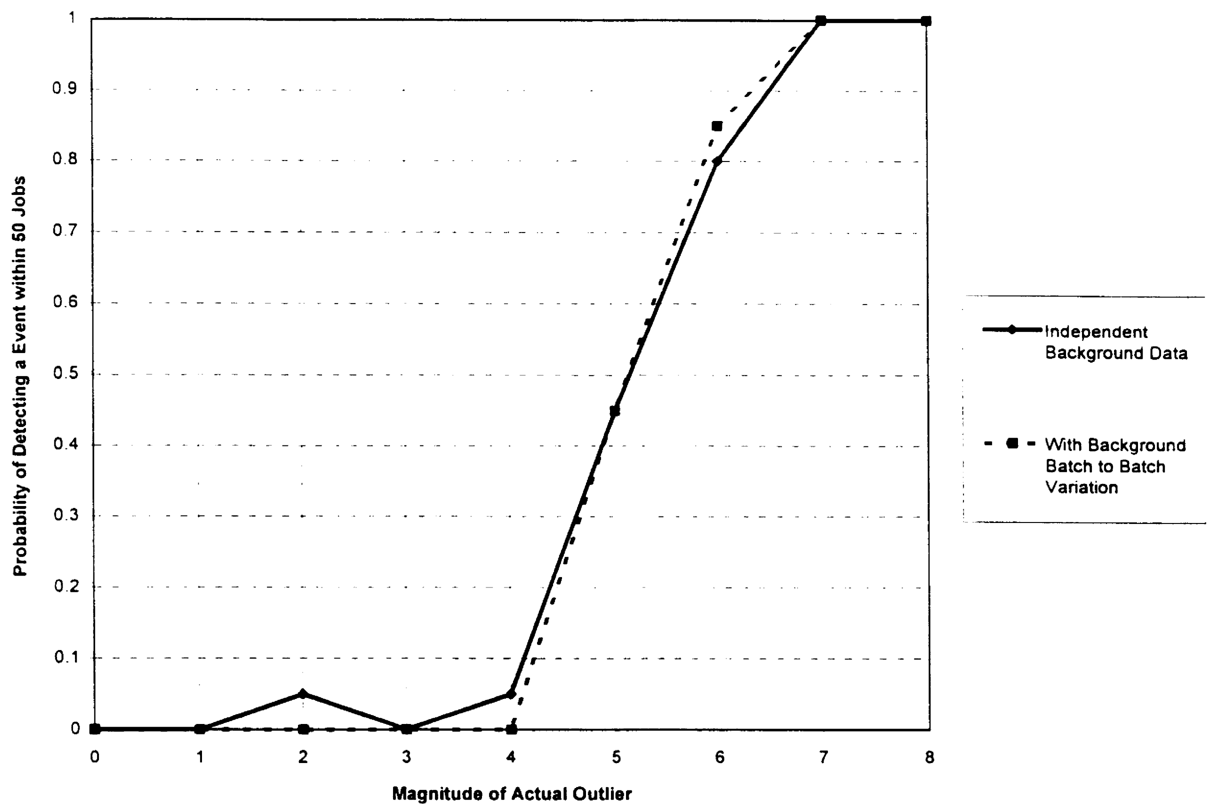

Figure 6-11: Outlier detection performance for the EWMA algorithm. Performance is shown for algorithm calibrations of an outlier threshold level of 3.5 and an upper control limit on the filtered outlier severity (L_t) of 0.05.

6.2.3 Shewhart Control Charts

The Shewhart control chart comparison will involve a tradeoff between sensitivity and detection speed that is partially a function of the sampling strategy used. A subgroup of size 5 was selected with samples taken at an interval of 20 jobs. This result is consistent with the general sampling recommendations in DeVor (1992) that suggest 5 as an appropriate sample size for most applications. The performance of the algorithm is evaluated in terms of the likelihood of detecting an event during the first sample after the event.

6.2.3.1 Shewhart Algorithm Performance

The characteristics of the Shewhart algorithm are shown in Figure 6-8. The first objectionable characteristic is that despite a complete baseline procedure. the algorithm is excessively sensitive to underlying batch to batch variation. There is a 7% probability of falsely declaring an event when nothing changed in the underlying process. The speed of detection for the Shewhart method is limited by the sampling strategy. Since the allowed detection period was only 25 jobs in this example, only one complete subgroup was evaluated, resulting in an average time to detection of 11.6 for a +3σ mean shift. Allowing a longer number of jobs to be evaluated would raise the probabilities for the smaller mean shifts and would raise the average time to detection for these smaller shifts (because events that had previously undetected will now be detected, pushing the probability up, but since these events are detected on the second sample, the average time to detection will be increased).

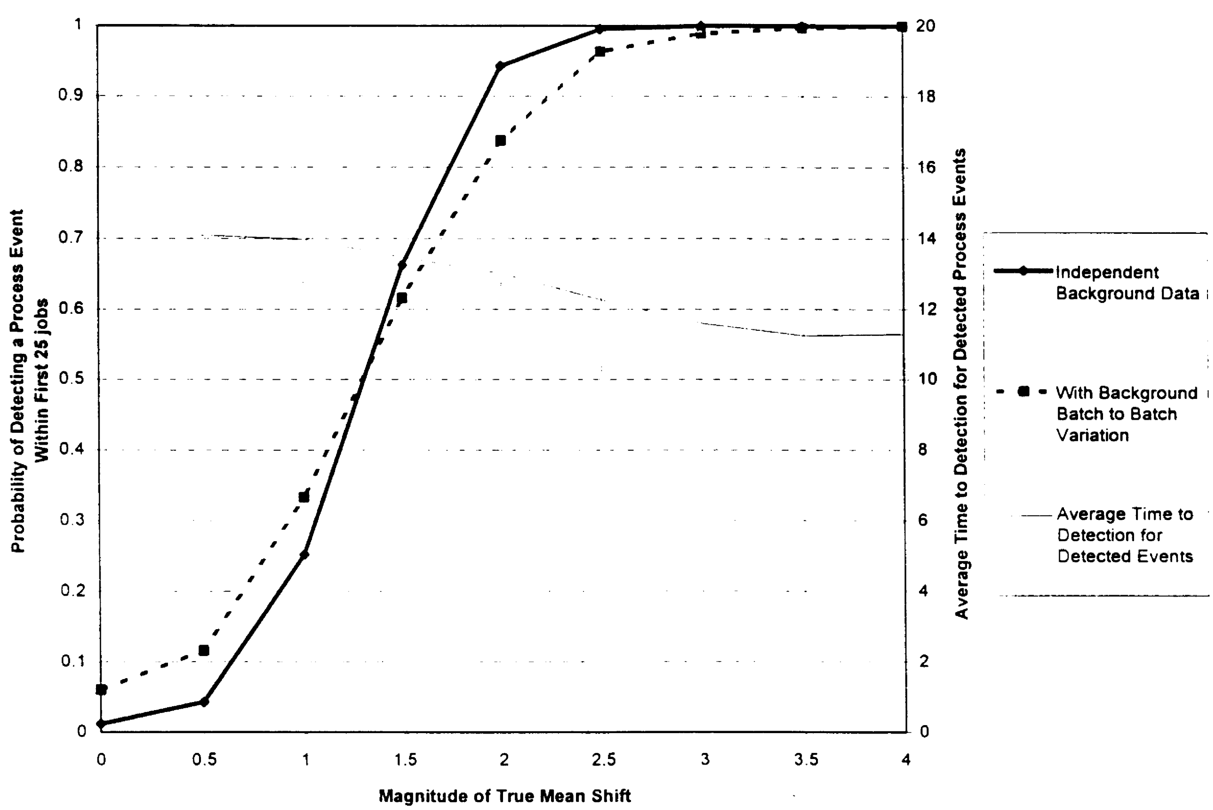

Figure 6-12: Performance for the Shewhart algorithm with subgroups of 5 taken at an interval of 20 jobs. Simulation results.

The sensitivity of the Shewhart method for changes in variation can be seen in Figure 6-13. As in the mean shift analysis above, in the absence of a true change, the probability of a false signal is near 0.05 within the first 30 jobs. The presence of batch variation did not significantly affect the overall variation change detection capability. Even large changes in variation may require more than 30 jobs to be detected.

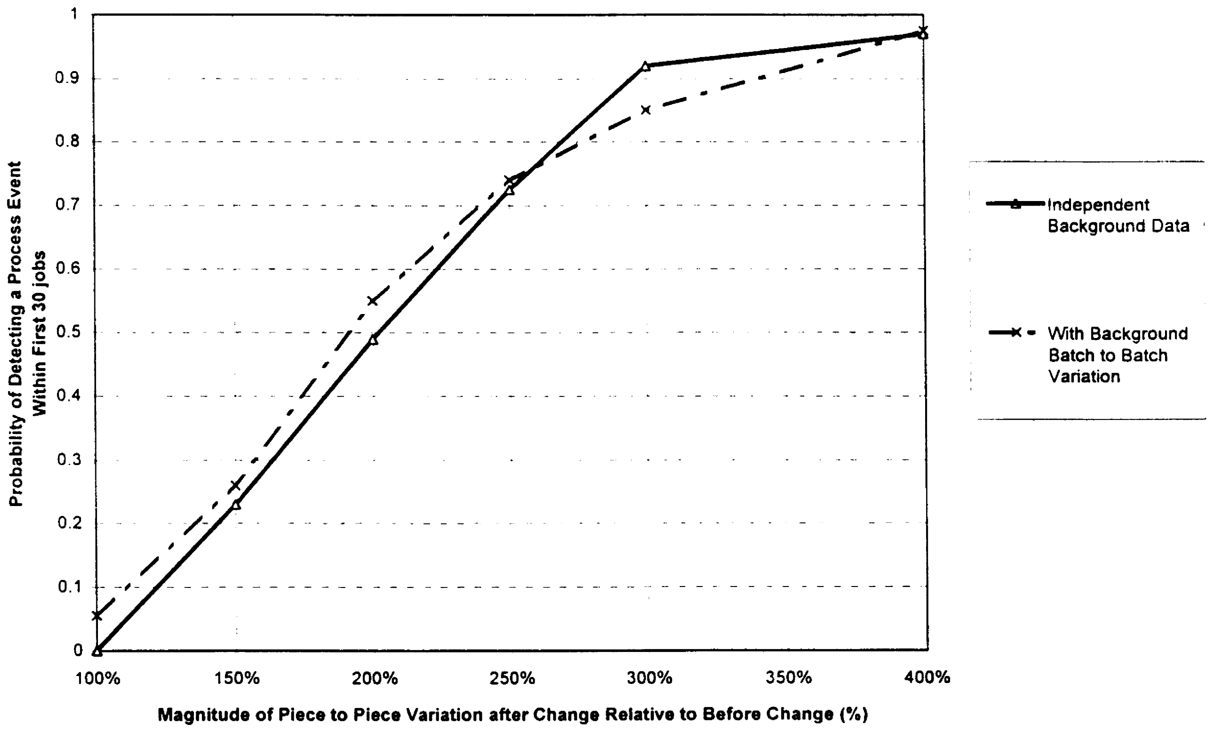

Figure 6-13: Detection capability for variation change with Shewhart control algorithm.

6.3 Comparisons and Conclusions

The specific search algorithm and the EWMA algorithm met the performance objective of being insensitive to underlying batch variation. In the absence of batch variation, all three algorithms successfully detected a 2σ mean shift within 50 jobs. In the absence of batch variation, the specific search algorithm detected a doubling of variation 75% of the time and the EWMA detected the change 60% of the time. With the presence of batch variation, the detection capability of the EWMA algorithm deteriorates to a 75% probability of detecting a 2σ mean shift and a 25% probability of detecting a doubling of the variation. The specific search algorithm is less sensitive to underlying batch variation; the probability of detecting a 2σ mean shift drops to 85% and the probability of detecting a doubling of variation rose slightly to 70%. The Shewhart method was relatively insensitive to underlying batch variation in terms of detection capability;

the 2σ mean shift was detected 84% of the time and the doubling of variation detection increased slightly to 55%.

6.4 In-Plant Experience with Algorithm

A preliminary version of the algorithm was implemented in the body shop. This algorithm examined data on an hourly basis. The tooling supervisor, tooling engineers and toolmakers were notified of mean shifts detected by the algorithm. Many of the detected conditions were deliberate events created by a planned adjustment of a tooling dimension. In these cases, the system served to confirm the process change and to identify unintended side effects. Several major events were detected and reported with high severities; these events would have taken much longer to detect without the monitoring system. The system also provided notification of less severe changes in the process; this notification helped identify sources of underlying variation in the process. The prioritization was observed to have the proper characteristics, giving more priority to major changes in the process. Examples of the types of events that were detected using the preliminary algorithm are presented. In addition to the notification of mean shifts, printouts were automatically generated and made available to the process experts for variation changes and outliers. Trend inormation was included on a summary report that was printed on a regular basis.

6.4.1 Mean Shift Detection

At the end of each hour of production, the most recent 100 jobs were examined for mean shifts. The process utilized a moving t-test to determine the most likely job sequence number that represented the start of a mean shift. The statistical significance of that mean shift was then used to determine if this shift was significant relative to the background variation. The magnitude of the mean shift was then compared to the range of the process mean established during a baseline period to determine the severity of the mean shift. Clamp failures and intentional tooling adjustments were detected. Figure 6-14 shows an example of a detected mean shift. This mean shift was detected after only two jobs. Most events were not detected as rapidly since data was only downloaded once per hour.

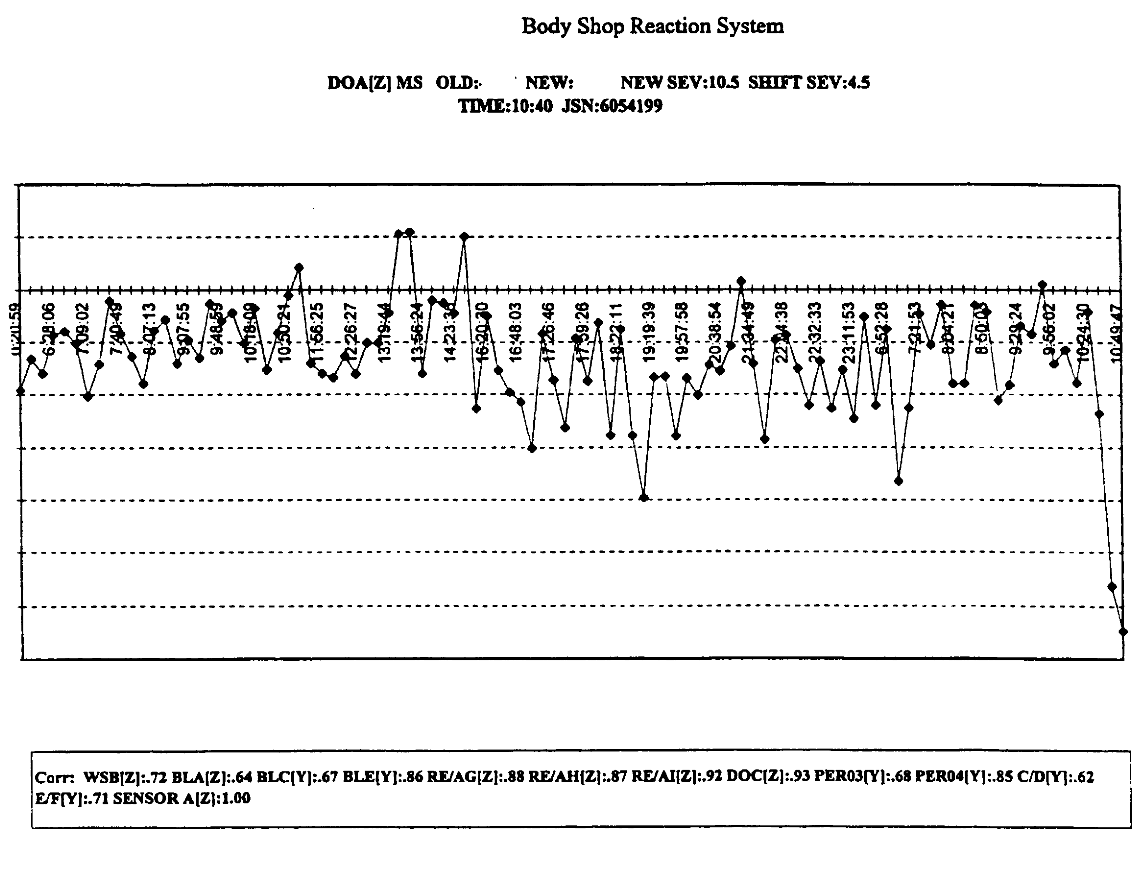

Figure 6-14: Mean Shift Detection Example.

6.4.2 Variation Change Detection

At the end of each hour of production. the most recent 100 jobs were examined for changes in variation. The method that was implemented in the plant compared the first 30 jobs from the 100 job sample to the last 30 jobs from the sample. The variation was quantified in terms of the "inner 80% range." The inner 80% range was selected to eliminate the influence of outliers on the characterization of variation. This is similar to the use of the inner quartile range to characterize the variation of a data set except in this case a larger fraction of the available data is included. Additionally, a larger portion of the data was utilized to establish the range than was available with the "inner quartile range." An example of a detected variation change is shown in Figure 6-15.

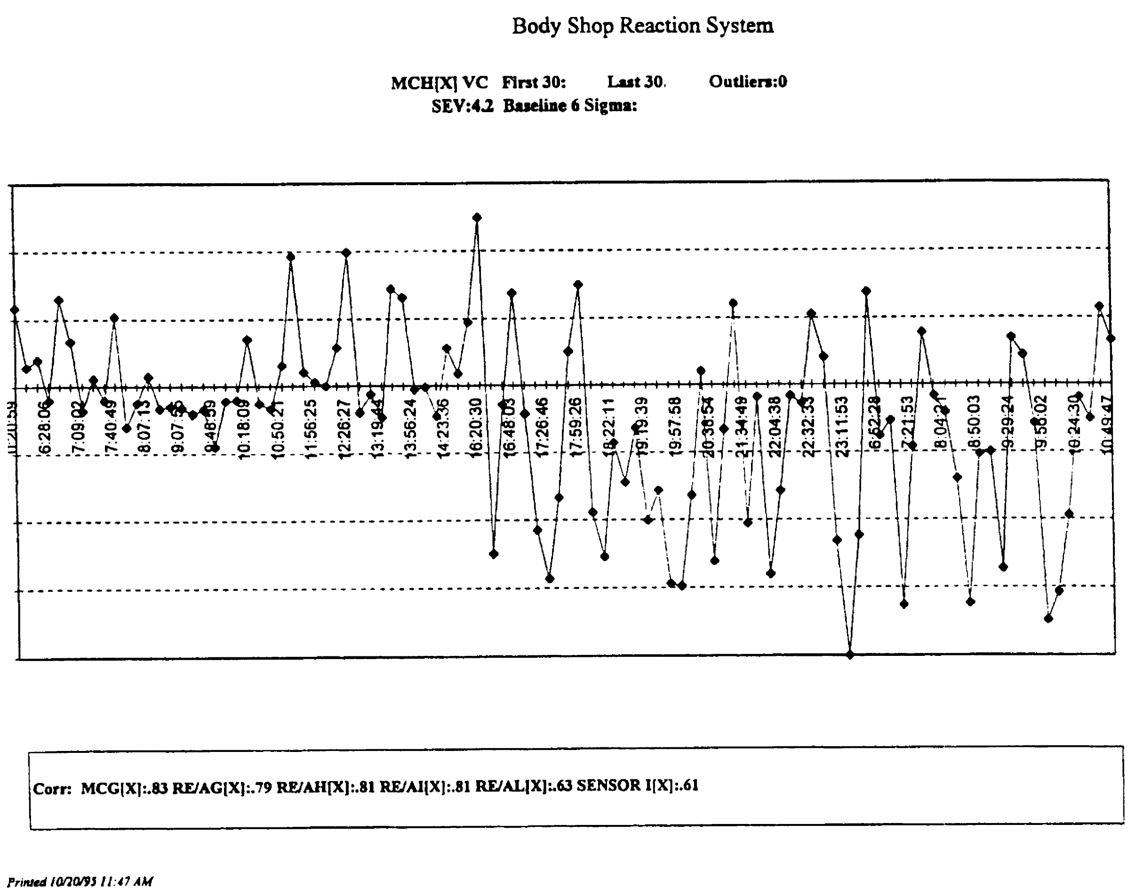

Figure 6-15: Variation Change Detection Example.

6.4.3 Outlier Detection

Since the sampling was done on a relatively infrequent basis, it was possible to compare each data point to the average of the process both before and after the point. Therefore, if a point was significantly different from the operating point of the process both before and after the point, then a measurement could be declared an outlier. Due to the high measurement frequency, a wider than standard threshold of +/- 3.5σ was used to identify outliers. This process was combined with a prioritizing comparison to the baseline data. The resulting process detected occasional part interferences and manufacturing pallet impacts on body-in-white dimensions. An example of outlier detection is shown in Figure 6-16. In this case, the algorithm also identified that both outliers occurred on bodies built on the same pallet. This information extracted from the data greatly accelerated the problem solving process.

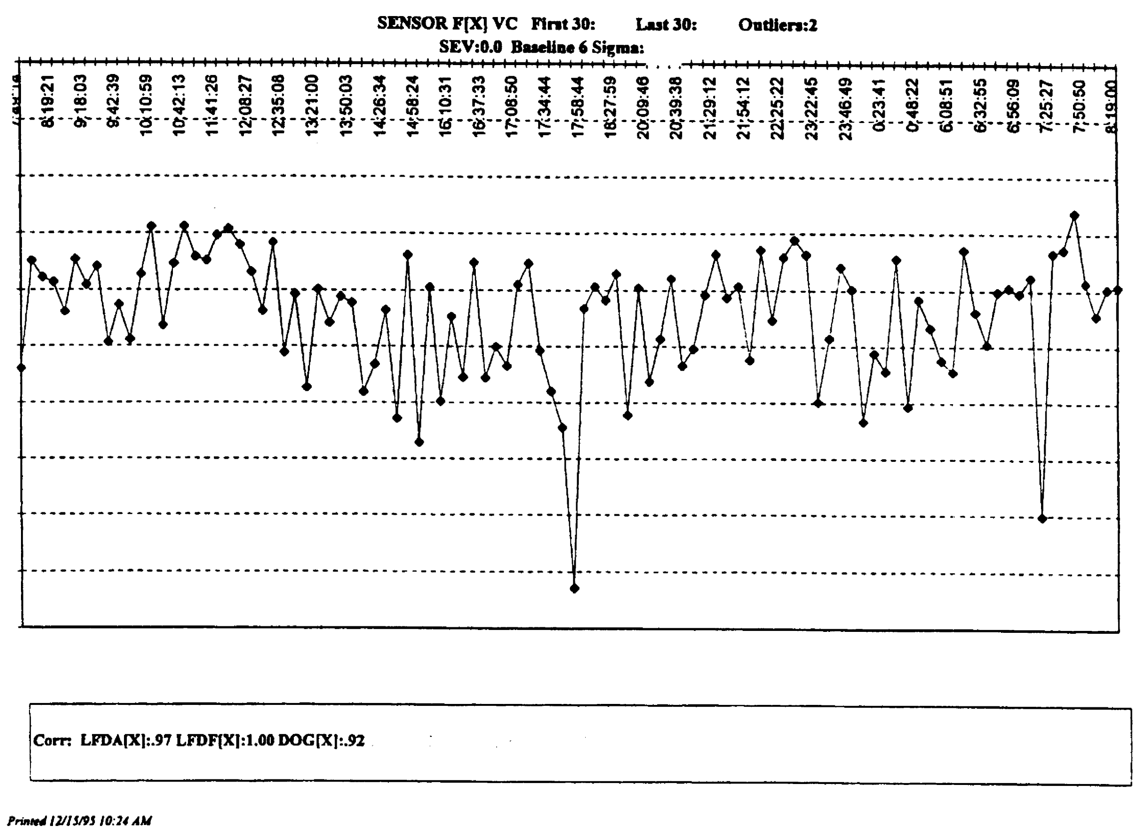

Figure 6-16: Outlier Detection Example.

7. The Management Control Process

The management objective is to place the statistical analysis within a disciplined approach to dimensional process control that facilitates rapid response to critical situations, accurate diagnosis of true root cause, and organizational learning to support proactive improvement and defect prevention.

The achievement of variation reduction driven by faster response to events is shown in Figure 7-1. The figure can be read as follows. The overall objective is reduced variation, shown in the lower left hand corner. The first objective set forth by the body shop was rapid recovery from process problems, as indicated by the top loop. This rapid recovery enables containment of problems within the body shop and facilitates a faster return to normal operation. Achieving rapid recovery, demands a faster response to events. Faster response to events can happen through two mechanisms. Both mechanisms are driven by data analysis. Pager notification is used to communicate process events identified by the processing algorithm to the process experts on the manufacturing floor. This notification occurs within one hour of production and enables containment of any problems within the body shop. The optical coordinate measurement stations also provide capabilities to accelerate response. Control limits implemented in the measurement system can halt the production line in response to an observed data condition. At this stage, line halting control limits are only implemented on issues where a clear relationship between measurement and a quality characteristic has been established.

The by-product of faster response to events is that through pager notification, better feedback is provided to the process expert. This feedback leads to improved learning about variation. Daily and weekly variation reports also contribute to learning about variation. The current method of identifying problems and solving them using the case study approach further contributes to learning about variation. Through the process of natural experiments that are made possible through more active observation of the process, much can be learned about the existing variation.

These learnings about variation lead to prevention activities. As the relationships between observed variation and root causes within the process are identified, operating procedures, incoming quality, preventive maintenance, and product and process design can all be appropriately pushed towards a state of lower variation. As prevention measures are implemented, the level of variation will continue to drop.

Once lower variation is established, the second trip through the advantages of faster response are observed. At this stage, accurate control limits can be established directly at the measurement stations to facilitate immediate response to events. After this level of variation is achieved, and the learning about variation is advanced, prediction of events can potentially lead to recovery before a problem happens. The overall objective is to support the transition from a reactive environment to a proactive environment. Once variation is understood and the required prevention measures have been identified and implemented, the need to measure the process diminishes. Reaching a state where these measurements are no longer required is an ambitious goal.

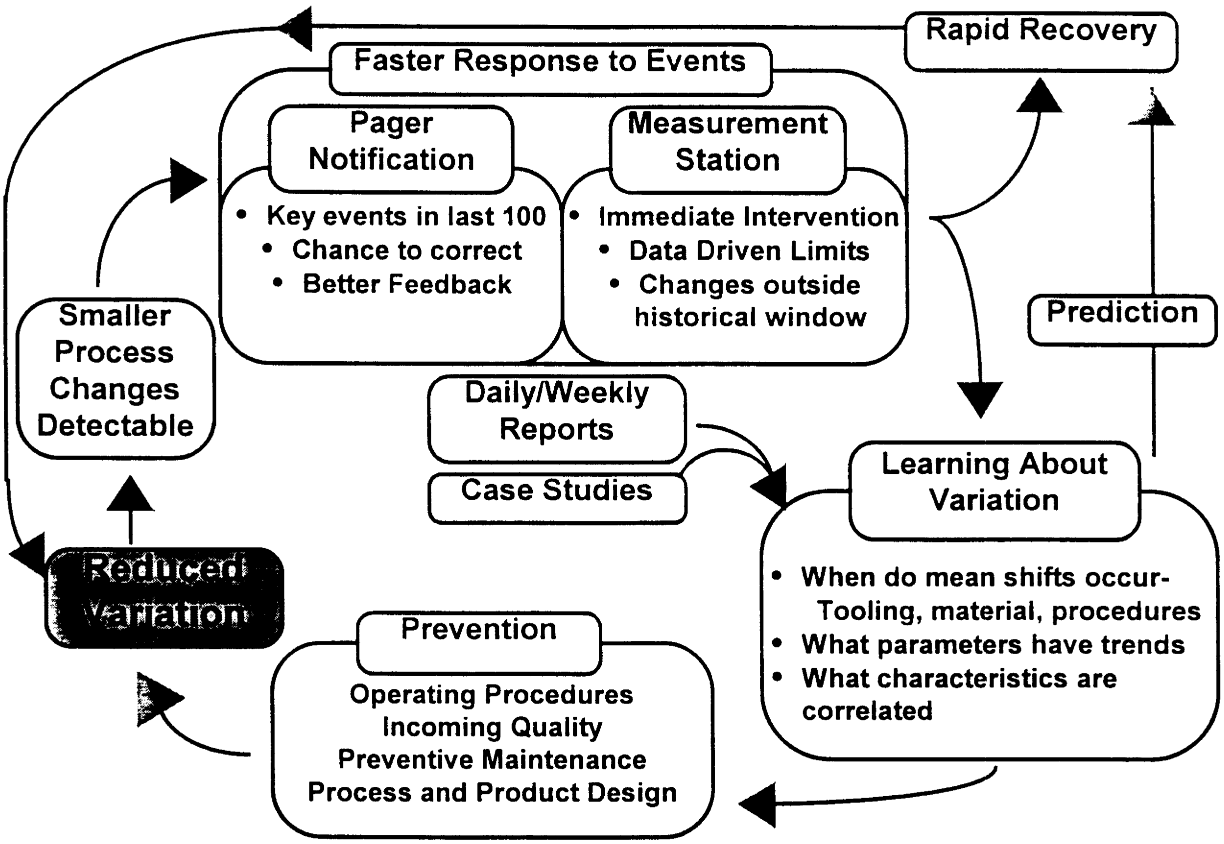

Figure 7-1: Body shop variation reduction driven through faster response to events.

7.1 Documentation and Learning

Documentation is an important part of the problem solving process. It is important because it facilitates the transfer and growth of knowledge so that errors are not repeated and problem solving efforts can be accelerated. There is an optimal amount of documentation that minimizes overall work; that point is yet to be determined. Technology can be used to expand the amount of information that is captured without increasing the time and effort to get the information. The minimum amount of information that should be captured answers the questions:

- What was the problem?
- What actions were taken?

Later review of these events can determine if they represent an opportunity for more fundamental improvement. In the production environment, it is often necessary to create a temporary solution to a problem. However, the temporary nature of the solution must not be forgotten. Once more time is available, events of the day should be reviewed. The purpose of this review is to determine if the true root cause has been identified or if the corrective action was responding to a symptom. These true root causes may either be a more fundamental technical cause or may be in the management process. Recall the fishbone diagram presented in Figure 2-1. Two additional questions to consider in this reflection on events are:

- What can be done to prevent this condition from occurring?
- How could this event have been detected sooner?

7.2 Management Control Flowchart

Problem solving efforts should be directed through a disciplined process (Csizinsky 1992). There are many variations on problem solving processes but the one component that they have in common is a disciplined methodology that strives to achieve true root cause correction rather than the mere alleviation of symptoms (Deming 1986, Shiba 1993). The Quality Network 5 step problem solving process is one such methodology that provides a strong basis for problem solving in the body shop. A flowchart has been developed for responding to dimensional changes that clarifies what decisions need to be made at what stages and by whom. The flowchart is intended to add discipline to the problem solving methodology and to enable investigation and correction to be conducted at the lowest possible level in the organization. The secondary objective of the flowchart is to promote organizational learning by including some level of documentation at certain stages in the problem solving process. The flowchart is not intended to hinder creativity in the problem solving process.

The flowchart, shown in Figure 7-2, represents the sequence of decisions and states that follow the detection of a process event. The flow is presented in the context of an Andon board. An Andon board is a visual device that is used to display the status of a process. A common implementation of an Andon board has a green light that means the system is running and a red light that means the system is stopped. Within the management control flowchart, there are three potential paths for reaction to an event. The first path is characterized by a production critical situation. The second path represents an opportunity for improvement, but not sufficient to interrupt production. The third path represents an event that was detected statistically but does not require active intervention. The flowchart is intended to ensure that corrective actions are taken and that the results are documented before the visual control is returned to a normally operating, solid green, condition.

Following the implementation of a corrective action, it is necessary to perform certain activities to confirm that the process has been improved. There are many complex interactions within the body shop, it is therefore necessary to check not only if the original problem was corrected, but also if new ones have been created. If new ones have been created, it is most likely that the true root cause has not been addressed, and the investigation should continue. To summarize:

- Establish corrective action
- Check to see if primary problem has been corrected
- Check for unanticipated side effects

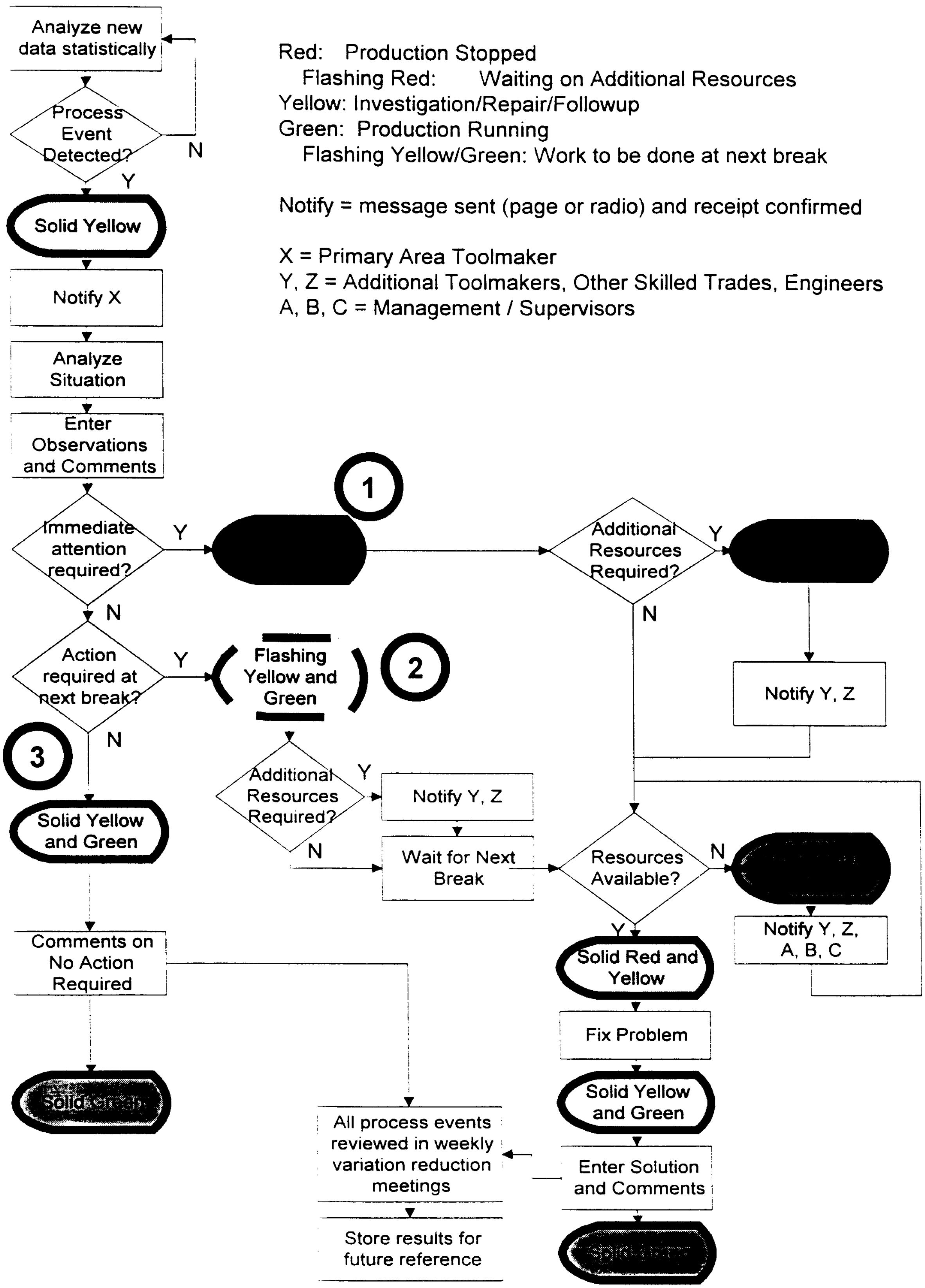

Figure 7-2: Management control flowchart.

The measurement equipment that is currently in use in the automotive body shop enables the detection of a large number of process events. Existing resources are unable to address each of these process events, and in all likelihood, it would not be economically justifiable to address all of these events. Therefore, a main function of the variation management process is to prioritize process events so resources can be allocated. There are 3 general classifications of problems:

- Process events that are known to have negative consequences
- Process events that are known to not have negative consequences
- Process events for which the consequences are unknown

In reality, there is less definition in the categories. therefore the following classification system is proposed:

- Events with unknown consequences
- Events known to have severe, uncorrectable, negative consequences - scrap
- Events known to have moderate negative consequences - rework
- Events known to have minor negative consequences - difficult assembly, minor fit impact
- Events known to have no negative consequences

The learning process works to eliminate events in the first category through better understanding of the relationship between changes in data and events in production.

7.3 Roles and Responsibilities

From the Dimensional Data Operating Vision (Parsons 1995) developed by the dimensional engineering team, the concept of a tool owner was identified as a key part of the effective control system. In addition to expert knowledge of the process equipment, the tool owner must be trained in problem solving techniques. The use of decision trees has been identified as an effective mechanism for empowering lower level troubleshooting in an organization (Lambert, 1996).

A different approach to dimensional control has been implemented in another assembly plant. Their efforts focus on a single toolmaker with responsibility for the dimensional control actions taken in response to feedback from the optical measurement systems. A key advantage in this approach is that the person doing the problem solving investigation can usually implement the required corrective action. This toolmaker works closely with an engineer who, among other responsibilities, is responsible for the overall dimensional quality of the body-in-white.

7.4 Visual Controls

The objective of the andon board and its control flow is to clearly indicate the status of the processes. A disciplined process must be followed from process event detection through corrective action and feedback of learning. The andon board attempts to reinforce this process.

Problem solving flowcharts and customized reaction plans should be posted in visible locations, in accordance with the existing synchronous process boards.

7.5 Auditing - QS-9000

The issue of immediate follow up on process events can be handled through the management control flowchart. The same information used to develop the organizational learning serves to confirm that corrective actions have been taken. The more critical area for auditing is for the entire variation management process. Variation management and variation reduction are often viewed as being in conflict with productivity (they are not in conflict in the long term), but due to this perception, it is necessary to audit the entire process on a regular basis. An auditing team consisting of the following members is proposed:

- Cadillac Quality (final customer driven)
- General Assembly (immediate customer)
- Independent Auditor (either corporate or external consultant)

This recommendation is close to what is provided in the QS9000 / ISO9000 quality certification systems. These systems are primarily concerned that a process exists and that the process is followed. The external certification is an attempt to insure that quality maintains its place.

The management control process should reward the process that is followed, not the results. An appropriate discussion of this issue can be found in Kaizen (Imai pp. 16-21). An example why the process should be emphasized over the results is to examine the case of dimensional variation. The best way to improve the process through measurement is to measure the points that are the most important to improving the process. A results oriented control system would create disincentives to measure dimensions with chronic problems because the variation would appear high and it represents a difficult problem, so improvement may not appear. The problem solving process should be data driven; however, evaluation should rely on the discipline and creativity shown in the problem solving process.

7.6 The use of technology in the management control strategy

Technology in the management control process is present at every step. The measurement system itself is a technological development that expanded the envelope of measurement accuracy in reduced time, to the point of obtaining data on each and every part produced. The next step in the technology chain was to gather and make the data available for analysis. The strategy capitalizes upon faster computers to perform more sophisticated analysis in real time. Engineers and toolmakers are now notified automatically of process changes through a paging network.

8. Conclusions and Recommendations

Observation in the manufacturing environment revealed that with the increased ability to measure production processes, there is a growing demand for methods to automate the processing of data. This processing is required to reduce the data stream to an amount of information that process experts can utilize for process improvement. Increasing measurement system capabilities also create special challenges for statistical process control in terms of correlation of data in both time and space.

Manufacturing systems that are "in-control" may still include underlying patterns of variation. Analysis of body shop process data revealed that for processes with batch to batch variation, the variation of the sample mean should be estimated directly from the baseline data and should not be estimated using a calculation that assumes independence.

Three categories of analysis methods were investigated: a specific search algorithm, the exponentially weighted moving average, and multivariate approaches. The strengths of the specific search algorithm include the rapid detection of specific changes in the process, categorization of process events, provision of supplemental information about the process event, and prioritization of process events. The strengths of the EWMA approach include the relatively intuitive method of breaking down variation into high frequency and low frequency components, the computational efficiency of the method, and the rapid detection of process events. The major strength of multivariate methods in the context of optical measurement data is the improved ability to prioritize process improvement effort through the use of principal components. Multivariate statistical process control offers an opportunity for improved "out-of-control" condition detection in parameters that are correlated.

The statistical processing methodology must be placed within a management control process. It must be recognized that people are the focus of the process and that any statistical system must work to support their ability to make informed decisions and take corrective actions. The system should also support the growth of process knowledge within the organization.

These analysis methods serve to enhance the learning about variation that takes place everyday on the manufacturing floor. These methods should support a proactive approach to variation reduction through disciplined prevention activities. These prevention activities focus on product and process design, supplier quality, operating procedures, and maintenance. The effective use of feedback mechanisms available in the production environment represents one step towards the goal of world class dimensional performance.

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