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STATISTICAL MONITORING OF POLICE FORCE FOR RAPID DETECTION OF CHANGES IN FREQUENCY

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December 1999

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U.S. Law enforcement agencies are authorized and expected to use the minimum level of force required to maintain law and order. Few civilian law enforcement agencies and no military law enforcement agencies proactively monitor the use of force. Furthermore, agencies that do monitor force use methods that produce simplistic data summaries. These data summaries provide late and limited information to decision-makers regarding conditions sufficient to warrant managerial intervention. This study models police force incidents as a Poisson process and monitors the process to detect departures from the model. Police force data is charted using a self-starting control chart scheme. The charts assist the decision-maker in determining if intervention is necessary to correct an out-of-control condition while simultaneously minimizing unnecessary intervention when shifts in the frequency of force are plausibly due to random variation. Force data from military and civilian law enforcement agencies illustrate the methods. Methods are implemented in a Microsoft Excel spreadsheet with Visual Basic macros for ease of use.

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STATISTICAL MONITORING OF POLICE FORCE FOR RAPID DETECTION OF CHANGES IN FREQUENCY

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ABSTRACT

U.S. Law enforcement agencies are authorized and expected to use the minimum level of force when maintaining law and order. Few civilian law enforcement agencies and no military law enforcement agencies proactively monitor the use of force. Furthermore, agencies that do monitor force use methods that produce simplistic data summaries. These data summaries provide late and limited information to decision-makers regarding conditions sufficient to warrant managerial intervention. This study models police force incidents as a Poisson process and monitors the process to detect departures from the model. Police force data is charted using a self-starting control chart scheme. The charts assist the decision-maker in determining if intervention is necessary to correct an out-of-control condition while simultaneously minimizing unnecessary intervention when shifts in the frequency of force are plausibly due to random variation. Force data from military and civilian law enforcement agencies illustrate the methods. Methods are implemented in a Microsoft Excel spreadsheet with Visual Basic macros for ease of use.

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LIST OF ACRONYMS

ANOVA	ANALYSIS OF VARIANCE
ARL	AVERAGE RUN LENGTH
CUSUM	CUMULATIVE SUM
EPC	ENGINEERING PROCESS CONTROL
GOF	GOODNESS OF FIT
LCL	LOWER CONTROL LIMIT
LDO	LIMITED DUTY OFFICER
NSSD	NAVAL STATION SECURITY DEPARTMENT
OPD	OAKLAND POLICE DEPARTMENT
SPC	STATISTICAL PROCESS CONTROL
UCL	UPPER CONTROL LIMIT
URL	UNRESTRICTED LINE

EXECUTIVE SUMMARY

Police officers are responsible for protecting the public. These officers are authorized to use force in the execution of their duties. Properly controlling the use of police force is critical. An excessive level or frequency of police force will degrade the relationship between the police and the public. To support quality improvement, police departments invest a large quantity of time and money training their officers to use the appropriate level of force. However, an effective system capable of monitoring police force does not exist.

This research develops a statistically based tool that assists police managers in rapidly detecting changes in police force frequency. Control chart schemes, used in Statistical Process Control, are developed and improved for the application of monitoring the use of force. A self-starting Shewhart style control chart is used to assist police managers in detecting transient special causes that change the police force frequency. Additionally, a self-starting cumulative sum control chart is implemented to permit detection of persistent shifts in police force frequency. These control charts are formulated in a Microsoft Excel spreadsheet with Visual Basic macros to support ease of use. The result is a software package that assists in quality improvement.

Data from both a civilian and a military police department are analyzed using the methods developed in this research. Force data is modeled as a Poisson process. The purpose of this research is to detect departures from this model while minimizing reaction to usual variation. The control charts provide useful information to the decision-maker

allowing effective monitoring of police force frequency. The identification of departures in police force frequency is important for police force quality control. The rapid detection of shifts in force frequency provides the feedback necessary to support learning while simultaneously preventing unnecessary interaction by police supervisors when the shift in force frequency is due to usual variation. The study concludes that the suggested method is an effective quality improvement tool for monitoring police force.

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The completion of this thesis signifies a major milestone in my continued education. This work would not have been possible without the help of certain individuals.

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I dedicate this research to the police officers of the Naval Station Security Department. Police work is hard, dangerous, and often thankless. To the men and women in police uniforms everywhere...thank you for protecting the public.

I. INTRODUCTION

A. OVERVIEW

Civilian and military law enforcement organizations are similar in many respects. These agencies are comprised of well-trained officers with various levels of supervision. In civilian law enforcement, the supervisors are officers who have performed well and progressed through the ranks. Accordingly, each senior level supervisor (Chief of Police, for instance) is an individual with an extensive background as a law enforcement officer. However, in the case of military law enforcement, the senior level of supervision usually consists of individuals with little or no law enforcement experience. Although a Security Limited Duty Officer (Security LDO) community has been established in the Navy, many shore base security officer billets are filled by officers of the Unrestricted Line (URL). Even if the security officer is a Security LDO, that officer is directly responsible to a base or station commander who is almost always a member of the URL. As a result, senior leaders in the military security organization must rely on their own management skills, instinct, common sense, and general experience to successfully manage the security function. First-hand experience in law enforcement is rarely available. Due to this experience gap, senior leaders of the military security organization are at a disadvantage when compared to their civilian counterparts.

B. BACKGROUND

The experience gap in the supervision of military law enforcement agencies can be problematic. One major liability is the potential for the unchecked use of force (Healy, 1997). Law enforcement agencies interact with the public on a daily basis. Some interactions result in the use of force while others do not. The levels of force (often referred to as a 'force ladder' where each level of force indicates the next rung on a ladder) are typically defined as (Roush, 1996):

(1) Officer presence.

(2) Voice.

(3) Physical restraint.

(4) High-impact strike.

(5) Deadly force.

The effect of excessive frequency of officer presence and voice is rarely serious. The excessive frequency of deadly force is serious and is typically identified without the need of detailed analysis. However, the telltale signs indicating an excessive frequency of physical restraint and high impact strike are hard to detect. In order to maintain confidence in the law enforcement agency, neither an excessive frequency nor an excessive level of force can be tolerated. Some factors that affect the frequency of the use of force include the incident type, officer training, officer experience, and level of supervision (Kertesz, 1992). Although policies exist to guide the use of force, there is variation in how different officers handle different incidents.

Quickly determining whether or not variation in the frequency of force is due to chance is critical to the supervision of a law enforcement agency (both civilian and military). Unnecessary and indiscriminate use of force by officers must be detected and addressed. Also, unnecessary intervention by supervisors when variation in the use of force is due to chance reduces the effect of intervention when action is necessary. Even if the law enforcement agency supervisor is steeped in law enforcement experience, he or she will have difficulty in separating the usual frequency of force from the unusual.

C. PROBLEM DEFINITION

There is a need for a process that assists both civilian and military law enforcement supervisors in monitoring and regulating force. Police agencies acknowledge the fact that there is an increasing incidence of highly publicized cases of police force used against citizens, and that technology is not being used to evaluate these trends (Moody, 1998). A 1992 business evaluation of "risk management and use of force" conducted by Louise Kertesz and reported in *Business Insurance* revealed that "Managing police liability requires good supportive supervision, excellent management, and leadership with vision and values" (Kertesz, 1992). This statement is true. However, it fails to address the importance and value of statistical evaluation in the risk management of the use of force. A more recent study conducted by Dennis Smith and reported in *Contemporary Sociology* states that "A problem that pervades this or any exploration of the topic of police brutality is the absence of meaningful measures of its extent, severity, or trends" (Smith, 1996). Most recently, a November 1998 study of the use of deadly force by Monterey County law enforcement agencies reveals that none of the eight police departments surveyed collects data concerning officer firearm discharges (Givens, 1998).

Although police force data is not typically collected nor analyzed, the use of force is recorded by law enforcement agencies in routine police reports. Each police incident results in the completion of a police report that states the offense and the police officer's actions. As a result, these reports contain detailed information regarding the use of weapons, pepper spray, restraints (handcuffs), etc. The crime prevention division of a police department reviews these reports and develops a crime database. However, the existing information regarding the use of force is not statistically analyzed.

D. OBJECTIVE

The objective of this study is to develop a statistical method for monitoring the frequency of police force. This study systematically evaluates police force data and the applicability of control chart methods through a series of research questions:

A. Can existing statistical parametric methods model civilian and military police force count data?
B. Can a self-starting Shewart control chart be developed to improve existing control chart methods?
C. Can cumulative sum control chart methodologies be applied to monitoring police force allowing shifts in force frequency to be detected?

E. SCOPE AND LIMITATIONS

There is no nationwide standard for tracking and monitoring police related statistics and this study does not intend to establish such a standard. Furthermore, force level definitions vary from department to department. The use of handcuffs provides one example revealing the difference in force definition. Many departments consider the use of handcuffs as a level of force. Other departments claim that handcuffs are used as a restraining tool and do not fit in the typical force ladder.

This thesis uses force data from the Naval Station Security Department (NSSD) in Pearl Harbor, Hawaii, and the Oakland Police Department (OPD) in Oakland, California. The military police department used in this study records each reported incident and assigns a force level to each report. The civilian police department records monthly force totals for lethal force and non-lethal force above level 2 (voice). Although the type of data and method of recording force data by the two police departments in this study vary greatly, the methods implemented in this study require count data only. This count data is typically retrievable from a nominal police department database. Many police departments do not record force incidents directly (as was the case for the Naval Station Police Department prior to a request made by the author). Any police department that has force data will be able to implement the methods developed in this study. Departments that do not track force will need to establish a minimal force count database prior to implementation. Fortunately, the self-starting aspect of the CUSUM control chart methods used requires a relatively small data set to get started. Finally, the type of force that the department is interested in tracking is independent of the methods used in this study. In short, one department may use these methods to track the frequency of all types of force according to that particular department's force definitions while another may track the frequency of a single specific force level, and a third department may track a combination somewhere in between.

F. OVERVIEW OF SELF-STARTING CONTROL CHART METHODS FOR POISSON DATA

This section provides the theory necessary to understand a self-starting control chart method for Poisson data. This section describes:

1. Basic control chart methods.
2. Poisson Shewhart style control chart with λ known.
3. Poisson cumulative sum (CUSUM) control chart with λ known.
4. Self-starting Poisson Shewhart style control chart with λ unknown.
5. Self-starting Poisson CUSUM control chart with λ unknown.
6. Discussion of average run length (ARL).
7. Discussion of CUSUM optimality properties.

1. Basic Control Chart Methods

Control charts are commonly used to monitor the variability of a process. Charting methods exist to monitor processes that generate continuous or discrete data. Basic control charts plot data X_i or a function of the data $a(X_i)$ against upper and lower control limits. If a data point plots above or below the upper or lower control limits then the process is out of statistical control[1]. The upper and lower control limits are chosen such that an out-of-control condition is not signaled as a result of chance for a given tolerance. Two basic charts used are the Shewhart style control chart and the cumulative sum (CUSUM) control chart. Each chart provides useful information. The information provided when these charts are combined is even more useful.

Shewhart style control charts provide information regarding transient isolated or special cause departures that affect the variability in a process. Transient causes affecting a process are not uncommon. In a vending machine manufacturing process for example, vending machine components are die-cast using molten aluminum. A shipment of aluminum contaminated by a foreign material may result in an increase in the number of die-cast vending machine components that are too porous for painting. The contaminated shipment of aluminum is a transient cause for the production of faulty vending machine

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[1] A process that is operating with only common causes of variation present is said to be in statistical control. A process that is operating in the presence of special causes is said to be out of statistical control (Montgomery, 1985).

components[2]. The Shewhart chart detects a transient condition when the number of components showing excessive porosity in the sample of vending machine components is plotted and compared to the upper and lower control limits.

Shewhart style control charts provide limited effectiveness for detecting persistent shifts in a process. Returning to the vending machine example, if the element heating the aluminum begins to fail, the temperature of the molten aluminum may be too high or too low for effective die-casting. The effect of the faulty heating element can result in the slow increase over time of the number of vending machine components that exhibit excessive porosity. The Shewhart style control chart is slow to detect these persistent causes that affect process variability. Because of the persistent but small nature of the shift in the process mean, the Shewhart style control chart may not provide a signal indicating an out-of-control condition. An individual trained in detecting trends in data plotted over time may identify a trend before the Shewhart chart signals a problem. Since the typical user of a control chart system is not trained in data trend analysis, another technique is used to assist in detecting persistent shifts in a process. The cumulative sum (CUSUM) chart is the preferred chart when detecting persistent shifts in a process. Like the Shewhart style control chart, the CUSUM control chart is a plot of data versus time and has upper and lower control limits. Additionally, the CUSUM is "tuned" to track data from a given distribution and to detect a shift in the mean of a certain size. The CUSUM signaling an out-of-control condition implies that the process mean has shifted. Since the

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[2] The family business of the author (Oak Manufacturing) produced coin operated gumball machines from the early 1950's until mid 1980's. Control chart methods were not used to monitor the die casting process.

process mean has shifted the chart is re-tuned and restarted to allow tracking of the data from the new distribution.

2. Poisson Shewhart Style Control Chart with λ Known

A Poisson Shewhart style control chart with λ known plots data against control limits. Determining the control chart limits is an important step in control chart development. Control limits are often defined as a function of the hypothesized distribution when the parameter of a process is known. Since the normal distribution is familiar and well behaved, an example using the normal distribution describes the concept behind control limit determination. A typical method for generating Shewhart chart upper and lower control limits for normal data involves using the mean and standard deviation of the distribution. Common limits are equal to the mean plus three standard deviations and the mean minus three standard deviations. These limits are called the "3-sigma" control limits. Unlike the normal distribution, the Poisson distribution is asymmetric (unless the rate λ is large). As a result of the asymmetry of the Poisson distribution, 3-sigma limits are inadequate for Poisson control chart limits. For Poisson data, upper and lower control limits are determined from the probability limits of the Poisson distribution with the given rate λ. Figure 1 is a Poisson Shewhart style control chart for charting data from a Poisson distribution with $\lambda = 6$. The upper control limit is 13 and the lower control limit is two. The upper and lower control limits are the values corresponding to a criterion level $\alpha = .005$ for a Poisson distribution with $\lambda = 6$. The result is if a point plots above 13, then the user is 99.5% sure that the plotted value is not from a Poisson distribution with rate $\lambda = 6$. The similar argument is used for a data point plotting below the lower control limit of two. Note that since the Poisson distribution is discrete, it is not possible to compute the exact values for a criterion level of $\alpha = .005$. In this case, $prob(x \leq 1 \mid \lambda = 6) = .017$ and $prob(x \geq 14 \mid \lambda = 6) = .004$. Figure 1 shows that the value plotted in period 25 is above the upper control limit of 13. The chart user is now able to investigate the cause of this out-of-control condition.

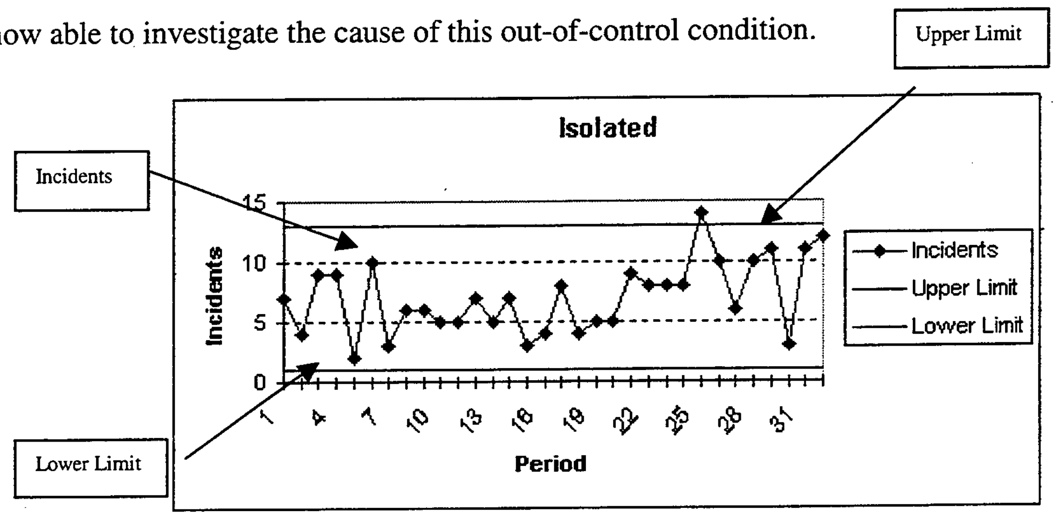

Figure 1. Typical Poisson Shewhart style control chart. Data is plotted from a Poisson distribution with mean $\mu = 6$. The upper control limit is 13 and the lower control limit is two. The data point in period 25 is above the upper control limit indicating a transient or special cause condition (i.e. the data point for period 25 is not likely to be from a Poisson distribution with rate $\mu = 6$)[3].

[3] The charts generated in this research use color to differentiate between upper and lower limits, etc. The color is lost when these charts are reproduced in black and white. Labels are added to Figure 1 to clarify the chart legend.

3. Poisson Cumulative Sum (CUSUM) Control Chart with λ Known

Unlike the Shewhart style control chart, the Poisson CUSUM does not plot raw data points. When the parameter λ is known, the CUSUM chart plots the cumulative sum of the deviations of the sample values X_i from a reference value *K*. Given that *K* is the reference value and X_i is the sample value for the i^{th} observation, the CUSUM control chart plots the value S_i^+ and S_i^- against the sample number, i, where $S_i^+ = \max(0, S_{i-1} + X_i - K^+)$ and $S_i^- = \min(0, S_{i-1} + X_i - K^-)$. The CUSUM control chart signals a persistent departure if the value S_i^+ crosses the upper control limit or the value S_i^- crosses the lower control limit.

The reference value *K* is a function of the process in-control mean and out-of-control limits for the mean. If μ_0 is the in-control mean, μ_u is the out-of-control mean for an upward shift, and μ_d is the out-of-control mean for a downward shift, then the associated reference values are K^+ and K^- respectively. The equations for calculating the reference values for a Poisson CUSUM control chart are $K^+ = \dfrac{\mu_u - \mu_0}{\ln(\mu_u) - \ln(\mu_0)}$ and $K^- = \dfrac{\mu_d - \mu_0}{\ln(\mu_d) - \ln(\mu_0)}$ (Hawkins and Olwell, 1998).

A typical CUSUM is shown in Figure 2. The process mean is $\mu_0 = 6$. The chart is tuned to detect an upward shift in the process mean $\mu_u = 7$ and a downward shift in the process mean $\mu_d = 5$. The average run length (ARL) for this chart is 100. A discussion of ARL is provided in part 6 of this section.

The upper control limit is 14 and the lower control limit is –12. The chart signals a persistent shift in the process mean in period 25. The shift is estimated to begin from the last point where the trend line (S^+ for an increasing trend or S^- for a decreasing trend) leaves the zero axis. In Figure 2, the shift in the process mean is estimated to begin in period 20.

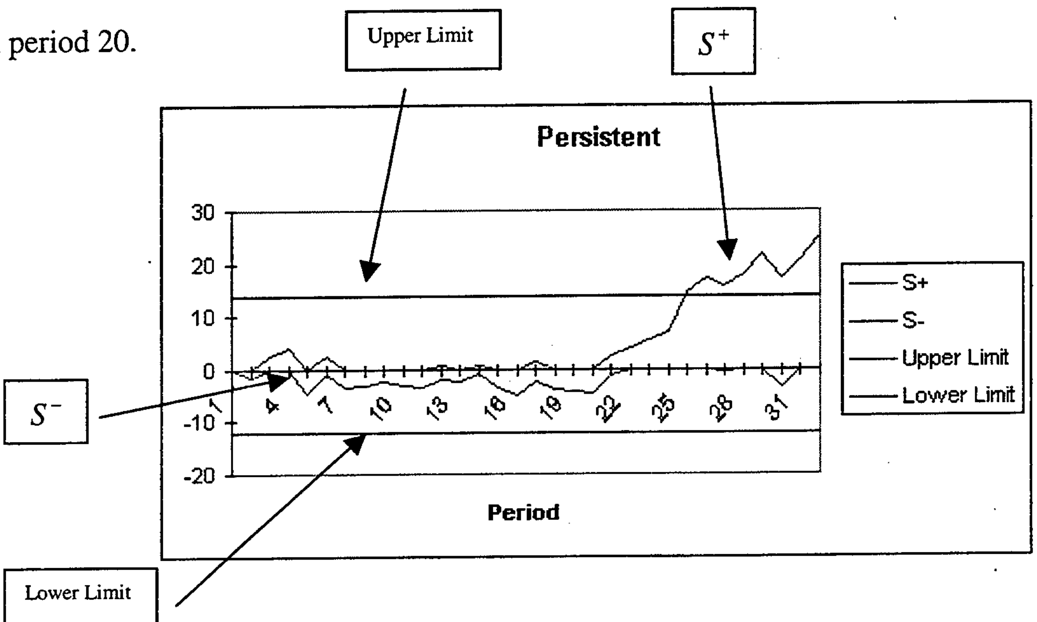

Figure 2. Typical CUSUM control chart. Data is plotted from a Poisson distribution with in-control mean $\mu = 6$. The out-of-control mean for an upward shift is $\mu_u = 7$ and the out-of-control mean for a downward shift is $\mu_d = 5$. The upper control limit is 14 and the lower control limit is -12. The average run length is 100. A persistent shift in the process mean is signaled in period 25. The shift is estimated to begin in period 20. (Note: the horizontal axis tick-marks can be misleading. The horizontal axis begins with '1' and the first axis-tick mark is '2')[4].

[4] The charts generated in this research use color to differentiate between S^+ (also called the 'increasing trend line'), S^- (also called the 'decreasing trend line'), upper and lower limits, etc. The color is lost when these charts are reproduced in black and white. Labels are added to Figure 2 to clarify the chart legend.

4. Self-Starting Poisson Shewhart Style Control Chart with λ Unknown

A well-defined process with extensive historical data lends itself to the implementation of the non-self-starting control charts described previously. In processes that are less well-defined, determining the exact process mean is difficult. Additionally, some processes undergo frequent shifts resulting in changes to the process mean. The result is a condition where extensive historical data necessary to determine the process mean is not available and the chart upper and lower control limits are more difficult to define. Regarding the force phenomenon studied in this research, police department managers could not provide force control limits. This study develops and implements a method to provide control limits for the Poisson self-starting Shewhart style control chart using probability limits. The result is a scheme that works when charting data that is plausibly Poisson.

Based on the property that the Poisson distribution is infinitely divisible, conditioning is used to develop upper and lower control limits for the Poisson self-starting Shewhart style control chart. Given the sum of a series of values X_i, the probability $P(X_n = x_n \mid \sum_{i=1}^{n} X_i = W) = binomial(W, 1/n)$ (Hawkins and Olwell, 1998). Using this relation, probability limits are used to determine the upper and lower control limits for the Poisson self-starting Shewhart style control chart. The method developed in this study uses the Microsoft Excel critical binomial value function CRITBINOM(n, p, α) to calculate these control limits. For this function, the first argument is W, the second is $1/n$ where n is the number of periods, and α is the confidence level. For the upper limit $\alpha = .995$ and for the lower limit $\alpha = .005$. For example, if the sum of the first four observations is 122, then $\sum_{i=1}^{4} X_i = 122$, p=1/4, and $\alpha = .995$ for the upper control limit. The value of CRITBINOM(122,.25,.995) is 43. Similarly for the lower control limit, the value of CRITBINOM(122,.25,.005) is 19. If the fourth observation is greater than or equal to 43 or less than 19, the data point indicates a likely transient special cause condition as the chance of a value outside this band given no special cause is only $(1-2\alpha)$. A Poisson self-starting Shewhart style control chart is shown in Figure 3.

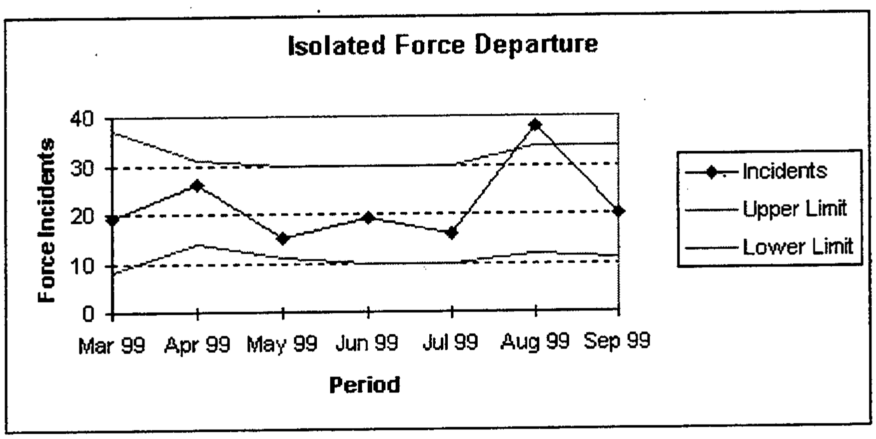

Figure 3. Typical Poisson self-starting Shewhart style control chart. The data points plot within the upper and lower limit until Aug 99. The data point for Aug 99 exceeds the upper control limit and indicates an isolated upward departure. The upper and lower limits of this self-starting Shewhart style control chart vary as a function of Poisson probability limits.

The data points are monthly readings from a process that is plausibly Poisson. In order to provide information for the decision-maker, limits are established that bound each data point. These upper and lower control limits (UCL and LCL) help in determining if a data point describes an in control or out-of-control condition. If a data point plots above the upper control limit or below the lower control limit, that point tells the decision-maker that the process may not be operating as intended. There is emphasis on "may not" be operating as intended since the point could plot outside the control limits purely as the result of chance. The basic idea behind calculating the upper and lower control limits involves establishing bounds such that a point plotting outside the limits is not likely to be the result of chance at some specific level (discussed previously in this section). Notice that the upper and lower control limits change for each period as more data is available. Also, note that as $n \to \infty$, $np = \lambda$. The result is $Bin(n, p) \to Pois(\lambda)$. The result of this implementation is an informative plot for the decision-maker indicating isolated or transient departures in a process where the signal describing a departure is not likely to be caused by chance given that no special cause occurred. In Figure 3 the data points from period "Mar 99" to "Jul 99" indicate that the system is in statistical control. The data point "Aug 99" exceeds the upper control limit and indicates the occurrence of an isolated or special cause departure in the process.

5. Self-Starting Poisson CUSUM Control Chart with λ Unknown

Like the self-starting Shewhart style control chart, the advantage of the self-starting CUSUM is in its ability to begin a control chart program with a much smaller data set than that required by non-self-starting methods. Like the non-self-starting CUSUM control chart, the Poisson CUSUM does not plot raw data points. When the parameter λ is unknown the CUSUM chart plots the cumulative sum of the deviations of the *transformed* sample values Y_i from a reference value K. Given that K is the reference value and Y_i is the transformed value of X_i for the i^{th} observation, the CUSUM control chart plots the value S_i^+ and S_i^- against the sample number, i, where $S_i^+ = \max(0, S_{i-1} + Y_i - K^+)$ and $S_i^- = \min(0, S_{i-1} + Y_i - K^-)$. Like the non-self-starting CUSUM, the self-starting CUSUM control chart signals a persistent departure if the value S_i^+ crosses the upper control limit or the value S_i^- crosses the lower control limit.

Understanding the role of the transformed value of the observation and the reference value is critical to understanding the development of self-starting CUSUM control charts. The following discussion explains the development of the transformed value Y_i for a Poisson self-starting CUSUM chart.

Assume a process follows a Poisson distribution. This process is monitored and the value recorded is a count value called X_i. Additionally, assume that the process in-control mean μ_0 is unknown. The statistic used to estimate μ_0 is the sample mean $\overline{X}_i$

(a sample of i in-control readings from the process). Next, let $W_i = i\,\overline{X}_i$. Conditioning on W_i yields $X_i \sim binomial(W_i, 1/i)$. In words, X_i are distributed binomial with W_i trials and a probability of success for each trial equal to $1/i$. The distribution of X_i does not rely on μ_0, the unknown parameter defining the Poisson distribution. If the process mean shifts from μ_0 to μ_1, then the conditional distribution of X_i is distributed binomial with probability equal to $\frac{\mu_1}{(i-1)\mu_0 + \mu_1}$ (Hawkins and Olwell, 1998).

The probability of success $p = \frac{\mu_1}{(i-1)\mu_0 + \mu_1}$ for this binomial distribution increases if $\mu_1 > \mu_0$ and decreases if $\mu_1 < \mu_0$. Monitoring the probability of success for this binomial distribution indicates an increasing shift if μ increases and a decreasing shift if μ decreases.

The cumulative probability A_i is calculated from the conditional probability of X_i where $A_i = prob[binomial(W_i, 1/i) \le X_i]$. Since the Poisson distribution is discrete, the value of A_i can only assume a limited number of values as $X_i \in \{0,1,2,...,W_i\}$. Although the values of A_i are limited, they are distributed independently from i to $i+1$ as a result of Basu's lemma (Dawid, 1979).

The value A_i is now transformed to a standard Poisson score. Since a few data points are used to estimate μ_0, the unknown mean of the Poisson distribution, let the approximation of μ_0 be m. Then the transformed value Y_i is determined by minimizing the function $\left|\sum_{j=0}^{Y_i} \frac{e^{-m} m^j}{j!} - A_i\right|$. There is no value that minimizes this function when $A_i = 1$. When $A_i = 1$, Y_i is determined by setting $Y_i = X_i$. If the estimated mean μ_0 of the Poisson distribution is exactly equal to the true distribution mean, then the mapping of X_i to Y_i is exact. Although the estimated mean μ_0 is not likely to be exactly equal to the true distribution mean, the mapping of X_i to Y_i is good as long as the estimated mean is not too far from the true mean. For a self-starting CUSUM, the mean for a Poisson distribution can be determined from as little as two or three data points (Hawkins and Olwell, 1998). The reference value K is determined as in the non-self-starting CUSUM. If μ_0 is the estimated in-control mean, μ_u is the out-of-control mean for an upward shift, and μ_d is the out-of-control mean for a downward shift, then the associated reference values are K^+ and K^- respectively. The equations for calculating the reference values are again $K^+ = \frac{\mu_u - \mu_0}{\ln(\mu_u) - \ln(\mu_0)}$ and $K^- = \frac{\mu_d - \mu_0}{\ln(\mu_d) - \ln(\mu_0)}$ (Hawkins and Olwell, 1998).

As previously stated, the Poisson self-starting CUSUM control chart uses the transformed value Y_i of the i^{th} observation X_i. The equations used to calculate S_i^+ and S_i^- are easily implemented in a computer-based spreadsheet. Calculating the transformed value Y_i is slightly more complex. The Poisson self-starting CUSUM control chart method written by Hawkins and Olwell uses a Visual Basic macro to calculate Y_i (Hawkins and Olwell, 1998).

A typical Poisson self-starting CUSUM chart is shown in Figure 4. The CUSUM in Figure 4 is tuned for a target in-control mean of 22.4 with an average run length of 100. The out-of-control mean for an upward shift is 27.1 and the lower out-of-control mean is 17.7. The upper control limit is 14 and the lower control limit is –13. The chart indicates that a shift in the process mean occurs with the "Aug 99" data point. The shift is believed to begin in "Jul 99" which is the last time the increasing trend line left the zero axis. When the self-starting CUSUM indicates a shift in the process mean, then the process mean has likely changed. Since the process mean changed, the data charted up to the shift is now known to be irrelevant to the data generated from the process with the new mean. This result requires that a self-starting CUSUM be restarted whenever a persistent shift in the process mean is signaled.

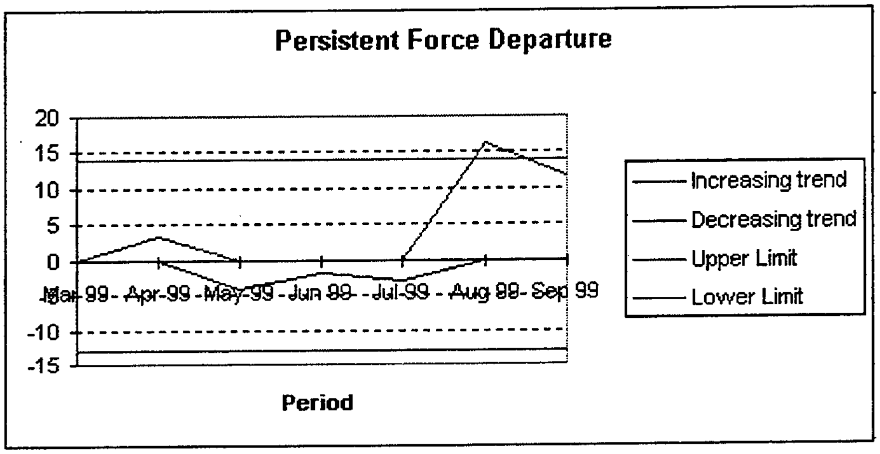

Figure 4. Typical Poisson self-starting cumulative sum (CUSUM) control chart. The target in-control mean is 22.4. The out-of-control mean for an upward shift is 27.1 and the out-of-control mean for a downward shift is 17.7. The upper control limit is set to 14 and the lower control limit is set to –13. The average run length is 100. The process is in statistical control until Aug 99. The shift in the process is believed to begin in Jul 99, the last time the increasing trend line was on the zero axis.

6. Discussion of Average Run Length (ARL) and CUSUM Control Chart Limits (H^+ and H^-)

Before a Poisson self-starting CUSUM is implemented, the average run length (ARL), upper, and lower control limits are determined. Determining the upper control limit H^+ and the lower control limit H^- for the CUSUM chart is slightly more complicated than determining the control limits for the Shewhart style chart. The limits are calculated using the reference value K and the average run length. Tables and software packages are available to calculate the upper and lower control limits for a CUSUM control chart as a function of the reference value and the average run length. The software package ANYGETH.exe is used in this research to determine the upper and lower control limit (Hawkins and Olwell, 1998).

Before explaining the method used to determine the upper and lower control limit, the theory supporting the calculation of the average run length is explained. The average run length is necessary for control chart implementation. If n = number of periods to a signal then the expected value of n (in control) is the ARL and the expected value of n (out-of-control) is the out-of-control ARL. ANYGETH.exe calculates these values. The trade-off by changing ARL for control chart implementation is analogous to the trade-off between type I and type II error in hypothesis testing. The ARL is the length of time in which one false alarm can be expected if the process remains stable. If the time period for data points is monthly, and the ARL is 100, then there will be (on average) one false alarm every 100 months (about one false alarm every 8.3 years). The higher the ARL, the longer a chart may progress without a false alarm although the speed of detection decreases. A smaller ARL is used if the decision-maker is concerned with rapidly identifying an out-of-control condition yet the possible number of false alarms increases. A longer ARL is used if the decision-maker is concerned about reacting to false alarms. Manufacturing applications typically use ARL's in the thousands. Well defined processes with dense data sets coupled with the extreme cost of shutting down a production line due to false alarms support the use of high ARL's (Montgomery, 1985). However, processes with sparse data sets (like the force incident data used in this research) use ARL's of 100 (Hawkins and Olwell, 1998).

If the upper and lower control limits for the CUSUM are known, the average run length can be calculated. Three methods are widely used to determine the average run length. These methods are (1) solving integral equations, (2) solving discrete Markov chain approximation to the integral equation, and (3) using simulation. An explanation of the integral equation and discrete Markov chain approximation follows.

The integral equation for continuous variables is (Hawkins and Olwell, 1998):

$$L(z) = 1 + L(0)F(k-z) + \int_0^h L(x)\,dF(x+k-z)\,.$$

$L(z)$, with $z \in [0,h)$, is the average number of future draws until a signal given $S^+ = z$. Notice that the equation is the sum of three distinct parts. The first part is the probability that another draw is needed. The probability that the next observation is needed given z is on the interval [0,h) is one since another observation is always drawn if z is on this interval. The second part is the probability that the next observation returns the CUSUM to zero multiplied by the average run length from zero. The third part is the integral of the ARL for the next value on the interval (0,h) times the probability that a next value occurs. (Hawkins and Olwell, 1998).

The discrete Markov chain approximation finds the solution to the equation $L(z) = 1 + \sum_{i=0}^{M} L(i)R_{i,z}$ where z is one of the $M+1$ states and $R_{i,z}$ is the transition probability from state z to state i (Hawkins and Olwell, 1998). This equation is the discrete version of the integral equation. In matrix form this equation is $(I - T)\lambda = \bar{1}$ where T is the transition probability matrix, λ is a vector of length M+1 of ARL values for CUSUMs starting in the corresponding states 0,1,...M and $\bar{1}$ is a vector of 1's with length M+1. Solving the matrix form results in the determination of ARL (Hawkins and Olwell, 1998). The result of the equations used to determine ARL is that given H and K, the ARL can be calculated. Similarly, given K and ARL, H can be calculated. It is typical for a decision-maker to determine an acceptable false alarm rate and time to detection by selecting an appropriate average run length. Since ARL is usually selected and the reference value K is calculated from the target in-control mean and out-of-control mean, the issue is solving for the upper and lower control limits H^+ and H^-. ANYGETH.exe uses the discrete Markov chain approximation to the integral equations for determining H^+ and H^- given ARL and K.

7. Discussion of CUSUM Optimality Properties

CUSUM methods possess certain optimality properties. Moustakides (1986), Ritov (1990), Gan (1991), and Yashchin (1993) explore the optimality properties of the CUSUM. Optimality in this sense refers to detecting when a process has shifted from a single known distribution to another known distribution (Hawkins and Olwell, 1998). In short, the CUSUM is optimal for detecting the persistent shifts for which they are tuned (Hawkins and Olwell, 1998). Fortunately, CUSUM's are robust resulting in a relatively broad area of near-optimal operation (Hawkins and Olwell, 1998). In this research, the CUSUM is typically tuned to detect a plus and minus one standard deviation shift in the mean. Testing for shifts of other sizes is implemented in this research as necessary. The Poisson self-starting CUSUM is not exactly optimal (as are all of the non-self-starting versions) unless the estimated mean $m = \mu_0$ exactly. However, the self-starting CUSUM nearly inherits these optimality properties because of the robustness of the CUSUM, resulting in control charts that provide rapid detection when the process mean changes (Hawkins and Olwell, 1998).

There is a large volume of information detailing the development and theory used in control chart methods. Further insight can be gained by reading *Cumulative Sum Charts and Charting for Quality Improvement* written by Douglas Hawkins and David Olwell.

G. RELATED RESEARCH

CUSUM methods are commonly applied in industry and to manufacturing processes for quality control. CUSUM methods can be applied to non-industry related processes (Yashchin, 1993). Research conducted by Emmanuel Yashchin suggests applications for CUSUM techniques in Engineering Process Control (EPC). Yashchin describes EPC situations where the process mean is in continuous motion. Statistical Process Control (SPC) as described by Yashchin is a process where abrupt changes at unknown times occur in the process mean. The police force phenomenon is likely to fit an engineering process control paradigm.

CUSUM methods are commonly applied in situations where the exact mean and standard deviation of the process are known. Police force results from a process that does not have an exact and defined mean and standard deviation. The self-starting CUSUM method is valuable in this type of application. Douglas Hawkins shows that self-starting CUSUM charts are preferred in situations where the process mean and standard deviation are not known *a priori* (Hawkins, 1987).

CUSUM methods are used to monitor crime. David Olwell applies self-starting CUSUM methods to the New York City Police Department (Olwell, 1997). Although the phenomenon of crime and the phenomenon of police force are different, the application of self-starting CUSUM methods is similar.

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II. METHODOLOGY

A. RESEARCH APPROACH

This research involves the analysis of existing force data taken from the Naval Station Security Department (NSSD), Pearl Harbor, Hawaii and Oakland Police Department (OPD), Oakland, California, databases. From these databases, police force count data is extracted. Exploratory data analysis is performed which includes determining statistical parameters of the data. Once the necessary parameters are determined, the appropriate CUSUM and Shewhart charting algorithms are applied. CUSUM tuning parameters (persistent UCL/LCL and ARL) are determined and these parameters are entered into the charting software package. The force count data is entered into the tuned charting software package and the control charts are generated.

B. DATABASE

OPD force data is maintained in a quarterly force summary report. There are two quarterly reports (the K-3 and K-4 report) which provide monthly totals of force incidents for the previous quarter. The OPD K-3 report summarizes the incidents involving lethal force and the OPD K-4 report summarizes non-lethal force. Since monthly force totals are the only force data available, these monthly totals are taken directly from the force summary report. A summary of the OPD force data is listed in Appendix A.

Police force data for NSSD is taken directly from the department incident tracking system. The volume of police calls for NSSD is relatively low. The low volume allows

NSSD to record each and every police call that results in an incident report. These reports are summarized by NSSD in a Microsoft Excel spreadsheet. NSSD did not track force data prior to March of 1999. Since March of 1999, force data is recorded by NSSD in the existing spreadsheet. This force data is extracted directly from the spreadsheet and totaled as incidents per month and incidents per week. A summary of the NSSD force data is listed in Appendix B.

C. SOFTWARE

Four software packages are used in the development of this study. S-Plus and Minitab are the statistical packages used for the exploratory data analysis (calculating mean, variance, ANOVA tables, etc). A computer based control chart plotter is used to chart the police force data. The author of this thesis modified a version of the CUSUM software package developed by Hawkins and Olwell. This modified version of the CUSUM software package is named 'Force Tracker.' Force Tracker is the computer based control chart plotter used to chart the police force data. The charting software is spreadsheet based with Visual Basic macros. The spreadsheet is implemented using Microsoft Excel. Force data and CUSUM tuning parameters are entered directly into Force Tracker. Force Tracker generates the associated control charts. An excerpt from Force Tracker's main data entry page and list of changes to the CUSUM package written by Hawkins and Olwell is located in Appendix C. This excerpt provides the general instructions available to ease the implementation of Force Tracker. This excerpt also summarizes the functionality added (by the author) to the charting software initially developed by Hawkins and Olwell. Finally, 'ANYGETH.exe' is a Fortran based software package developed by Hawkins and Olwell. ANYGETH.exe calculates the upper and lower CUSUM control chart limits. ANYGETH.exe requires the proposed distribution of the data being charted, the target in-control and out-of-control mean and the average run length (ARL). The proposed distribution is selected and ANYGETH.exe produces the exact theoretical reference value *K*. The (*K*, ARL) pair is entered into ANYGETH.exe and the appropriate control limits are calculated. A brief set of instructions for using ANYGETH.exe (for Poisson data) is included in Appendix D. Appendix D also includes an example of determining the upper control limit for a self-starting Poisson CUSUM with a target in-control mean of five, an out-of-control mean for an upward shift of eight, and an average run length of 100. ANYGETH.exe calculates the upper control limit of nine with an in-control ARL of 99.1.

Force Tracker is designed to support easy implementation. The user of Force Tracker need only input the initial tuning parameters followed by the force count data. The tuning parameters are only changed when the system is initially installed and following shifts in the process signaled by a control chart. The update graph button generates the control charts for the force data entered by the user. Figure 5 shows a portion of the Force Tracker input screen. The 'change parameters' button in Figure 5 opens a window allowing the user to enter the control chart tuning parameters. Figure 6 shows the 'change parameters' dialog box.

Force Tracker and ANYGETH.exe are available at a University of Minnesota CUSUM web site. The web site is: http://www.stat.umn.edu/~cusum/ .

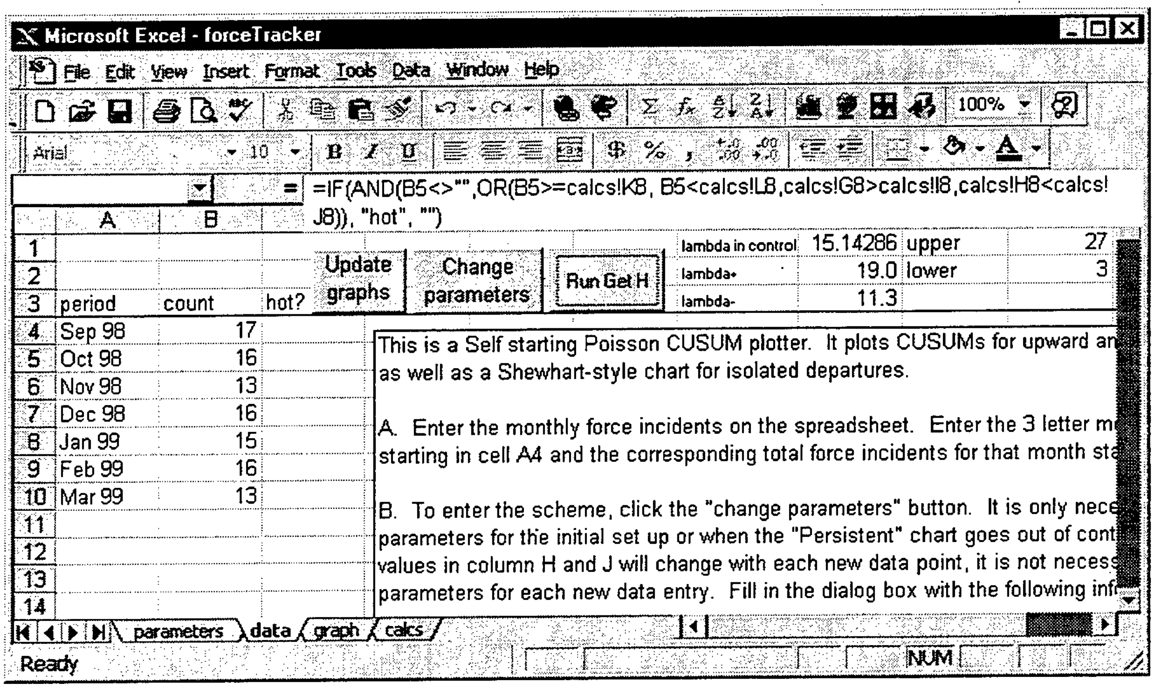

Figure 5. Force Tracker input screen. Column A is the period of report entry field. Column B is the force data entry field. The 'Change parameters' button displays a window allowing CUSUM tuning parameter manipulation. The 'Run Get H' button launches the ANYGETH.exe program directly from the spreadsheet. Columns G through J provide values used when executing ANYGETH.exe. Row 4 indicates that in Sept 98, there are 17 total force incidents.

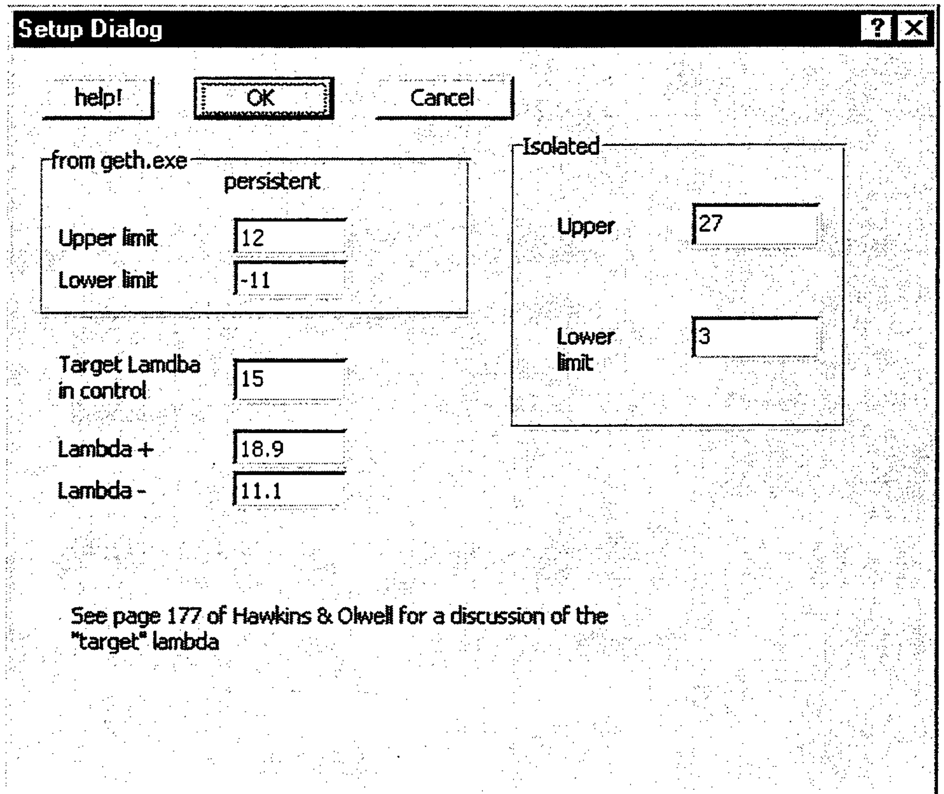

Figure 6. Force Tracker 'change parameters' dialog box. The isolated upper and lower limits are the initial Shewhart chart control limits. The self-starting algorithm developed in this research calculates the remaining Shewhart control limits. The target Lambda is the expected distribution mean. Lambda+ and Lambda- are the target mean plus and minus the square root of the target mean (for this example). The persistent upper and lower limits are the values of the decision interval. These values are the calculated by ANYGETH.exe.

D. EXPLORATORY DATA ANALYSIS

The hypothesized parametric distribution for the police force data is the Poisson distribution. Data is often believed to be Poisson if the data is count data with few responses given many opportunities for a response. The police force data is discrete count data with few force incidents given numerous police interactions. Three tests evaluate the data to determine the plausibility of modeling using the Poisson Distribution. The first test is a "mean equals variance" rule of thumb. This test compares the sample mean and the sample variance. The null hypothesis that the data is Poisson may be rejected if the sample mean and sample variance is not roughly equal. This rule of thumb is applied to both the OPD and NSSD data sets and indicates that the force data is plausibly Poisson.

The second test is the dispersion test. The dispersion test is a formal extension of the "mean equals variance" rule of thumb. This test generates a dispersion statistic d, which follows a chi-squared distribution if the data is from a Poisson distribution. The dispersion statistic is calculated by $d = (n-1)s^2 / \overline{X}$ where s^2 is the sample variance, $\overline{X}$ is the sample mean, and n is the number of samples. If the dispersion statistic is larger than the appropriate chi-squared critical value, then the data is overdispersed. If the data is overdispersed, then the null hypothesis that the data is Poisson may be rejected. The dispersion test is recommended as a simple and effective test in this type of application (Hawkins and Olwell, 1998). The dispersion test is applied to both the OPD and NSSD data sets.

The third test is the chi-squared goodness of fit test (chi-squared GOF). This test compares the data to a random sample from the hypothesized distribution. The chi-squared GOF test has limited application when working with small data sets. If the number of data points per bin is less than five, the test may not be accurate. Since the NSSD data set is small, the chi-squared GOF test is not used. The OPD data set is tested using the chi-squared GOF test to see of the data is plausibly Poisson. The data is divided by calendar year to see if each year is plausibly Poisson. Additionally, the data set is tested as a whole to see if the entire data set is plausibly Poisson with a single rate. Table 1 shows the results of the Poisson plausibility tests for the OPD data set. The degrees of freedom (df) for the chi-squared value (column six of Table 1) vary as the number of bins used in the chi-squared GOF test are selected to allow at least five data points per bin.

Period	Sample Mean	Sample Variance	Dispersion test Statistic	Chi Squared value, 99% confidence	Chi Squared GOF P-value (degrees of freedom)	Poisson Plausible?
1995	25.42	37.36	16.17	24.73	.614 (4 df)	YES
1996	17.17	16.15	10.35	24.73	.989 (3 df)	YES
1997	12.33	14.16	13.03	24.73	.669 (2 df)	YES
1998	14.00	13.09	10.29	24.73	.445 (2 df)	YES
1995 - 1998	17.08	42.67	119.92	76.15	.002 (7 df)	NO

Table 1. Summary of dispersion test and chi-squared GOF test for Oakland Police Department data. Per year, the data is not over dispersed and the chi-squared GOF test does not suggest rejecting the null hypothesis that the data is Poisson. Poisson distribution is plausible per year. The period 1995 – 1998 (entire force data set) is not plausibly Poisson with a single rate equal to 17.08. This result is not unexpected, as the process mean is believed to have changed, causing the overdispersion. It is the goal of this research to detect these changes in the process mean.

Based on these results, the entire OPD data set (1995-1998) is not plausibly Poisson with a rate equal to 17.08. This means the null hypothesis that the data is Poisson with a single constant rate is rejected. However, if the data is broken down by year, the hypothesis that the data is Poisson is not rejected. This result is not unexpected, as the process mean is believed to have changed, causing the overdispersion. It is the purpose of this research to identify these changes in the process mean. The three tests conclude that the OPD data is plausibly Poisson when evaluated by year. Similarly, the NSSD data set is plausibly Poisson when broken down by week. The sample mean for the NSSD data set is 4.56 with a variance of 7.03. Since there are 32 weeks in the data set, the dispersion statistic is 47.49 and the associated $\chi^2_{31,.01}$ is 52.19. Since the dispersion statistic is less than the chi-squared critical value, the null hypothesis that the data is plausibly Poisson is not rejected.

Periodic or seasonal effects may trigger an out-of-control condition when no such condition exists. Periodic or seasonal effects do not prevent the implementation of a control chart scheme. However, the implementation is simpler if these effects do not exist. The 'seasons' for OPD are broken down by hot and cold months. Hot months are June through August. Figure 7 shows the results of the one way ANOVA/Tukey's Method for OPD by monthly effects and Figure 8 shows the results of the one way ANOVA/Tukey's method for OPD by seasonal effects. Analysis of variance (ANOVA) shows that it is plausible to conclude that there are no monthly or seasonal effects.

One-way Analysis of Variance (MONTH)

```
Analysis of Variance for forceByMonth
Source     DF        SS        MS        F        P
month      11     156.7      14.2     0.26    0.989
Error      36    1953.8      54.3
Total      47    2110.5
                                   Individual 95% CIs For Mean
                                   Based on Pooled StDev
Level       N      Mean     StDev  ----------+---------+---------+------
Jan         4    20.000    12.780            (-----------*------------)
Feb         4    18.750     6.994          (-----------*------------)
Mar         4    18.000     9.416         (-----------*-----------)
Apr         4    20.000    10.677            (-----------*------------)
May         4    16.250     6.898      (-----------*------------)
Jun         4    18.000     6.164         (-----------*-----------)
Jul         4    15.750     4.646     (-----------*------------)
Aug         4    16.000     5.477     (------------*-----------)
Sep         4    17.750     0.957        (------------*-----------)
Oct         4    16.250     7.042      (-----------*------------)
Nov         4    13.500     6.137  (------------*-----------)
Dec         4    16.500     3.317      (------------*-----------)
                                   ----------+---------+---------+------
Pooled StDev =    7.367                     12.0      18.0      24.0
```

Figure 7. One-way ANOVA by month of Oakland Police Department force data. Significant monthly effect does not exist.

One-way Analysis of Variance (SEASON)

```
Analysis of Variance for forceByMonth
Source     DF        SS        MS        F        P
season      1      12.8      12.8     0.28    0.599
Error      46    2097.7      45.6
Total      47    2110.5
                                   Individual 95% CIs For Mean
                                   Based on Pooled StDev
Level       N      Mean     StDev  -----+---------+---------+---------+-
cold       32    17.594     7.348            (-----------*-----------)
hot        16    16.500     5.317   (---------------*----------------)
                                   -----+---------+---------+---------+-
Pooled StDev =    6.753               14.0      16.0      18.0      20.0
```

Figure 8. One-way ANOVA by season of Oakland Police Department force data. Significant seasonal effect does not exist.

The NSSD data set is too small to conduct a useful one-way ANOVA test. Furthermore, seasonal effects are unlikely due to the stable weather conditions in Hawaii. The data for NSSD are assumed to be independent without monthly or seasonal effects.

E. CUSUM CONTROL CHART PARAMETER DETERMINATION

The self-starting CUSUM implementation in this study requires the determination of the following parameters:

(1) Estimated in-control mean (μ_0)

(2) Upper and lower limit for the out-of-control mean (μ_h and μ_l)

(3) Reference value (K^+ and K^-)

(4) Average run length (ARL)

(5) Persistent shift upper and lower control limits (H^+ and H^-).

These parameters are defined and explained in chapter I section F of this study (Overview of self-starting control chart methods for Poisson data). Self-starting CUSUM control charts allow the use of small data sets when determining the target in-control mean. For this study, the first four observations are used to determine the target in-control mean. For a CUSUM control chart restart following an out-of-control signal, the last four observations are used to determine the new target in-control mean. Ideally, the user provides information used to determine the upper and lower limits for the out-of-control mean. Again, in a well-defined process, these upper and lower limits for the out-of-control mean are relatively easy to determine. In non-manufacturing applications for control chart methods, the out-of-control limits are more difficult to define. Neither OPD nor NSSD have established trigger points for 'unusual' shifts in the occurrences of force. Process out-of-control limits for this study are calculated by setting the out-of-control limit equal to the target mean plus or minus the square root of the target sample mean. For example, $\mu_h = \mu_o + \sqrt{\mu_o}$ and $\mu_l = \mu_o - \sqrt{\mu_o}$. The decision interval (H^+ to H^-) is calculated using the reference value (K^+ and K^-) and the average run length. The software package ANYGETH.exe calculates the decision interval values. These values are entered into Force Tracker. The result for the data sets used in this study is a control chart scheme tuned to detect a shift in the process mean of approximately fifteen-percent.

ANYGETH.exe calculates the in-control and out-of-control ARL's when determining the upper and lower CUSUM control limits. In order to show the effect of varying ARL on time to detect a shift and false alarm rate, the ARL is varied for the OPD data set. The tested values for ARL are 10, 100, and 1000. Table 2 shows the time to detection for the OPD data set given the associated ARL. Due to the robustness of the CUSUM method, the decrease in sensitivity when detecting a departure is minimal when ARL is varied (Hawkins and Olwell, 1998). For the OPD data set, the time to signal an out-of-control condition with an ARL of ten is four months. The time to signal an out-of-control condition with an ARL of 100 is six months. This result provides useful insight into the trade-off between time to detection and false alarm rate. As ARL increases, the false alarm rate increases geometrically while the time to detection increases linearly.

Average Run Length	**CUSUM upper control limit (UCL)**	**CUSUM lower control limit (LCL)**	**CUSUM decreasing trend begins**	**CUSUM out of control signal indicated**	**Expected number of months to signal trend**	**Observed number of months to signal trend**
10	6	-5	April 1995	July 1995	2.6	4
100	18	-15	April 1995	Sept 1995	4	6
1000	32	-25	April 1995	Dec 1995	11.2	8

Table 2. Sensitivity of time to signal an out-of-control condition for Oakland Police Department data. The control chart is tuned to detect a shift in the mean equal to 5.6. Average run length is varied with all other parameters held constant. The time to detection varies from 4 month to 8 months. The average number of false alarms (as a function of ARL) varies from 1 in 10 months to 1 in 1000 months. As ARL increases geometrically, time to signal an out-of-control condition increases linearly. The expected number of months to signal an out-of-control condition is calculated by ANYGETH.exe. The expected number of months to signal a departure is based on the process undergoing a step change in the mean of the magnitude which the chart is tuned to detect. Note that the expected and observed number of months to signal an out-of-control condition are close.

The ultimate determination of ARL rests with the decision-maker. The desire to detect shifts quickly must be balanced with the ability to handle false alarms. This study uses an ARL of 100.

III. RESULTS

A. OAKLAND POLICE DEPARTMENT FORCE DATA CHARTED

Oakland Police Department data is charted starting with the 1995 data set. When a CUSUM departure occurs (the point when the increasing (decreasing) trend line crosses the upper (lower) control limit) the process is declared to be out-of-control (Hawkins and Olwell, 1998). This out-of-control signal tells the decision-maker that investigation into the shift of the process mean is warranted. If the process is declared to be out-of-control, the departure is estimated to begin at the last point when the increasing (decreasing) trend line left the zero axis if the process undergoes a step shift in the mean (Hawkins and Olwell, 1998). Figure 9 shows the first control chart indicating a departure in force rate. The CUSUM chart is tuned with a target in-control mean of 32.3, an out-of-control mean for an upward shift of 37.9, an out-of-control mean for a downward shift of 26.2, an upper control limit of 18, and a lower control limit of –15. The ARL is 100 for an upward shift, 98 for a downward shift, and the combined in-control ARL is 50.

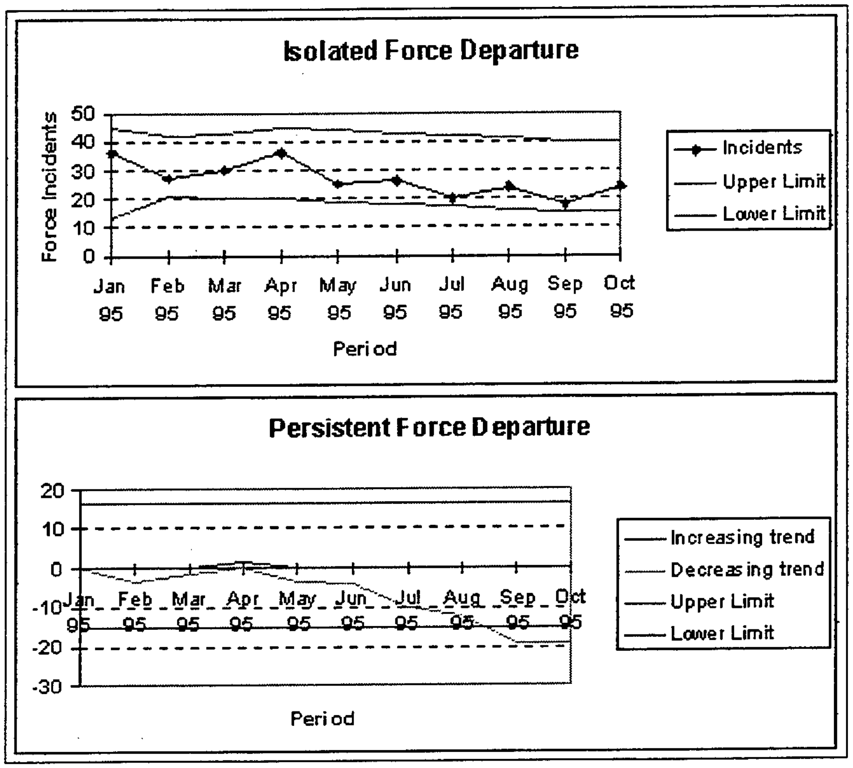

Figure 9. Oakland Police Department chart with initial force data. Isolated departure did not occur. Decreasing shift in force rate signaled in September, 1995 on the persistent force departure chart. The decreasing trend is estimated to begin in April, 1995.

The CUSUM signaling an out-of-control condition implies that the process mean has shifted. Since the process mean has shifted the chart is re-tuned and restarted to allow tracking of the data from the new distribution. The CUSUM is restarted from the last point that the chart is believed to be in control. Figure 10 shows the first restart for OPD data. This restart again signals a departure in September, 1995. The CUSUM chart is tuned with a target in-control mean of 24.8, an out-of-control mean for an upward shift of 29.8, an out-of-control mean for a downward shift of 19.9, an upper control limit of 17, and a lower control limit of –13. The ARL is 106 for an upward shift, 109 for a downward shift, and the combined ARL is 54.

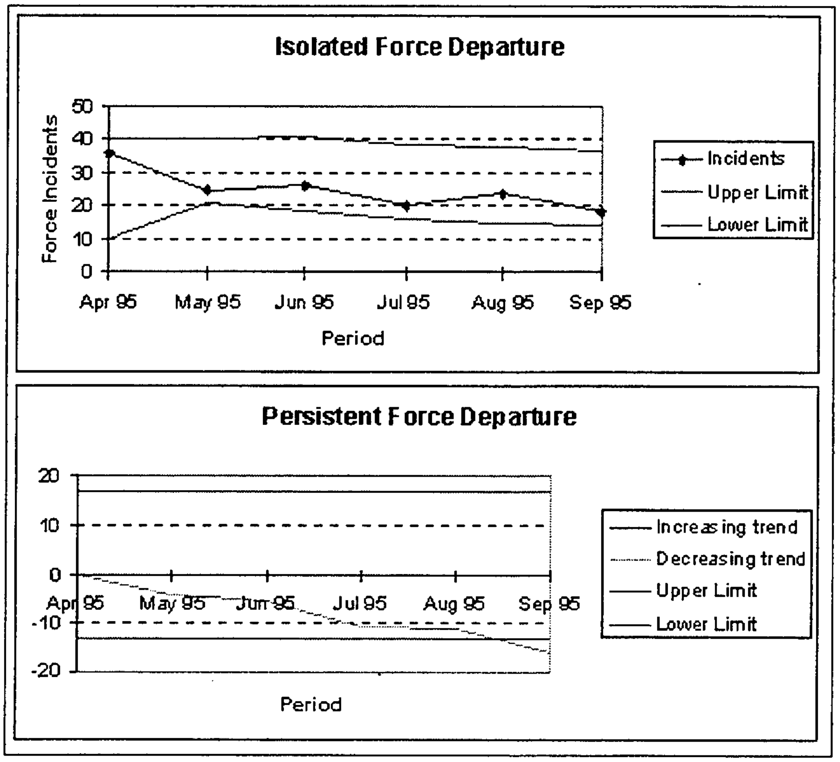

Figure 10. Oakland Police Department charts restarted from April, 1995. Decreasing shift in force rate signaled in September, 1995. Decreasing trend is estimated to begin in April, 1995. Since the departure is again signaled in September, 1995 the force rate decrease is estimated to be a linear drift and not a step change.

The fact that the re-tuned chart detected the departure again in September, 1995, implies that the shift in the process mean was due to a linear drift and not a single step change. Since the chart signals an out-of-control condition due to a linear drift in the process mean, the chart is restarted in October, 1995. Figure 11 shows the control chart for OPD data when restarting with the October, 1995 data point. This chart continues in control and signals the next departure in August, 1996. The CUSUM chart is tuned with a target in-control mean of 22, an out-of-control mean for an upward shift of 26.7, an out-of-control mean for a downward shift of 17.3, an upper control limit of 17, and a lower control limit of –12.5. The ARL is 98 for an upward shift, 95 for a downward shift, and the combined ARL is 48.

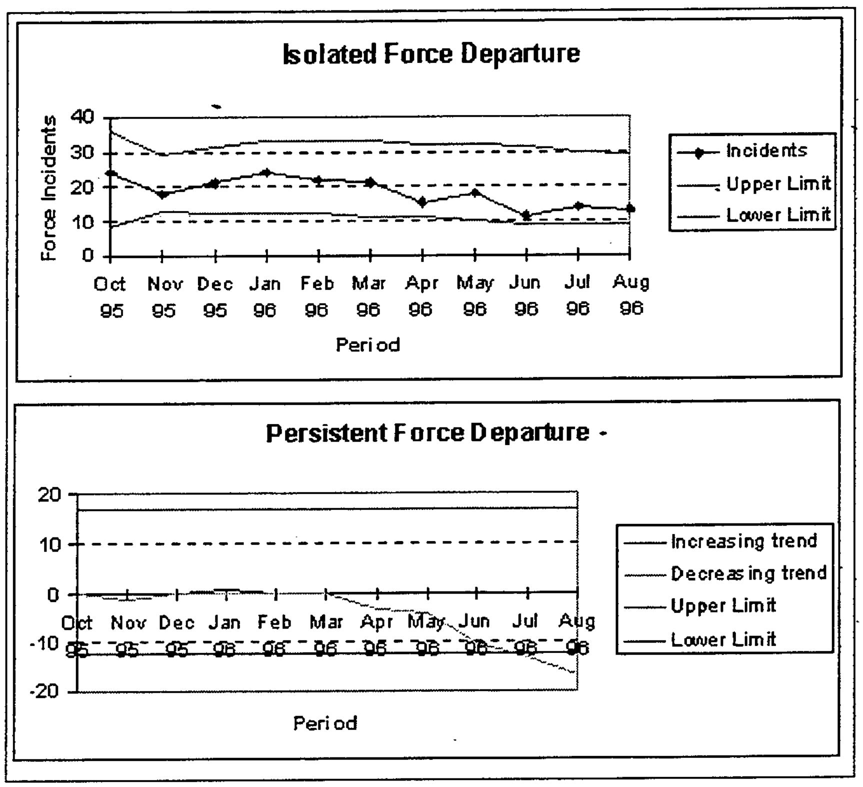

Figure 11. Oakland Police Department charts restarted from October, 1995. Decreasing shift in force rate signaled in August, 1996. Decreasing trend in force rate begins in March, 1996.

The out-of-control condition is estimated to begin in March, 1996 and is signaled in August, 1996. An OPD chart restart is required. Since the change in the process mean is likely to be the result of a linear drift in the process mean, the restart occurs in August, 1996. Figure 12 is the OPD chart restarted in August, 1996. The CUSUM chart is tuned with a target in-control mean of 15.8, an out-of-control mean for an upward shift of 19.8, an out-of-control mean for a downward shift of 11.8, an upper control limit of 12, and a lower control limit of –12. The ARL is 83 for an upward shift, 78 for a downward shift, and the combined ARL is 40.

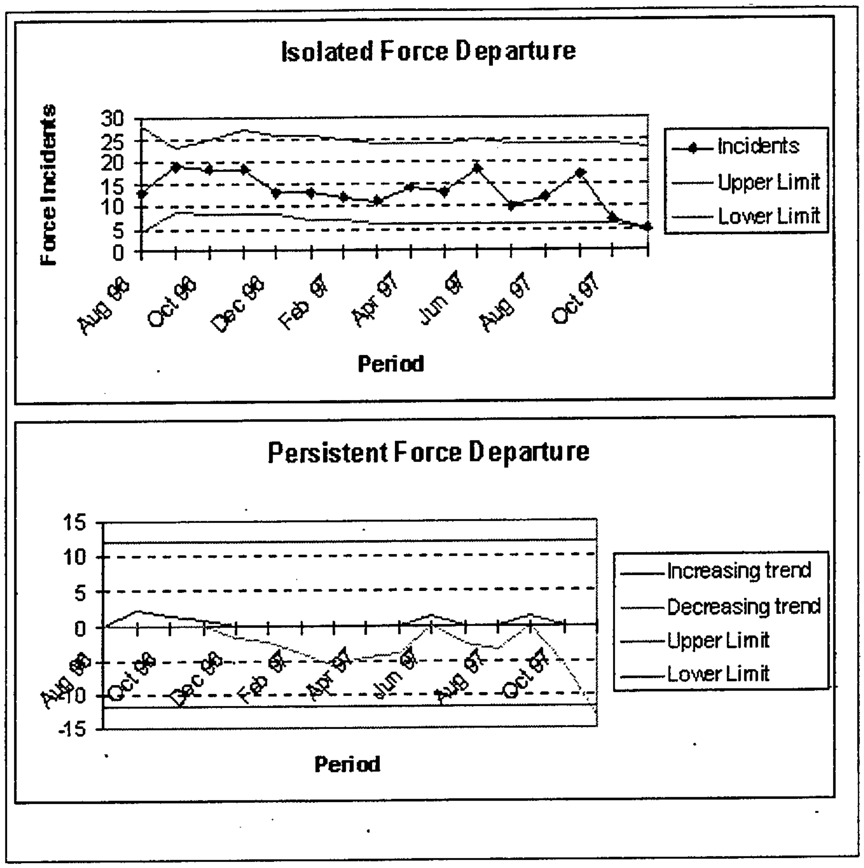

Figure 12. Oakland Police Department charts restarted from August, 1996. Decreasing shift in force rate signaled in November, 1997. Decrease in force rate begins in September, 1997. Isolated downward departure signaled in November, 1997.

OPD chart is restarted in November, 1997. Figure 13 is the November, 1997 restart. The chart shows an increase in the process mean beginning in November, 1997 and signals an out-of-control condition in September, 1998. It is likely that the October and November 1997 data points forced the CUSUM shift since the chart shows a continual increase from the November, 1997 signal. The CUSUM chart is tuned with a target in-control mean of 11.5, an out-of-control mean for an upward shift of 14.9, an out-of-control mean for a downward shift of 8.1, an upper control limit of 12, and a lower control limit of –11. The ARL is 108 for an upward shift, 91 for a downward shift, and the combined ARL is 49.

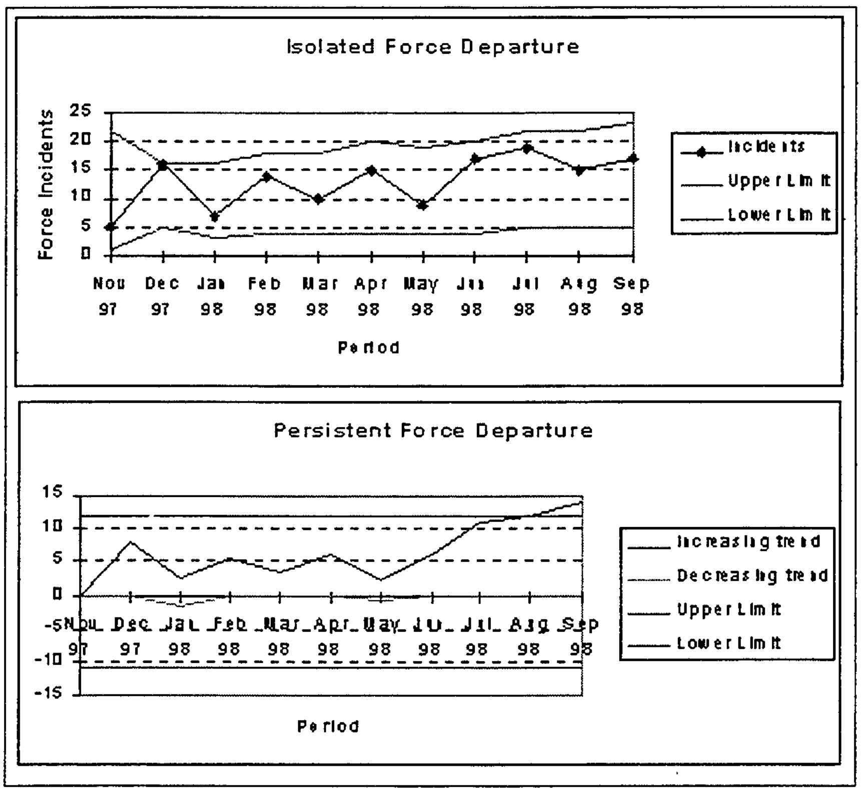

Figure 13. Oakland Police Department charts restarted from November, 1997. Increasing shift in force rate signaled in September, 1998. Increasing trend begins in November, 1997.

The final OPD chart restart occurs in September, 1998. The chart shows an in control condition from September, 1998 to March, 1999. Figure 14 is the September, 1998 restart. The CUSUM chart is tuned with a target in-control mean of 15, an out-of-control mean for an upward shift of 18.9, an out-of-control mean for a downward shift of

11.1, an upper control limit of 12, and a lower control limit of –11. The ARL is 77 for an upward shift, 118 for a downward shift, and the combined ARL is 47.

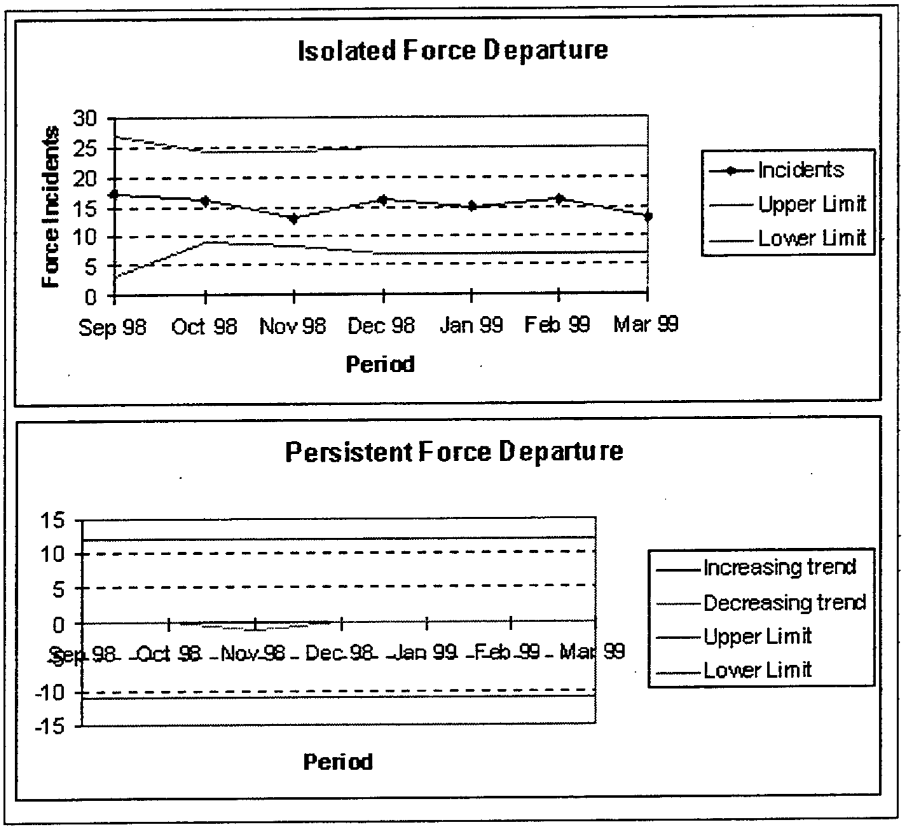

Figure 14. Oakland Police Department charts restarted from September 1998 to March 1999. The chart indicates that force process is in statistical control.

Figure 15 is the entire OPD data set charted over time. This chart also reveals the observed changes in the process mean over time.

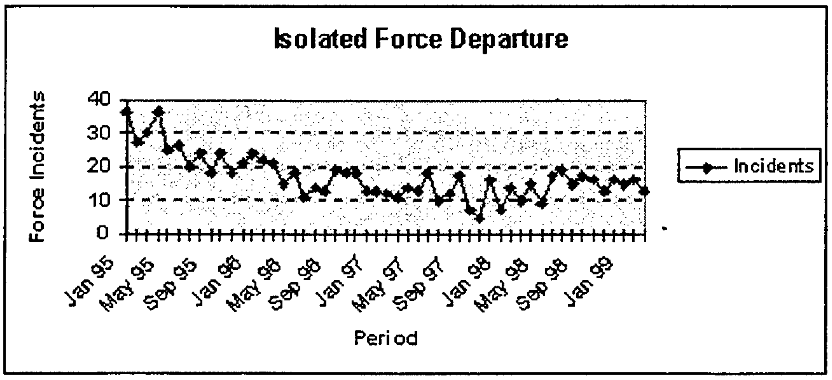

Figure 15. Oakland Police Department data plotted from January, 1995 to March, 1999. General decreasing trend from January, 1995 is visible.

The size of the shift in mean that a control chart is tuned to detect affects control chart performance. In order to demonstrate the effect of changing the size of the decision interval, the OPD data set is plotted again using different values for the out-of-control mean. In the first set of charts, the out-of-control mean is the target mean plus and minus about 15% of the mean (i.e. attempting to detect a shift in the mean of about 15%). The next set of charts is tuned to detect a much larger shift in the process mean. With the average run length held constant, the chart is set to detect a mean shift of 50%. Figure 16 shows OPD data charted from April, 1995, when tuned to detect a larger shift in the process mean. The CUSUM chart is tuned with a target in-control mean of 32.3, an out-of-control mean for an upward shift of 48.3, an out-of-control mean for a downward shift of 16.3, an upper control limit of 8, and a lower control limit of –4. The ARL is 96 for an upward shift, 69 for a downward shift, and the combined ARL is 40.

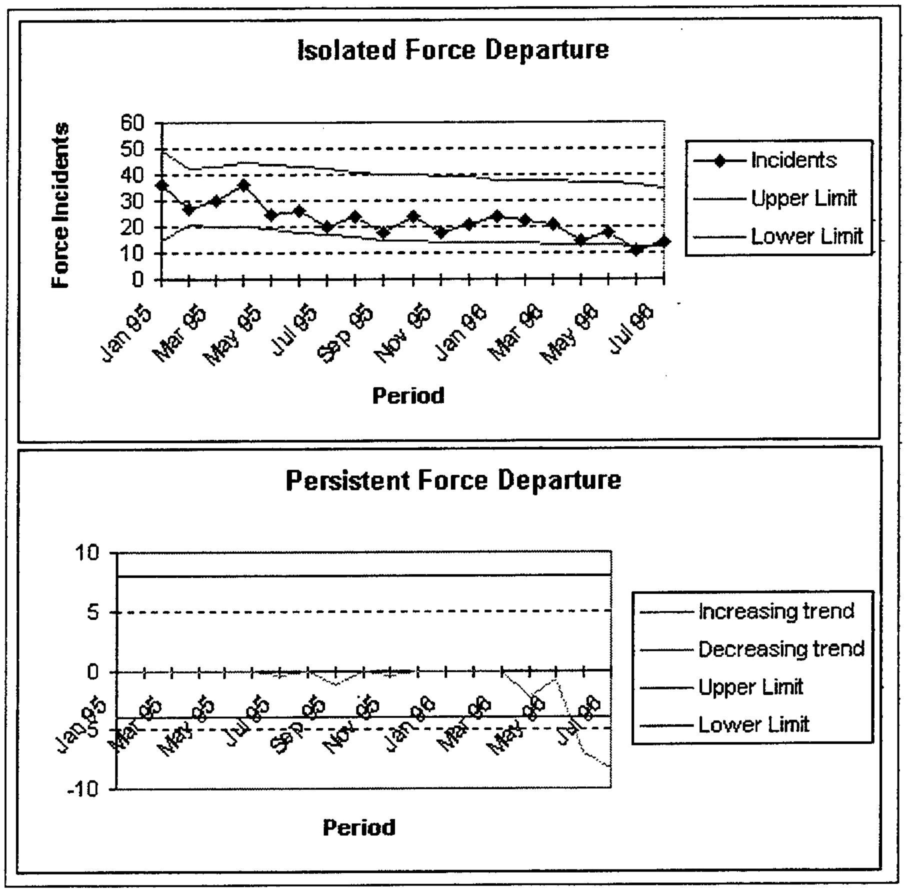

Figure 16. OPD data plotted when attempting to detect a larger shift in the mean (shift of 50%). An isolated departure occurs in June, 1996. A persistent shift is detected in July, 1996. The shift is estimated to begin in June, 1996. This chart takes longer to detect the shift than the previous charts that are tuned to detect a smaller shift in the mean (shift of ~15%).

The chart for OPD is restarted in August, 1996. Figure 17 is the OPD restart. A decrease in the process mean is detected in November, 1997. The CUSUM chart is tuned with a target in-control mean of 14.5, an out-of-control mean for an upward shift of 21.5, an out-of-control mean for a downward shift of 7.5, an upper control limit of 8, and a lower control limit of –5. The ARL is 76 for an upward shift, 72 for a downward shift, and the combined ARL is 37.

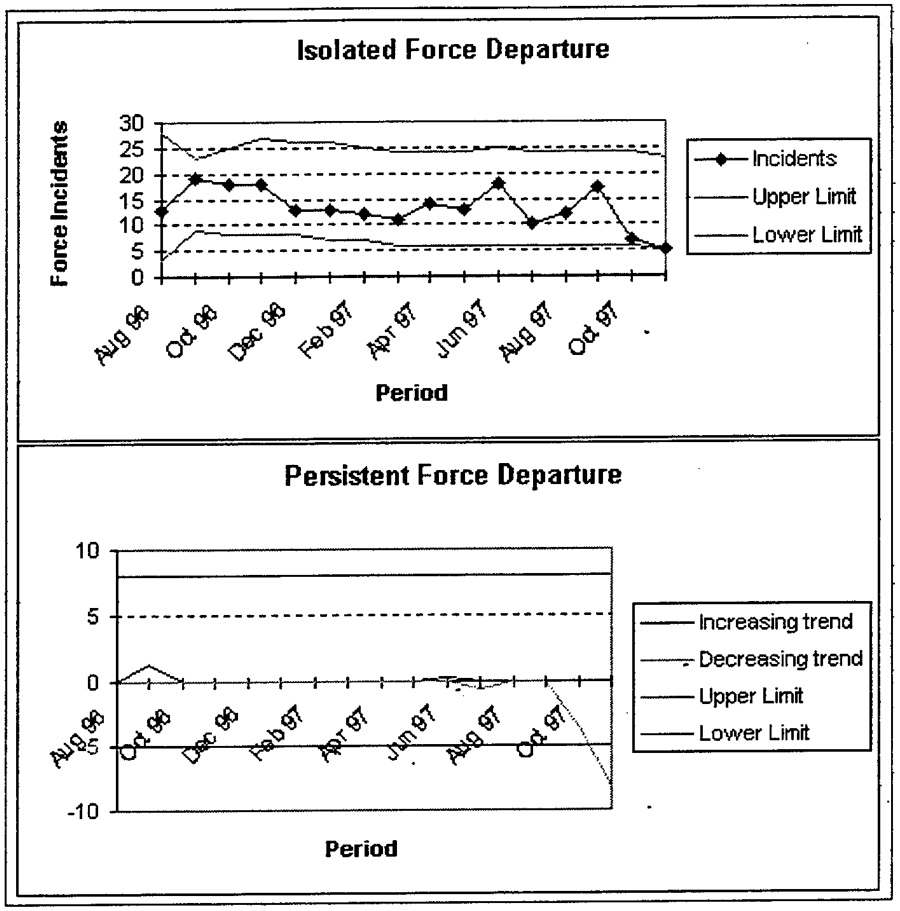

Figure 17. OPD data plotted when attempting to detect a larger shift in the mean (shift of 50%). A persistent shift is detected in November, 1997. The shift is estimated to begin in September, 1997. This chart takes longer to detect the shift than the previous restarted charts that are tuned to detect a smaller shift in the mean (shift of ~15%).

OPD chart is restarted in December, 1997. Figure 18 is the next restart. The CUSUM chart is tuned with a target in-control mean of 11.5, an out-of-control mean for an upward shift of 17.3, an out-of-control mean for a downward shift of 5.8, an upper control limit of 9, and a lower control limit of –5. The ARL is 134 for an upward shift, 141 for a downward shift, and the combined ARL is 69.

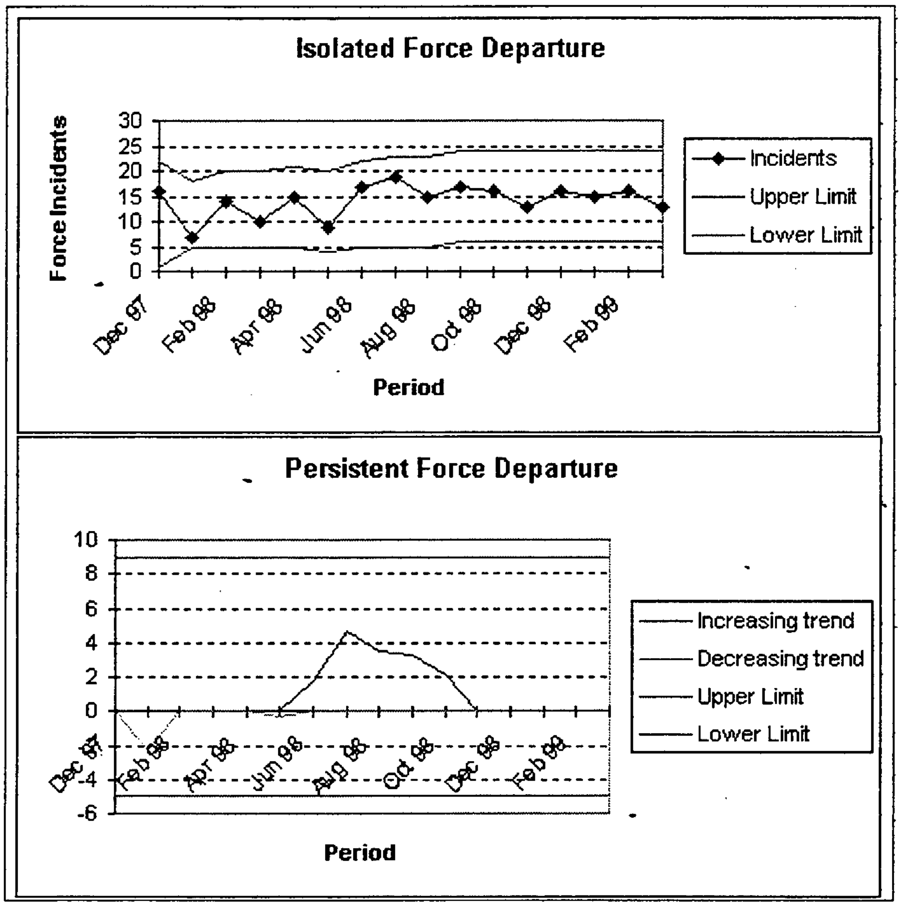

Figure 18. OPD data plotted when attempting to detect a larger shift in the mean (shift of 50%). Although the chart does not signal a departure in the process mean, the increasing trend line shows that the force rate between May and November, 1998 is higher than the target mean.

The control chart tuned to detect the smaller shift in the process mean (shift size approximately equal to a 15% shift in the target mean) detected four shifts in the process mean. These shifts are:

(1) Decreasing shift signaled in September, 1995

(2) Decreasing shift signaled in August, 1996

(3) Decreasing shift signaled in November, 1997

(4) Increasing shift signaled in September, 1998.

The chart tuned to detect the larger shift (shift size approximately equal to a 50% shift in the target mean) with all other parameters held constant detected two shifts in the process mean. The shifts are :

(1) Decreasing shift signaled in July, 1996

(2) Decreasing shift signaled in November, 1997.

This result shows the effect of changing the shift size that the CUSUM control chart is tuned to detect. A trade-off in looking for larger shifts may result in a longer time to detect a smaller shift. In this study, the chart tuned to detect the larger shift detected the first departure almost one year later than the chart tuned to detect the smaller shift in the process mean. One benefit from tuning to detect a larger shift in the process mean is that the CUSUM is more robust against model mis-specifications (i.e. if the process is not exactly Poisson) (Hawkins and Olwell, 1998).

The Oakland Police Department, like other police departments, uses a degree of lethal force within the scope of operations. For the purpose of this study, lethal force is combined with non-lethal force and the combined force rate is charted. However, each force phenomenon can be charted independently. Since the impact of an out-of-control frequency of lethal force is likely to be substantial, it may be desirable to chart lethal force in its own category. The ability to chart the parameter of interest is a great benefit to these control chart methods. To indicate this benefit, the lethal force data for OPD is charted. A dispersion test of the OPD lethal force data set results in a dispersion statistic equal to 82.65 and the chi-squared statistic equal to 76.15. OPD lethal force data is slightly overdispersed. However, it is again likely that the data is comprised of Poisson distributions with different rates. The OPD lethal force data is charted using a Poisson self-starting CUSUM plotter. Since the incidence of lethal force is much smaller than the incidence of non-lethal force, a minimum data set to determine the target mean of one year is used. The data is charted from January, 1996. Figure 19 shows the chart of OPD lethal force data. The CUSUM chart is tuned with a target in-control mean of 1.6, an out-of-control mean for an upward shift of 2.8, an out-of-control mean for a downward shift of .3, an upper control limit of 6, and a lower control limit of –1.5. The ARL is 64 for an upward shift, 143 for a downward shift, and the combined ARL is 44.

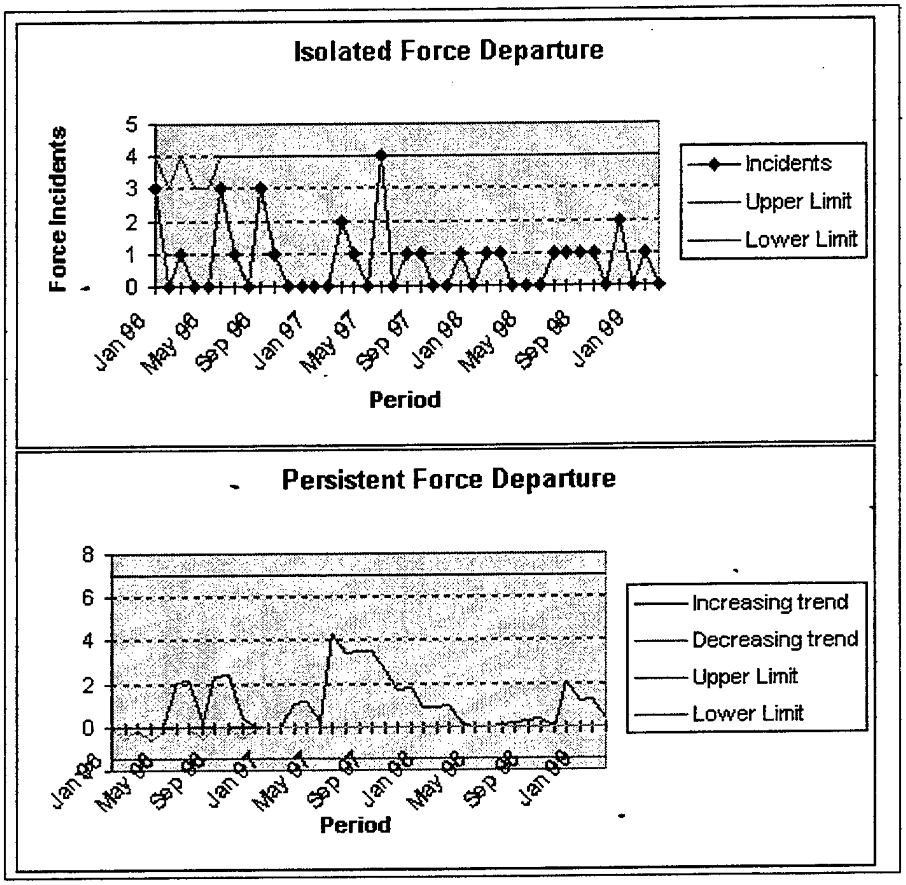

Figure 19. OPD lethal force charted from January, 1996. Isolated departure occurs in June, 1997. A persistent shift in the force rate is not detected. OPD lethal force rate is in statistical control.

An isolated departure is indicated in June, 1997. The process is in statistical control from June, 1997 to the last data point March, 1999. Since the process is in statistical control, the police department managers do not need to expend intensive effort in chasing usual variability in force.

B. PEARL HARBOR POLICE DEPARTMENT DATA CHARTED

The NSSD data set is small. The first four months of data determine the tuning parameters. The charting shows no isolated or persistent out-of-control conditions. Figure 20 shows NSSD data charted. The CUSUM chart is tuned with a target in-control mean of 22.4, an out-of-control mean for an upward shift of 27.1, an out-of-control mean for a downward shift of 17.7, an upper control limit of 14, and a lower control limit of –13. The ARL is 106 for an upward shift, 99 for a downward shift, and the combined ARL is 51.

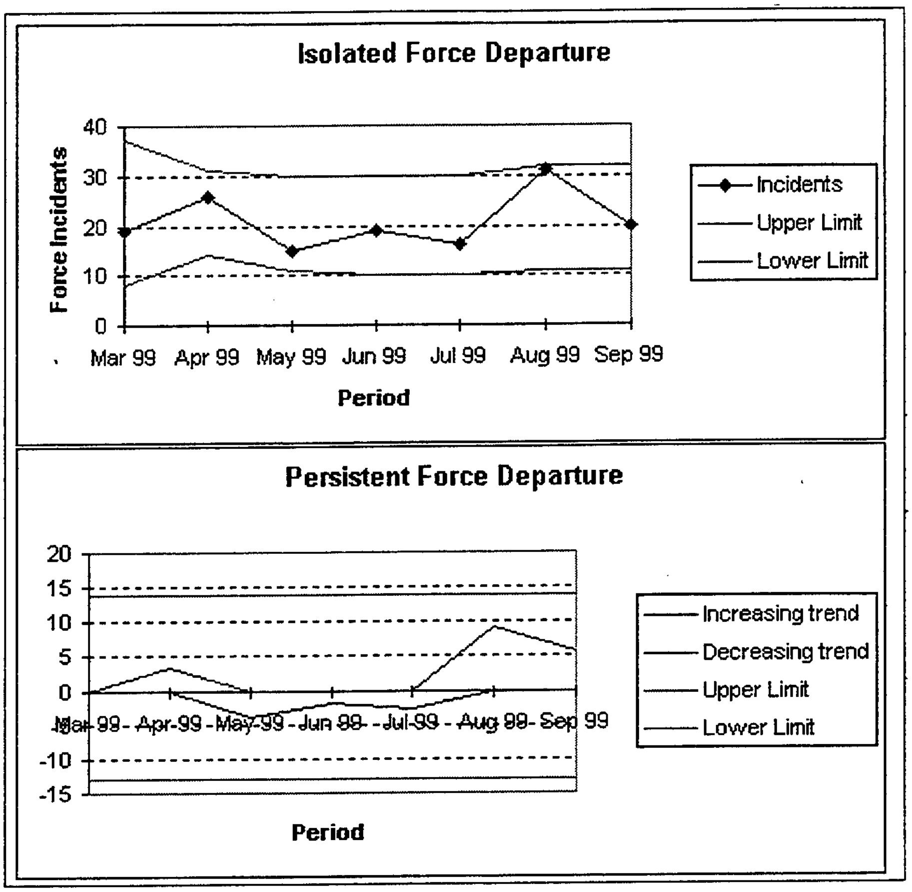

Figure 20. Naval Station Security Department force data charted using a monthly sampling interval. August, 1999 is nearly an isolated departure. The process is in statistical control. NSSD can continue to collect and chart data.

The reporting period for a control chart scheme can affect the information provided to the decision-maker. For effective control charting, the reporting period is chosen such that periodic effects are 'smoothed out.' It is undesirable to have a control chart signal a departure every two weeks as the result of a pay day phenomenon. Additionally, the number of incidents that each data point represents decreases as the number of sample increases. However, increasing the reporting period can improve the sensitivity of detection (with an associated trade-off in false alarm rate).

The reporting period for the NSSD charts is monthly. However, the data is available in a form that supports charting by period as frequently as force incidents per shift. The rate is sufficient to support charting by week. Figure 21 shows NSSD data charted with a reporting period equal to one week. The CUSUM chart is tuned with a target in-control mean of 4.3, an out-of-control mean for an upward shift of 5.4, an out-of-control mean for a downward shift of 3.2, an upper control limit of 10, and a lower control limit of –8. The ARL is 97 for an upward shift, 98 for a downward shift, and the combined ARL is 49.

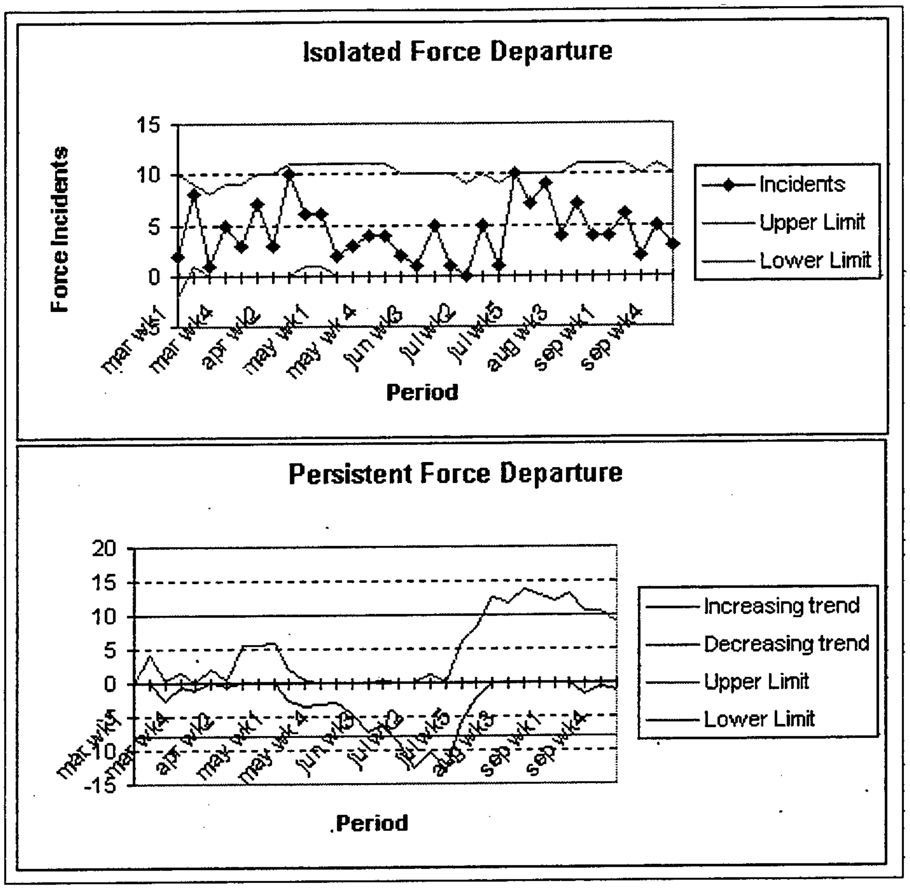

Figure 21. NSSD force data plotted by week. Decreasing trend signaled in July week 1. The decreasing trend is estimated to begin in May week 2. More frequent sampling results in detection of a shift that was undetected in the monthly reporting scheme. Trade-off for increased sensitivity of detection is increase in possible number of false alarms.

The process continues in control until a decreasing trend is signaled in the first week of July, 1999. The decreasing trend begins in the second week of May, 1999. An increasing trend begins in the fourth week of July, 1999. An isolated departure is signaled in the fifth reporting week in July, 1999.

IV. CONCLUSIONS, RECOMMENDATIONS, AND FURTHER RESEARCH

A. CONCLUSIONS

There is an inherent tendency to react to usual variation when monitoring a process. According to Dr. W. Edwards Deming, the managers fail when they do not understand variation. Additionally, Dr. Deming stated that "Views not backed by data are more likely to include personal opinions, exaggeration and mistaken impressions." (Walton, 1986)

This study develops a methodology that assists law enforcement decision-makers. This statistical method is effective in the monitoring of police force frequency. The control chart software package developed in this study is called 'Force Tracker.' Force Tracker provides rapid detection of an out-of-control force condition. Furthermore, Force Tracker minimizes the potential for unwarranted reaction to usual variation. In the cases of the Oakland Police Department and the Naval Station Security Department, usual variation in force incidents is present. The charts generated by Force Tracker assist the decision-maker in resisting the urge to react to this usual variation. Changes in the force frequency for both police departments also occur. Force Tracker identified these shifts in the process mean assisting decision-makers in deciding if managerial intervention is warranted.

For the Oakland Police Department, persistent shifts in the process mean are detected in September, 1995, August, 1996, November 1997, and September, 1998. The last persistent departure (September, 1998) is the only increasing trend. It is possible that the effect of the force reducing efforts made in 1995 are diminishing or losing their value. This information is valuable to the OPD supervisors so that necessary intervention can stop the observed increase in force frequency. Force Tracker output for the OPD data set shows that OPD force frequency has decreased from January, 1995 until September, 1998. A one-way retrospective ANOVA confirms the result that the mean force rate in 1995 is higher than the following years. This test further supports Force Tracker's correct detection of the decrease in the process mean. Furthermore, the one-way ANOVA does not establish that 1998 is significantly different from 1997. Force Tracker, however, signals a departure (increasing trend) in November, 1997. This is an added benefit to Force Tracker since in the CUSUM method, the order of the observations is preserved. An ANOVA does not preserve the order of the data. Figure 22 is the one-way ANOVA of OPD data by year.

```
One-way Analysis of Variance (YEAR)

Analysis of Variance for forceByMonth
Source     DF        SS        MS        F        P
year        3    1217.2     405.7    19.99    0.000
Error      44     893.3      20.3
Total      47    2110.5
                                   Individual 95% CIs For Mean
                                   Based on Pooled StDev
Level       N      Mean     StDev  -+---------+---------+---------+-----
1995       12    25.417     6.112                                (----*----)
1996       12    17.167     4.019            (----*-----)
1997       12    12.333     3.822  (-----*----)
1998       12    14.000     3.618      (----*----)
                                   -+---------+---------+---------+-----
Pooled StDev =    4.506           10.0      15.0      20.0      25.0
```

Figure 22. One-way ANOVA by year of Oakland Police Department force data. 1995 mean is significantly higher than other years.

The isolated departure in November, 1997 indicates an unusually good month. Persistent shifts in the force rate occur as well. Interestingly enough, OPD was not aware that there was such a significant decrease in police force frequency. It is not the purpose of control chart methods (nor is it the purpose of this study) to identify the underlying cause for a shift in the force frequency. However, the author contacted OPD with the output from Force Tracker in an effort to gain insight into the possible causes of the decrease in the force frequency.

Initially, certain obvious possible causes for the decrease in force frequency are ruled out. OPD reports no change in use of force regulations and no changes in use of force reporting procedures. Additionally, the decrease in force rate is not believed to be a function of the change in crimes or calls dispatched. Table 3 summarizes the annual 'Category A' calls dispatched by OPD and the associated percent decrease in calls. 'Category A' calls are those calls that involve potential danger for serious injury to persons, prevention of violent crimes, serious public hazards, or felonies in progress with possible suspect on scene. Table 3 also summarizes the percent decrease in force incidents per year for OPD.

Year	Number of Category A calls	Percent change in Category A calls from previous year	Annual force incidents	Percent change in annual force incidents from previous year
1995	15,869	N/A	305	N/A
1996	15,846	-.14%	206	-32.46%
1997	15,155	-4.36%	148	-28.16%
1998	15,381	1.49%	168	13.51%

Table 3. Summary of Oakland Police Department 'category A' calls and annual force incidents. Percent change shown from the previous year. It is not likely that the decrease in force rate is related to the decrease in the number of 'Category A' calls dispatched.

Further investigation into the potential causes of the decrease in force frequency results in the following three possibilities. First, OPD instituted a Community Policing Program in 1995. Second, OPD had a new police chief assigned. Third, OPD instituted a command chaplain in 1995. The decrease in force rate may be attributed to the previously described causes individually, a combination of the three, or to some other unknown factor. Determining the cause of the decrease is difficult largely because of the lateness of the inquiry. Had Force Tracker been used by OPD in 1995, the possible causes for the decrease in force rate could have been investigated in real time. Early detection is beneficial to organizations, it allows the reinforcement of successes. This rapid detection allows the development of lessons learned and reinforces the institution of new practices.

Force Tracker output for the Naval Station Security Department data set shows that NSSD force frequency is in statistical control when charted monthly. The value of Force Tracker for NSSD is largely in preventing reaction to variation. August, 1999 has a large number of force incidents that appears to be due to variation since the upper control limit is not exceeded. When the NSSD data set is charted using weekly reporting periods, a decrease in the force rate is detected. The frequency of the reporting period can be increased so long as periodic effects do not result in control chart signals which is why the data is aggregated by week. Along with the increase in the reporting frequency is an associated increase in the possible number of false alarms. The decision-maker sets the tone for the trade-off in detection and false alarms. NSSD can implement the use of Force Tracker to continue monitoring police force frequency.

B. RECOMMENDATIONS

As society becomes more sensitive to police force incidents, the pressure upon law enforcement managers will intensify. In order to pursue quality control of police force, police departments should implement Force Tracker to assist in monitoring police force frequency. Force Tracker uses software that is readily available and simple to implement. The data required to implement the use of Force Tracker is minimal. Force Tracker provides information, not data. Decision-makers need this information to aid in the allocation of scarce resources (time and money).

C. FURTHER RESEARCH

The possibility exists to model force using statistical regression. Force can be modeled as the response variable to certain available predictor variables. However, since most police departments do not statistically monitor police force, useful data sets are difficult to find. The Oakland Police Department data set is not sufficient in its current form to support regression. The Naval Station Security Department data set is of the form to support regression analysis. As the interest in monitoring police force increases, the data sets available for regression analysis may improve. Additionally, this study merely scratches the surface of the possible applications for control chart techniques. Multivariate applications for monitoring force may become necessary.

Statistically tracking police force is in its infancy. This research marks the beginning of the application of Statistical Process Control techniques to the phenomenon of police force frequency.

APPENDIX A. OAKLAND POLICE DEPARTMENT FORCE DATA SUMMARY

Month	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force incidents
January 1995	0	36	36
February 1995	6	21	27
March 1995	0	30	30
April 1995	1	35	36
May 1995	2	23	25
June 1995	3	23	26
July 1995	1	19	20
August 1995	3	21	24
September 1995	1	17	18
October 1995	0	24	24
November 1995	2	16	18
December 1995	0	21	21
January 1996	3	21	24
February 1996	0	22	22
March 1996	1	20	21
April 1996	0	15	15
May 1996	0	18	18
June 1996	3	8	11
July 1996	1	13	14
August 1996	0	13	13

Month	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force incidents
September 1996	3	16	19
October 1996	1	17	18
November 1996	0	18	18
December 1996	0	13	13
January 1997	0	13	13
February 1997	0	12	12
March 1997	2	9	11
April 1997	1	13	14
May 1997	0	13	13
June 1997	4	14	18
July 1997	0	10	10
August 1997	1	11	12
September 1997	1	16	17
October 1997	0	7	7
November 1997	0	5	5
December 1997	1	15	16
January 1998	0	7	7
February 1998	1	13	14
March 1998	1	9	10
April 1998	0	15	15
May 1998	0	9	9
June 1998	0	17	17
July 1998	1	18	19
August 1998	1	14	15

Month	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force incidents
September 1998	1	16	17
October 1998	1	15	16
November 1998	0	13	13
December 1998	2	14	16
January 1999	0	15	15
February 1999	1	15	16
March 1999	0	13	13

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APPENDIX B. NAVAL STATION SECURITY DEPARTMENT FORCE DATA SUMMARY

Month	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force
March 1999	0	19	19
April 1999	0	26	26
May 1999	0	15	15
June 1999	0	21	21
July 1999	0	16	16
August 1999	0	31	31

Week	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force incidents
1	0	2	2
2	0	8	8
3	0	1	1
4	0	5	5
5	0	3	3
6	0	7	7
7	0	3	3
8	0	10	10
9	0	6	6
10	0	6	6
11	0	2	2
12	0	3	3
13	0	4	4
14	0	4	4
15	0	2	2
16	0	7	7
17	0	5	5
18	0	1	1
19	0	0	0
20	0	5	5
21	0	1	1
22	0	10	10
23	0	7	7
24	0	9	9
25	0	4	4
26	0	7	7

Week	Lethal force incidents	Non-lethal force incidents	Lethal and non-lethal force incidents
27	0	4	4
28	0	4	4
29	0	6	6
30	0	2	2
31	0	5	5
32	0	3	3

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APPENDIX C. FORCE TRACKER DIRECTIONS AND SUMMARY OF FUNCTIONALITY ADDED TO EXISTING CONTROL CHART SCHEME

FORCE TRACKER DIRECTIONS:

This is a Self-starting Poisson CUSUM plotter. It plots CUSUMs for upward and downward shifts, as well as a Shewhart-style chart for isolated departures.

A. Enter the monthly force incidents on the spreadsheet. Enter the 3-letter month abbreviation starting in cell A4 and the corresponding total force incidents for that month starting in cell B4.

B. To enter the scheme, click the "change parameters" button. It is only necessary to change parameters for the initial set up or when the "Persistent" chart goes out-of-control. Although the values in column H and J will change with each new data point, it is not necessary to change parameters for each new data entry. Fill in the dialog box with the following information:

> 1. Target lambda in control (lambda is the expected average number of force incidents). Unless other historical data is provided, use the number calculated in spreadsheet cell H1.
> 2. Enter the out-of-control upper and lower tuning values ("lambda+ " and "lambda-", respectively). Unless other historical data is provided, use the value in cell H2 for lambda+ and use the value in H3 for lambda-.
> 4. Enter the isolated upper and lower control limits. Unless other historical data is provided, use the value in J1 for upper and use the value in J2 for the lower limit.
> 5. Enter the value for the persistent upper and lower limit. See handout for guidance on calculating these values.
> 6. Click the "OKAY" button any time that you need to return to the data sheet.

C. To see the charts click the "Update graphs" button.

D. If the chart doesn't appear to work properly, ensure that the persistent lower limit (under change parameters) is a negative number.

E. If any chart goes out-of-control, the word "hot" will appear in the column C. An out-of-control "Persistent" chart indicates a shift in the average force incidents and an out-of-control isolated chart indicates a point change. The out-of-control chart is reason to investigate the potential cause for the change in force frequency. Recall that the shift can be high or low. An upward shift may indicate a lack of officer supervision or an increase in the number of police calls. A downward shift may indicate heightened awareness or a decrease in the number of police calls. If the "Persistent" chart crosses the decision level (high or low out-of-control), new data and parameters must be entered. Continue to part F for new data stream entry directions.

F. Begin the new data stream by using the last in control force value and the most recent force value. The last in control value is the number in column B just before the entry that caused "hot" to appear. The most recent value is the number in column B with that caused "hot" to appear. Enter these two data points in cells B4 and B5 with the corresponding months for these values in cells A4 and A5. Delete all remaining data and follow part B above to enter the new parameters.

HISTORY OF CHANGES BY R.C. WEITZMAN

1. Add month to calculation sheet for plot X-axis

2. Make Shewart chart control limits function of data with CRITBINOM function. "YUCL" & "YLCL" for first data point entered by user.

3. Change trigger for "hot" to CRITBINOM limits.

4. Change plot colors (limits in red; trends in blue and green).

5. Add StatHelper portion for lambda in control, lambda+, lambda-, upper and lower.

6. Change chart titles and axis to create force specific labels.

7. Add 'run ANYGETH.exe' button to allow execution of ANYGETH.exe directly from spreadsheet.

8. Put min() function for 'An' so the value 1 is never returned thus preventing CRITBINOM failure from returning 'VALUE#'.

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APPENDIX D. DIRECTIONS FOR USING ANYGETH.EXE

- Select the desired distribution from the main menu. For the Poisson Distribution, select number 3.
- Enter the target in-control and upper out-of-control mean. If using Force Tracker, these values are calculated in spreadsheet cells H1 and H2.
- ANYGETH.exe calculates the exact theoretical reference value. Round this value to the nearest half unit. For example, if the exact theoretical reference value is 3.2, use 3.0. If the value is 1.62, use 1.5 and so on.
- Enter –999 999 to deny the option to Winsorize. Winsorization is not used in this application. For information regarding Winsorization, refer to *Cumulative Sum Charts and Charting for Quality Improvement* by D. Hawkins and D. Olwell.
- Enter 'z' to select a zero start CUSUM.
- Enter the average run length (ARL). An ARL of 100 is recommended.
- ANYGETH.exe will calculate the upper control limit. This value is entered into the Force Tracker 'Change Parameter' window.
- To calculate the lower control limit, repeat the steps listed above. Use the target in-control mean and lower out-of-control mean. The lower control limit calculated by ANYGETH.exe will be a positive number. However, since the lower control limit must be non-positive, enter the negative of the number calculated. For example, if ANYGETH.exe calculates 13 for the lower control limit, enter –13 into the Force Tracker 'Change Parameters' window.

The following example shows how ANYGETH.exe is used to determine the upper and lower control limits for a CUSUM control chart for a Poisson process with an estimated mean equal to 5 and an out-of-control mean for an upward shift of 8. The average run length is 100.

```
h:\thesis\anygeth.exe
Program to calculate cusum decision intervals
Copyright 1997, D M Hawkins and D H Olwell
A run log will be written on file ZZRUNLOG.GTH
Which distribution do you want? (Give its number from this menu:)
        1     Normal location
        2     Normal variance
        3     Poisson
        4     Binomial
        5     Negative binomial
        6     Inv Gaussian mean
3
 Enter the in-control and out-of-control means
5 8
The exact theoretical reference value is        6.383
Enter the reference value you want to use
6
What are the Winsorizing constants?
(say -999 999 if you don't want to winsorize or don't understand the question)
-999 999
Do you want zero-start (say Z) or FIR (say F)?
z
Enter ARL
100
```

```
h:\thesis\anygeth.exe
        5     Negative binomial
        6     Inv Gaussian mean
3
 Enter the in-control and out-of-control means
5 8
The exact theoretical reference value is        6.383
Enter the reference value you want to use
6
What are the Winsorizing constants?
(say -999 999 if you don't want to winsorize or don't understand the question)
-999 999
Do you want zero-start (say Z) or FIR (say F)?
z
Enter ARL
100
h      9.0000 arls     145.9     135.9
h      7.0000 arls      66.6      61.1
h      8.0000 arls      99.1      89.2

k   6.0000 h  8.0000 ARL      99.11
           h  9.0000 ARL     145.86

DI      9.0000, in-control ARL      99.1, OOC ARL       5.1, FIR ARL       3.4
Would you like another run?
```

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