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Airborne particulate contamination effect on high voltage breakdowns during tube conditioning

Armida J. Carbajal

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**AIRBORNE PARTICULATE CONTAMINATION EFFECT ON
HIGH VOLTAGE BREAKDOWNS DURING TUBE
CONDITIONING**

BY

ARMIDA J. CARBAJAL

**B.S. BIOLOGY, UNIVERSITY OF NEW MEXICO, 2006
B.S. PSYCHOLOGY, UNIVERSITY OF NEW MEXICO, 2006**

THESIS

Submitted in Partial Fulfillment of the
Requirements for the Degree of

Master of Science

Statistics

The University of New Mexico
Albuquerque, New Mexico

May 2010

DEDICATION

“I can do all things through Christ, who strengthens me”

—Philippians 4:13

To my beloved brother--*Daniel the Great*

**I dedicate this thesis to you because you are my best friend, my greatest role model
and my greatest inspiration.**

ACKNOWLEDGMENTS

I would like to thank Curtis Storlie, my thesis advisor for his guidance, support, and undying patience throughout this research as well as, in reaching my other academic and career goals. I only have gratitude for Curt for always being very understanding and helpful during all the situations I faced during my education both in personal life events and obstacles within this research I was able to count on Curt. I feel very privileged to have been able to work with such a brilliant individual.

I would also like to thank Marnie LaNoue, for inspiring me to become a statistician and I am very grateful that she accepted to be a committee member. I learned everything I could from Marnie while studying quantitative analysis in the Psychology department at UNM. Marnie has an amazing ability to teach statistics so that it is relevant and applicable. Additionally, Marnie taught statistics with a deep ethical commitment to humanity emphasizing the importance of honesty in our research. These standards have benefited me as a statistician tremendously and it is the standard of my research.

A special thanks to Michele Guindani for being my thesis committee member on such a short notice. I am very grateful for Michele's amicable and positive personality. Michele has also reminded me that becoming a statistician is a lot more than attending classes and conducting your own personal research but how important it is to stay on top of the latest statistics research. His view has added an entire new facet to my role as a statistician.

I would like to thank Melecita Archuleta, the manager at SNL that procured funding for my research. A special thanks to Kate Bogart, for stepping in as my new manager and seeing this research through. Lastly, and most definitely not least a special thanks to my parents who have encouraged and kept me strong through all of my life's tribulations.

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ABSTRACT OF THESIS

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B.S., Biology, University of New Mexico, 2006

B.S., Psychology, University of New Mexico, 2006

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Abstract

In this research we examine high voltage breakdowns (HVBs) during neutron tube conditioning which has been a problem for decades. In the recent past there has been much debate on whether or not to procure a real-time airborne monitoring system for the commercial production of neutron tubes in order to determine the effect and calculate the impact of airborne particles. The main problem is, such monitoring system is costly, and with the exact causes of HVBs not being fully known, the expense must be justified.

The goal of this thesis was to analyze the instrumentation used in airborne particle monitoring in order to assert that the instruments were reliable in obtaining the data needed to make improvements. General reliability studies on the instruments were conducted followed by a quasi-experiment which led to the finding that airborne particulates have a measureable effect on external HVBs. This finding led to an observational study on the production floor which examines internal HVBs. An

exploratory analysis of the data obtained was conducted and preliminary results showed that the particles may influence the occurrence of internal HVBs in the tubes. As a result of this research the data justified the need to have a real-time airborne monitoring system in order to conduct further research and funding for the system was granted.

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Chapter I

Introduction

The goal of this thesis is to determine if airborne particulate contamination increases the likelihood of high voltage breakdowns (HVBs) in vacuum neutron generator tubes. Neutron tubes are a subcomponent of a neutron generator (NG) that produces neutrons. Neutron tubes are used in future commercial product design, development, lifecycle testing, as well as NG product production. Production yields can diminish unexpectedly and the causes need to be identified. Mathematical analyses are used to make data-driven decisions and maintain production capability and product yield (Galaviz, M., 2008).

The highest product yield loss is observed during the neutron tube conditioning sequence. This operation is near the end of the build sequence, and a yield loss this late is costly in both time and money. The leading cause of the loss is due to HVBs. The greatest challenge with HVBs during the conditioning sequence is determining why they occur. The vacuum sealed neutron tube is a small linear accelerator used as a neutron source, (Jing, S., Li, W., Gu, L. & Liu, L. 2000). In order to test the function of a vacuum sealed neutron tube it is necessary to apply a high voltage across the tube without breakdown. This form of testing confirms the tube's functionality, and it is simply referred to as functional testing via the method of conditioning. Some HVBs are expected, in fact, the intent of the conditioning sequence is to "clean up" the inside of the tube, which naturally results in HVBs (D. Lifke, personal communication, September 21, 2009). This is because during conditioning, current is shot across a tube and a particulate

or contaminant will attract the current causing a breakdown. Excessive HVBs are thought to be a product quality issue. If a tube has internal imperfections that are “cleaned up” during the conditioning sequence resulting in expected internal HVBs, and the tube also has additional HVBs from other causes, the tube would be rejected due to excessive HVBs (Lifke, D, 2009). Ultimately, it is the total count of HVBs that rejects a tube, regardless of the cause. Occasionally there are unexpected HVBs that can crack or puncture the tube, resulting in immediate tube rejection. For the purpose of this study, HVBs will be discussed in general terms as a negative occurrence since HVBs will only be related to non-conforming units which require re-work or were scrapped.

In 1981, during functional testing, T. K. Mehrhoff (1981) observed HVBs were a prevalent cause for rejection of neutron vacuum tubes. Thus HVB's have been a persistent primary cause of neutron tube loss. Therefore, the goal is to determine if airborne particulate contamination increases the likelihood of HVBs in vacuum neutron tubes.

It is known that the critical size in particulate contamination for the neutron tubes is between 5 to 10 microns. The plot of particulate types and sizes is shown in *figure 1*, and displays types of material that lie within this range. The type of particle is also of interest, i.e. insulator, conducting airborne particulates that generate or can hold a static charge are a heightened issue because as small particles increase in number they bind together. If the type of particulate contamination is known specific methods of intervention to prevent contamination of the neutron tube product can be taken.

As an example, production experienced a problem with salt contamination. A sudden increase in tube failures during the functional testing was observed during a

heavy snowfall winter. The tubes were sent for post-mortem analysis and particles of NaCl (salt) were identified within the tube assemblies. It was determined that the tubes that failed were assembled during these winter months when salt was used in the parking lots and sidewalks around the production facility to reduce slippery surfaces. When these two pieces of information were connected, the cause of tube loss was identified and the cause was salt contamination.

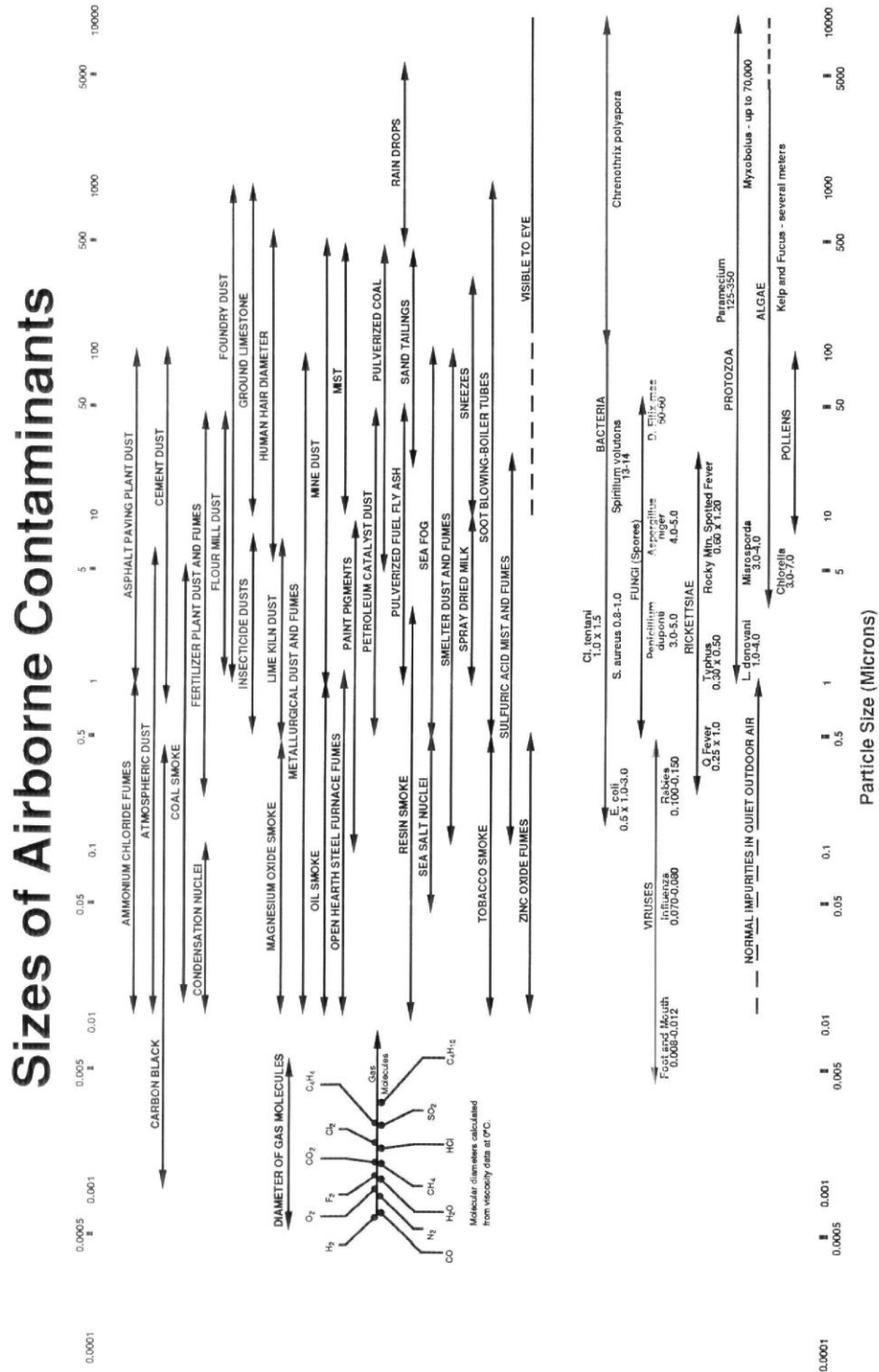
A major problem with particulate data is timely detection and identification of particulate contamination. The current process involves a weekly surface sample of several work areas, and a single point air sample of each room. The surface sample requires tedious visual inspection under a microscope where particulates are manually counted by an inspector and then an estimated amount is determined based on numerical assumptions. The data for the surface sample is then manually entered into a data base along with the single point air sample. The data can be collected as fast as 3 days after sampling but may take up to two weeks. The production floor then only has old data with which it must make reactive decisions about work stoppages.

No real-time airborne particulate monitoring is in place to determine the condition of work areas during production. The consequences from salt contamination were a significant yield loss. Therefore, neutron tube production concluded that a real-time air monitoring system was needed to provide the production engineers with the necessary data to halt production if high particulate concentrations were detected to prevent these events from happening again. The MET ONE Handheld Airborne Particle Counter (HHPC-6) was selected for its monitoring capabilities, 500 sample data buffer, ease of data downloads, and remote network capabilities to be used in developing the monitoring

system in the fall of 2007. Later, it was debated whether or not the proposed network was actually feasible.

A detailed background on neutron tubes, HVB's and particulate metrology are given in Chapter 2. Studies are conducted to determine the reliability of using the HHPC-6 in monitoring airborne particulate contamination that may lead to tube loss in Chapter 3. Studies are conducted to understand the effect of airborne particulates on external HVBs during conditioning in Chapter 4. Finally, in Chapter 5, a study is conducted to determine the effect of airborne particulates during piece part assembly of a neutron tube until the process of Conditioning. All of these components of this research resulted in important information about airborne particulate contamination effect on the neutron tube.

Figure 1, Particle Size Chart



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Chapter II

Problem Background

To better understand the neutron tube yield loss problem it is essential to understand the theory behind HVBs in vacuum sealed tube settings. It is also important to understand how particules are involved in HVB phenomena. In this chapter a review of the relevant literature is presented. The theory behind particulate metrology and behind the function and calibration of particle monitoring is reviewed in *Section 2.1*. Past studies involving vacuum-sealed tubes and HVBs within the neutron tube production center, as well as, in other facilities that produce vacuum sealed tubes are reviewed in *Section 2.2*. A schematic diagram of the neutron tube has been provided as a reference tool for the neutron tube problem discussion, *figure 2*.

2.1 Particulate Metrology

This thesis is based on the assumption that particulate contamination is most likely what causes tube failures during testing. Realistically, there are many factors involved in completely eliminating the tube loss due to HVBs. However, if particulate contamination is a contributing factor, then the model developed in this research will identify the particles as a function that increases the probability of HVB losses.

Clean room environments decrease particulate concentrations. However, clean rooms are expensive to build, launch and maintain. The production line is currently not all within a clean room environment and prior to investing in a real-time particulate monitoring system to alert production of high particulate rates, a relationship revealing the negative effect of particles on production must be found.

One of the purposes of this study is to determine if the particles being measured by the sensors used in airborne particulate contamination control could be reliable as the first line of detection. To make this determination the methods at which these devices collect the particulate data were evaluated, *Appendix A*.

A review of two past studies where discrete airborne particulate counters (DAPCs) were used in non-clean rooms was done in order to deduce how well the DAPC in this study would trend relationships. The review can be found in *Appendix B*, in summary the use of particulate count data in research reveals quantifiable relationships and reliable uses of particulate monitors. The literature furthers the potential for developing a model to identify the problem in neutron tube production and airborne particulate contamination.

The key findings in these studies showed that airborne particulate monitors can be used in non-clean-room settings and that DAPCs are a reliable source of detection even outdoors. In the study by Klepeis, N.E., Ott, W.R., and Switzer, P., (2007) smoke particles are found within the 0.02-2 micron range and the level of coincidence occurring in a non-clean room setting did not eliminate the instruments ability to characterize the smoke particulate behavior. Therefore, it is reasonable to assume that the use of the HHPC-6 in non-clean room areas will be a reliable method of monitoring. Additionally, the study at the LIGO facility using the Model 227 provided promising data for the purpose of cleaning an area and the HHPC-6 is from the same manufacturer and functions similar to the 227 model. These studies increase the confidence of the reliability of the HHPC-6 instrument used in this study. In Chapter 3, simple studies are conducted

to determine the reliability of the HHPC-6 for the use of particulate monitoring in neutron tube production floor.

2.2 Understanding High Voltage Breakdowns

The phenomena behind general high voltage breakdowns in vacuum sealed tubes will only be examined where particulates are the source of contamination. Understanding the various factors behind HVBs is beyond the scope of this research. At SNL, contamination is defined as anything that affects the form, fit, or function of the product of interest. Therefore, the interest is to quantify at what level particulates are considered contamination in the manufacturing of neutron tubes.

In a study on vacuum breakdowns conducted at SNL, [insulator] particles between 10 and 50 micron diameter were deliberately placed on the cathode (target) *see figure 2*, (Brainard, J.P &Reidel A.A., 1976). The cathode was bombarded for a short time period with ions generated from the [gap in voltage] and, these particles were found to induce a breakdown, (Brainard, J.P & Reidel, A.A., 1976). It was later generalized that particulates of size 5 microns or greater on the target surface caused HVBs of the [neutron tube], (Purson et al, LANL, 1996). A special glove box system was designed for the target loading phase which created a Class 10, (no more than ten *0.5 micron* particles per cubic foot), to prevent particulate contamination on the target (Purson et al, 1996). When NG production was relocated to SNL, the glove box system was placed in a clean room. This was a further improvement since it prevents particulate contamination prior to parts entering the glove box. Identifying the targets' sensitivity to particulates reduced HVBs caused specifically by particulate contamination on the target. With HVBs

continuing to be a prevalent issue, further investigation on the other tube assemblies is required and that is the goal of this research.

The manufacturing of the neutron tube does not take place in a clean environment as described above for the target loading process. Although, the production areas do have preventative contamination controls in place they are not of clean room grade. The amount of airborne contamination control varies among the areas. Following subassemblies in non-clean room areas; the product moves into a certified clean room where the tube is welded. Then the tube is moved to a lower level certified clean room where it becomes a vacuum sealed tube. After it is sealed preventative airborne contamination controls are no longer used. The tube goes to an area for what are considered to be dirty processes (i.e. the processes themselves produce high particle counts) and finally it is moved to functional testing for conditioning.

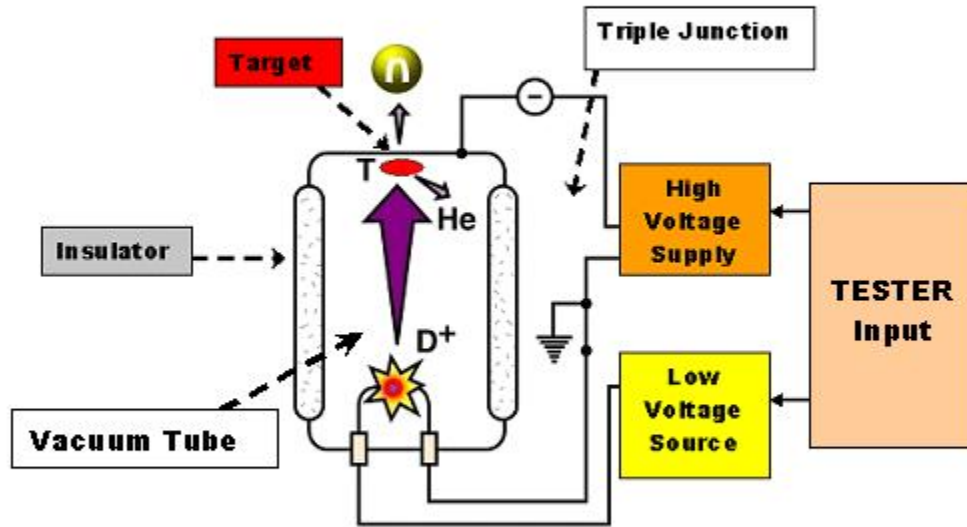
The functional testers used in the neutron tube conditioning process categorize breakdowns into two types, either internal high voltage breakdowns (IHVBs) or external high voltage breakdowns (EXHVBs). Mehrhoff (1981) examined three types of HVBs: the insulator wall, vacuum, and external. Insulator wall breakdowns occur along the high voltage insulator and it was found that this type of breakdown originates at the “triple junction” area where the cathode meets the insulator vacuum side, *figure 2*. The vacuum breakdown was defined as occurring through the tube but not touching the insulator. An external high voltage breakdown occurs on the external side of the tube (Mehrhoff, 1981). The difference between an IHVB and EXHVB is signaled by the tester during conditioning as “light and sound.” If the tester “sees” light, and detects “sound” it means

the HVB happened externally. This is meant literally; since the tester has sensors that see light and detect sound. These occurrences indicate an EXHVB occurred.

In *Appendix C*, HVBS in SF₆ gas vacuum system applications by Maller, V.N. & Naidu, M.S., (1981) are reviewed as an example of the different ways that particles present HVB problems in practical applications. Additionally, a study Brainard and Reidel (1976) conducted on dielectric particles including salt is reviewed as background for the research done in this thesis.

In Chapter I, the salt contamination in neutron tube production resulted in significant losses was discussed. The HVBS increased during that season both internally and externally, despite special precautions taken with the target. Further steps need to be taken to determine where other contamination vulnerabilities exist. Particulate counters can be used to identify the presence of contaminants effectively by a non-destructive method.

Figure 2, Schematic Diagram of a Neutron Generator



This figure was adapted from an illustration provided by Lifke, D. (2009) and modified with information found in Mehrhoff, T.K. (1981).

Chapter III

Implementing Statistical Process Control in Neutron Tube Production

In this chapter preliminary experiments were used to determine the ability of the HHPC-6 to perform airborne particulate monitoring for the needs of the production floor (ANNEX). Trial baselines were developed for the rooms in the ANNEX in order to implement the multivariate T^2 - control chart. The T^2 -chart is useful in implementing statistical process control (SPC). When there are multiple correlated data sources such as particulate counts, SPC helps identify shifts in the process. This in turn can help us understand the relationship between HVBs and particle counts.

3.1 Reliability of Airborne Particulate Monitor Instrumentation

As discussed briefly in Chapter 1, there was some apprehension in regards to the reliability of instruments selected for particulate monitoring in the ANNEX. The concern was based on how well the particulate counters (DAPC) tracked particles that would actually affect the product. The concern stemmed from the large amount of variation in particle counts when multiple DAPCs sampled a single location. Therefore, the ANNEX community assumed that one DAPC per area was not sufficient. However, due to limited funds, there was only one DAPC per room. Before the study could use the HHPC-6 as the instrument to track particulate effects, we needed to determine how much measurement variability existed within the DAPC.

In ASTM (2001) Designation: F 649-01 a secondary method for calibrating a DAPC was described using a comparison procedure. The idea is to use one DAPC under test and another DAPC as a reference. The reference DAPC is calibrated in accordance

with ASTM (2003), discussed in *Appendix A*. The secondary calibration method in ASTM (2001) uses an aerosol chamber, *figure 3*, prepared by attaching a blower to one end of the chamber and a filtered air supply line is placed in the center of the chamber so that it exhausts and mixes with the air from the blower. At the other end of the chamber the inlet line of plastic tubing would be attached to the inlet of the two DAPCs. The sample tubes inside of the chamber are placed as close together as possible so that a nearly identical sample can be obtained.

In this experiment the purpose of using the secondary calibration method in ASTM (2001) is not to calibrate, but to determine if multiple instruments are needed for a single room. The premise behind the secondary method of calibration is a comparison study of two DAPCs and a single sample of air. This can be used to determine if DAPCs truly vary in collecting a single sample of air, by showing that the DAPCs are statistically collecting the same information even though visually (i.e. on the DAPC display screen) the air sample reading is different, see display in *figure 4*. This experiment was a “proof of concept” pilot study using the procedure in ASTM (2001) as a very general guideline to test the hypothesis.

The following DAPCs were available for use to replicate the procedure: a HHPC-6 used often for demonstrations, usually not in a clean environment would play the role of the test DAPC. Another HHPC-6 that was considered to be close to new was available to be used as the reference DAPC. Both of the instruments were purchased simultaneously, and had the same calibration expiration dates. The only difference was the amount of usage each instrument underwent. It would have been preferred to have a

reference instrument that had a recent calibration, and was only used for the purpose of secondary calibration; however, this was not possible.

A simple linear regression analysis on the instruments for each particulate size was selected to test the significance of the relationship between the instruments. The R^2 was used to measure the variability and agreement between the two instruments since R^2 takes into account the paired nature of the experiment. The residuals were expected to be correlated, if the DAPCs were collecting a similar air sample. Six plots of the raw data with Test DAPC vs Reference DAPC were used to display this relationship.

One of the limitations of the study was that it would not be controlled by an air chamber as in ASTM (2001) and even though the nearly new instrument is the reference DAPC, it does not meet the specifications described in ASTM (2003) since it had not been recently calibrated. In general, the pilot study will capture the needed result. The data obtained from the reference particle counter and the test particle counter is to be no more than twice the variance anticipated in order to conclude the instruments are the same. The expected variance is $\pm 15\%$ for the smallest size range ($x_1=0.5-0.7\mu$) and ± 20 to 30% for the other particles sizes (ASTM, 2001). The instruments can be considered to be measuring air particle samples differently if the instrument variation is within the range of $\pm 40\%$ or greater. However, small sample count (<1000 particles) resulting from short sample times (i.e. 1 minute collection), will result in wide differences between measurements and the data will be outside of the limit and fall two [or more] standard deviations [away from] the mean 95% of the time (ASTM, 2001).

3.1.1 Experiment 1: Pilot Study for Instrument Variation

Method

Particle Data

Data were collected from two Met One HHPC-6 Handheld Airborne Particle Counters. The counters record date, time, counts, sample labels, volume, alarm flags, temperature and relative humidity. The counts include six sizes of particulates labeled as $x_1 = (0.5-0.7\mu)$, $x_2 = (0.7-1\mu)$, $x_3 = (1-2\mu)$, $x_4 = (2-5\mu)$, $x_5 = (5-10\mu)$, and $x_6 = (>10\mu)$. The HHPC-6 count mode was placed on “Totalize” which is the particle count as it accumulates during the sample period. The sample period was set for 1 minute which is equivalent to collecting 0.1 cubic foot of sampled air. The delay timer of the counters was set to collect a sample every 9 minutes. The data is easily obtained after the experiment is completed using the HHPC-6 Utility software which allows the user to download the data onto a computer.

Materials and Apparatus

In addition to the HHPC-6's, Tygon tubing, an Enviroco clean air flow lab bench, a polypropylene male T-pipe fitting and a flask clamp were used. Two pieces of plastic tubing placed on one end to fit the “Hose Barb Fitting” of the HHPC-6, *figure 4*. The other end was attached to an arm of the T pipe fitting. A final long piece of the Tygon tubing was attached to the long end of the T pipe fitting and was clamped at the top of the lab flow bench, *figure 6*.

Design and Procedure

This apparatus was configured under the design idea described by ASTM (2001). Two HHPC-6 instruments were selected for this experiment. The instrument settings

were manually set as described in the *Particle Data* section and placed inside the flow bench. The Tygon tubing was attached to each instrument through the T-pipe fitting and then clamped as stated in the *Apparatus section* and illustrated in, *figure 5*.

The clean flow lab bench was then turned on during the data collection to reduce the probability of problems with coincidence since no chamber was constructed. The particle counters were started simultaneously. The particle counters were left collecting samples over a weekend, Friday, Saturday, Sunday, and stopped on Monday. Once the data was collected the instruments were stopped and the data was downloaded using the HHPC-6 Utility software. A total of 418 air samples were collected during the experiment period.

Results

A simple linear regression analysis was conducted for each count size which were labeled, $x_1 \dots x_6$, where x_1 is the smallest particulate size range and x_6 is the largest particulate size range using R software. After the experiment was completed, it was discovered that the test DAPC and the reference DAPC were not labeled. In the experiment design drawings only the numbers 1 and 2 were recorded, but a serial number which uniquely identifies each instrument was not recorded. For simplicity purposes, the instrument data was labeled as I1 for instrument 1 and I2 for instrument 2. Although the lack of tracking the DAPCs created a labeling drawback because we no longer knew which was the test or reference DAPC; for the purpose of the analysis the results could still be obtained since the regression analysis output would still show if one DAPC significantly predicts the other regardless of order. Additionally, the analysis would also show the explained variability of the test DAPC for reference DAPC or vice versa.

There was no pre-set α level. The regressions were used to test for any level of significance. I1 significantly predicted I2 particulate counts for all of the particulate sizes, *table 1*, with p -values $< .05$, however this was not the statistic of interest. We used the regression analysis to obtain R^2 values. I1 explained a significant proportion of the variance of I2 for particle groups x1 through x3, *see Adjusted R^2 values in table 1*. Normally, a $R^2=0.90$ or better would indicate good agreement between the devices. However, in accordance with ASTM (2003) a $R^2=0.85$ shows that this is within the expected variance and it can be concluded that the instruments are the same for x1. In this study x1 $R^2=0.9087$, therefore the instruments had good agreement. For x2 $R^2=0.7437$, this acceptable in accordance with ASTM (2003) which states that for particle sizes x2 to x6 a $R^2=0.80-0.70$ is the expected agreement between instruments for these size ranges. Therefore, x2 with a $R^2=0.7109$ was within the acceptable limit to consider the instrument reading to be equivalent.

In accordance with ASTM (2003) an instrument with a $R^2=0.60$ or less is considered to be different. Although, x4, x5 and x6 did not have significant R^2 values, it cannot be confirmed that the instruments did not have good agreement. This is because the number of particles obtained in each sampling period were all <1000 particles for all sizes. According to the ASTM (2003), small sample counts will result in wide differences 95% of the time. For x4 the highest particle count obtained in a sample of air was 60, for x5 the largest sample particle count was 5, and for x6, the largest particle count obtained in a sampling period was 1. These small air samples did not provide the data needed to make a conclusion. Without a method to pump a unified controlled air sample to get the air readings needed, this data could not be obtained. However, it was concluded that I1

significantly predicted I2, for x1, x2, and x3 and it was determined that this was enough information to reject the null hypothesis that more than one instrument is needed per area.

To check for non-linear relationship between the independent variables, fitted line plots for each regression was evaluated, *figure 6*. The linearity between the instruments begins to degrade as the particulate size increases. This was also observed by the *Adjusted R²* values, as the proportion of explained variability of I2 by I1 progressively decreased as particulate size increased.

3.1.2 Experiment 2: Calibration Study

Additional Analyses

The assumption that more than one DAPC per area was rejected since I1 generally predicted the particulate count for I2. When the pilot study was conducted, the calibration due dates were approximately two months away. This spiked interest in the amount of drift that occurs among instruments during their calibration periods. The manufacturer recommends one year maximum between calibrations. However, since calibration and maintenance can be costly, it was desirable to potentially extend the calibration period beyond a year.

The experiment was repeated for the instruments the day after calibration occurred. Although it was the intent to repeat the study during the Friday start, Monday end time frame, unexpected delays in stopping the experiment occurred. The instruments have a “rotating buffer,” meaning that once the 500 sample buffer is full, the instrument continues to run, but when a new sample is made, the first record stored in the memory buffer is deleted and the new entry is added to the end of the memory buffer. Therefore, this data set took place Saturday night (9:22 PM) until Tuesday morning (8:32 AM). A

total of 499 air samples were collected however, the data were affected by the personnel traffic in the laboratory where the experiment was conducted. The largest particulate size, x had wide variation between instruments. The high variation in large particles was most likely because of personnel presence; making it difficult for the DAPCs to collect a homogenous sample without a controlled air chamber.

Additionally, the same problem with low particle counts obtained during the sampling period was encountered. All of the groups obtained particle counts that were <1000 . For x_1 the maximum particle sample collected during a sampling period was 943, for x_2 the $\text{max}=134$, x_3 $\text{max}=89$, x_4 $\text{max}=50$, x_5 $\text{max}=4$ and for x_6 the $\text{max}=2$. Therefore, the R^2 values were affected by the small sampling periods and wide variation was expected.

The simple linear regressions were repeated for the six particulate sizes given by I1 and I2 after calibration. After calibration I1 explained a significant proportion of the variance in I2 only for x_1 and x_2 , *table 2*. However, the *Adjusted R^2* increased for particulate sizes x_1 , x_2 , x_4 , and x_5 showing greater agreement. The *Adjusted R^2* slightly decreased in x_3 but considering the low particle count obtained during sampling, it was considered to still explain a significant proportion of the variance between the instruments. The R^2 values for x_3 , x_4 , and x_5 were not considered to demonstrate good agreement between the devices since they all had R^2 values <0.70 . However, considering their low particle counts during the sampling periods, the increase in R^2 values was considered to be notable, and it was concluded that instrument agreement improves substantially after calibration. The variance explained by I1 for I2 was not significant in x_6 ; clearly having close to nonexistent air samples affected the relationship.

To check for a non-linear relationship between the independent variables, fitted line plots for each regression were evaluated, *figure 7*. The linearity between the instruments did not degrade as rapidly as the particulate sizes increased after calibration, unlike the first experiment. The general trend however did follow, so as particle size increases the instruments variation begins to broaden and lose linearity. This was also observed by the *Adjusted R²* values decreasing as particle size increases.

From this study, we could not truly validate the need for only one monitor per room however, it was concluded that the data that was collected was sufficient to make the decision. From the study, we did get an idea of the measurement error involved in these devices and without a budget to do further validation testing these results were considered acceptable. However, it concluded that annual calibration was necessary in order to reduce instrument drift and decrease sample variability. The calibration period could not be extended. In fact, as found by Peacock et al. (1986) discussed in *Appendix A*, the most consistent data is obtained when using a 6 month calibration period. However, since the data is needed for general trending purposes, a strict level of precision would only result in unnecessary calibration costs.

3.2 Implementing Multivariate Control Charts

Control charts identify occurrences of special causes of variation that come from outside the usual process (Johnson, J.A. & Wichern, D.W., 2007). Johnson and Wichern (2007), suggest that control charts make the variation visible and allow one to distinguish common from special causes of variation. A major objective of statistical process control is to quickly detect the occurrence of special cause variation so that an investigation of

the process and corrective action may be conducted prior to manufacturing nonconforming units.

Typical control charts are usually Univariate control charts, where data is plotted in time order and horizontal lines, called control limits indicate the amount of variation due to common causes (Johnson & Wichern, 2007). Although, the univariate control chart is very useful, there are six particulate sizes we are trying to see. Therefore, six univariate charts would be needed to oversee the data. Additionally, the airborne data uploaded from the HHPC-6 may be carrying one or more important characteristic that would be difficult to analyze from six univariate charts. Furthermore, the particulates of each size are highly correlated. High correlations among variables can make it impossible to assess the overall error rate that is implied by a large number of univariate charts (Johnson & Wichern, 2007).

3.2.1 T^2 -Chart

The implementation of the multivariate T^2 -chart control chart would be economically the right thing to do for continuous monitoring. A T^2 -chart can be applied to a large number of characteristics and the points are displayed in time order making the patterns and trends visible (Johnson & Wichern, 2007). The multivariate control procedure in this case is used for multivariate observations $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$. We assume that $\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_n$ are independently distributed as a multivariate normal with $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

To set control set control limits, we approximate that $(\mathbf{X}_j - \bar{\mathbf{X}})' \mathbf{S}^{-1} (\mathbf{X}_j - \bar{\mathbf{X}})$ has a chi-square distribution, (Johnson & Wichern, 2007).

For the j th point, we calculate the T_j^2 -statistic

$$T_j^2 = (\mathbf{x}_j - \bar{\mathbf{x}})' \mathbf{S}^{-1} (\mathbf{x}_j - \bar{\mathbf{x}})$$

We then plot the T^2 -values on the time axis. The lower control limit is zero and typically the upper control limit

$$\text{UCL} = \chi_p^2(.05) \text{ or, sometimes, } \chi_p^2(.01).$$

There is no centerline in the T^2 -chart. As an example of constructing the T^2 -chart that can be used to implement statistical process control into the ANNEX production floor the six particulate sizes can be used as the variables. The six variables are defined as,

X_1 = number of particles of size 0.5-0.7 μ ,

X_2 = number of particles of size 0.7-1 μ ,

X_3 = number of particles of size 1-2 μ ,

X_4 = number of particles of size 2-5 μ ,

X_5 = number of particles of size 5-10 μ ,

X_6 = number of particles of size >10 μ ,

where μ = microns. The trial baseline data for $\bar{\mathbf{X}}$ was obtained using the collection period from May 31, 2008 to June 13, 2008 for all of the areas. This trial baseline was selected because this was the trial baseline for conditioning which is the content of Chapter 4. While the control chart is not discussed in Chapter 4, the control charting was used to make a decision to conduct the study in Conditioning and the trial baseline was selected because during that two week period there were no notable product failures. Additionally, it seemed to be a good trial baseline for room A.

A function was written in MATLAB to create the multivariate T^2 -chart. The particulate data is naturally skewed right as seen in, *figure 8*. The T^2 -chart is based on the

chi-square distribution which is only valid if X_1, \dots, X_6 have a normal distribution.

Therefore the $\log(X_i+0.01)$ was used to transform the data. The 0.01 was added to all of the values prior to taking the log because the particulate samples obtained can equal zero.

The following limits were placed on the chart in *figure 9*

$$UCL = \chi_6^2(.997) = 19.80$$

$$2\sigma = \chi_6^2(.95) = 12.59$$

$$\sigma = \chi_6^2(.67) = 6.90$$

The T^2 -plot can then be used to analyze incoming data points as they are obtained, as an example of how the T^2 -chart is analyzed, room A of the ANNEX will be examined for the trends that can be seen using multivariate control charting. The period of June 19, 2009 to July 6, 2009, was used in order to go over various notable events detected by the control chart. For example *figure 9*, displays room A in control. The x-axis is currently the observation number, since the actual label is a time and date. To keep the charts neat, the time and date was not used as a label. Therefore the title gives the time periods being viewed.

The ANNEX is not a clean room, and although it contains some rooms that have airborne particle contamination control, room A does not. Therefore, the rooms in the ANNEX can be affected by the outdoor activities that occur around the building. The following discussion is of a paving event that resulted in alarms with a notable pattern, *figure 10*. On June 22 9:54AM, (tab X:13 in figure), paving events began, although the start application of laying the asphalt did not alarm, the alarm occurred at 12:54PM (tab X:15) which is when the second application of the asphalt occurred. This repeated on

June 23 at the exact same times (tabs X:36 & X:39). On June 24th however, the giant spike (tab X:57) was a false alarm. This point alarmed because the particles were notably lower than expected therefore they were very different from the data resulting a high T^2 -score. However, the following (tab X:60) marks 9:54AM. Then no alarm occurred at the expected 12:54PM, but shortly after a high point was seen at 1:54PM (tab X:64).

Although it did not alarm, it had a higher score than observations not occurring during the paving activities. We see the control chart goes back into control each time the paving ceases and the peaks repeated on June 25th which marked the final day of paving with two peaks at 9:54AM and 12:54PM (tabs X:84 & X:87).

In *figure 11*, we see room A go out of control again. This time the event that caused the chart to spike occurred indoors. Prior to discussing those peaks, we can note that room A was in control after the paving ceased, until June 28th at 12:54AM (tab X:50), which can be neglected since it was a false alarm due to particulate counts being lower than normal. Then on June 29th (tab X82), we have another alarm however the cause was unknown. The notable events occurred on July 1st and 2nd during an electrical audit. At 9:54AM and 10:54AM (tabs X:130 & X:131), the auditors were examining electrical equipment in room A, this involved a process which included opening panels of equipment which had not been open in several years and releasing dust particles. In addition, there were more people than normal generating particles in room A during this time. We see the particles drop which it is reasonable this was due to their lunch break and start back up again at the 12:54PM (tab X:135) reading. This same event was repeated on July 2nd, except the first spike occurred at 8:54AM. Some tabs were excluded for July 2nd to keep the chart looking neat. Once the electrical audit ceased the room went

back into control. There was one more alarm on July 3rd 3:54PM (tab X:185), however, this was another false alarm due to lower particles than normal.

Finally, in *figure 12*, we see things return back to normal, however, there is one notable event that occurs that creates quite the spike. On July 4th at 9:54PM (tab 24), we see that room A went out of control. This event was caused by the firework particles entering the building through the ventilation system. A hump that did not alarm after the firework peak is seen, and this is most likely residual firework particles. Then the control chart for room A returns back to normal. The T^2 -chart control chart is a very effective method for identifying trends for rooms in the ANNEX. The only false alarm generated by the T^2 -chart, is when particles are very low and therefore their score differ significantly from the mean, giving these times high T^2 -scores. However, with examination of the raw data, it is quickly known that there is no actual concern.

Figure 3, Chamber

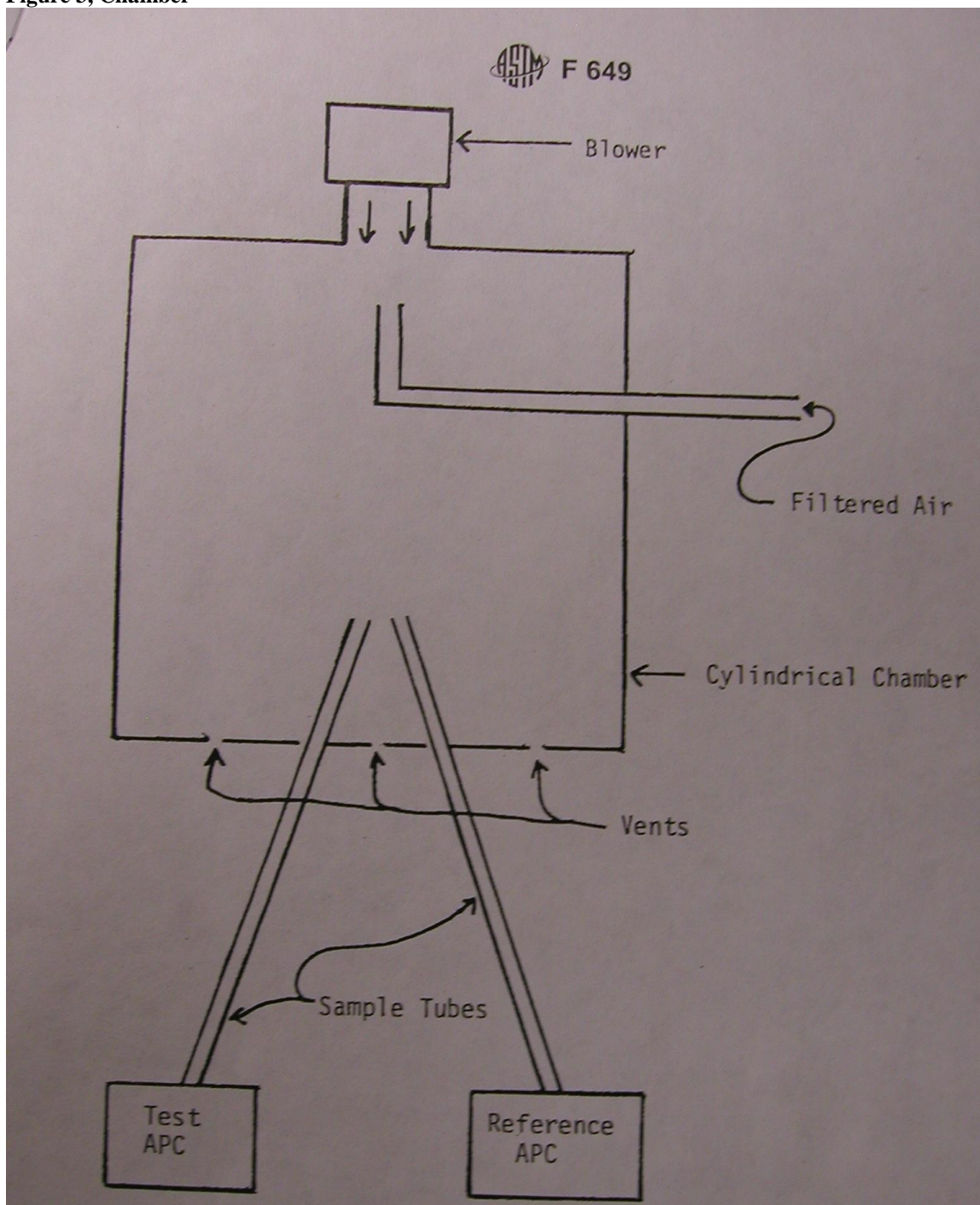
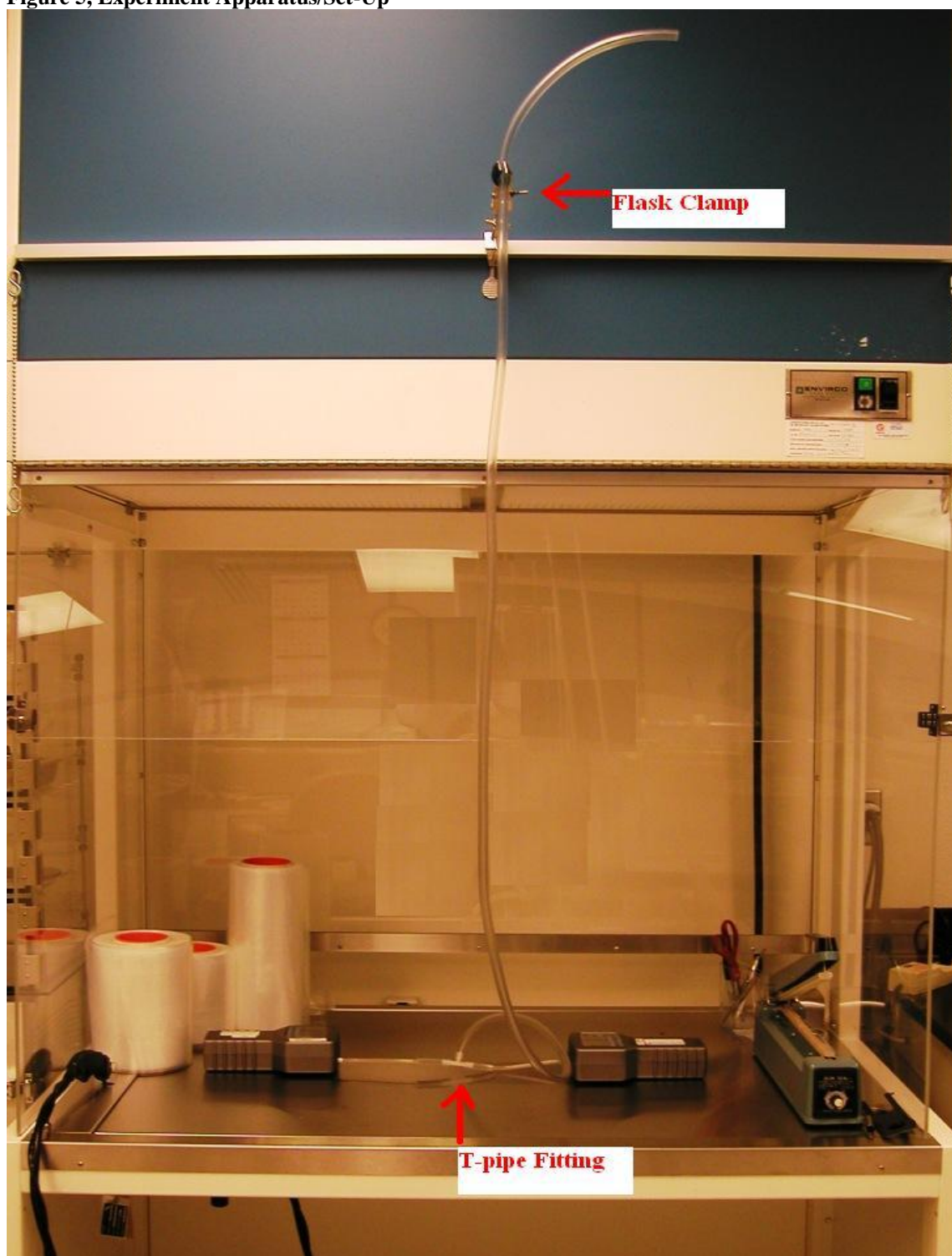


Figure 4, Hose Barb Fitting



Figure 5, Experiment Apparatus/Set-Up



***Note:** The HHPC-6's were lying flat in order to allow for an even sample to enter each DAPC.

Figure 6, Pilot Study Fitted Line

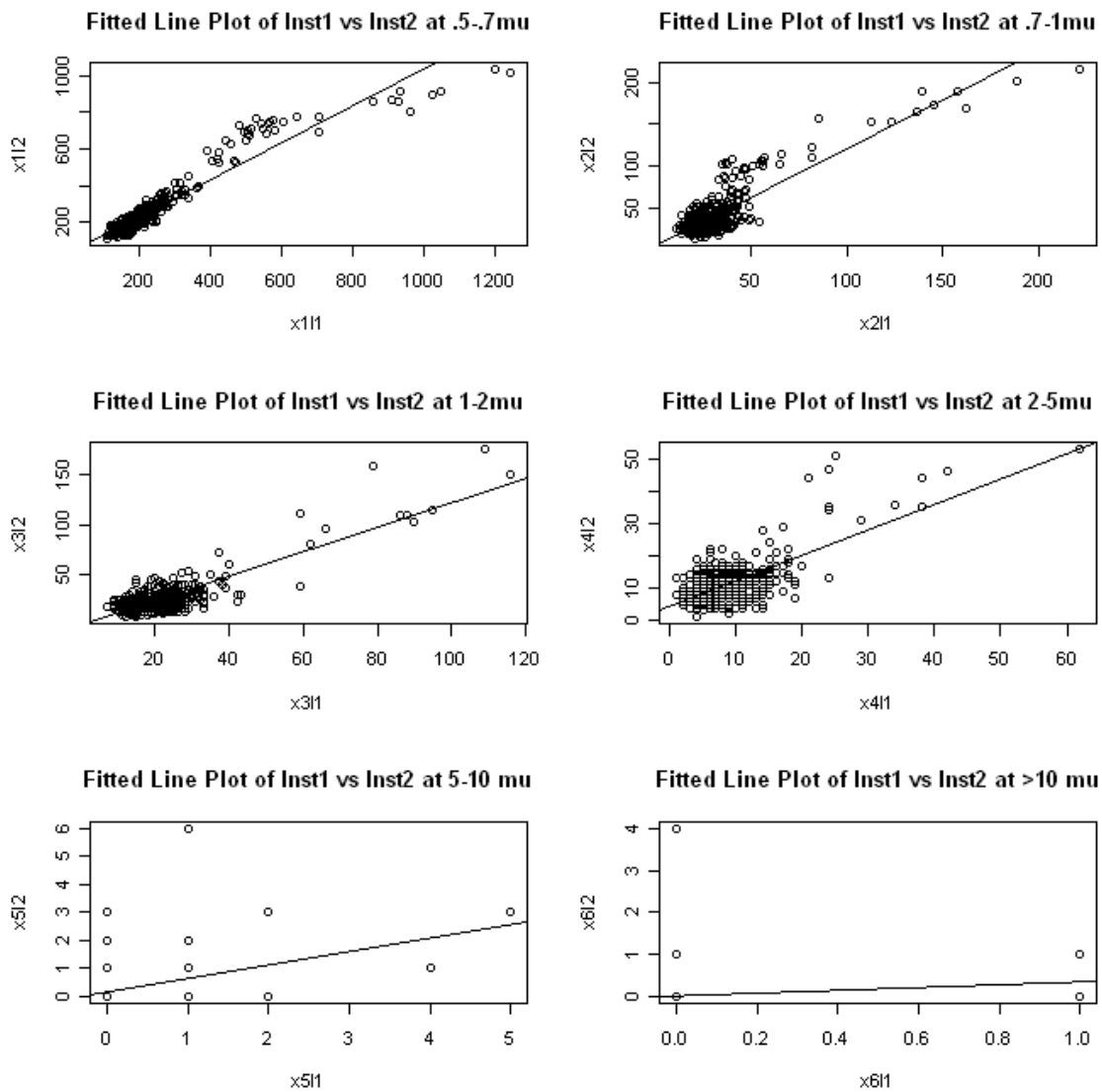


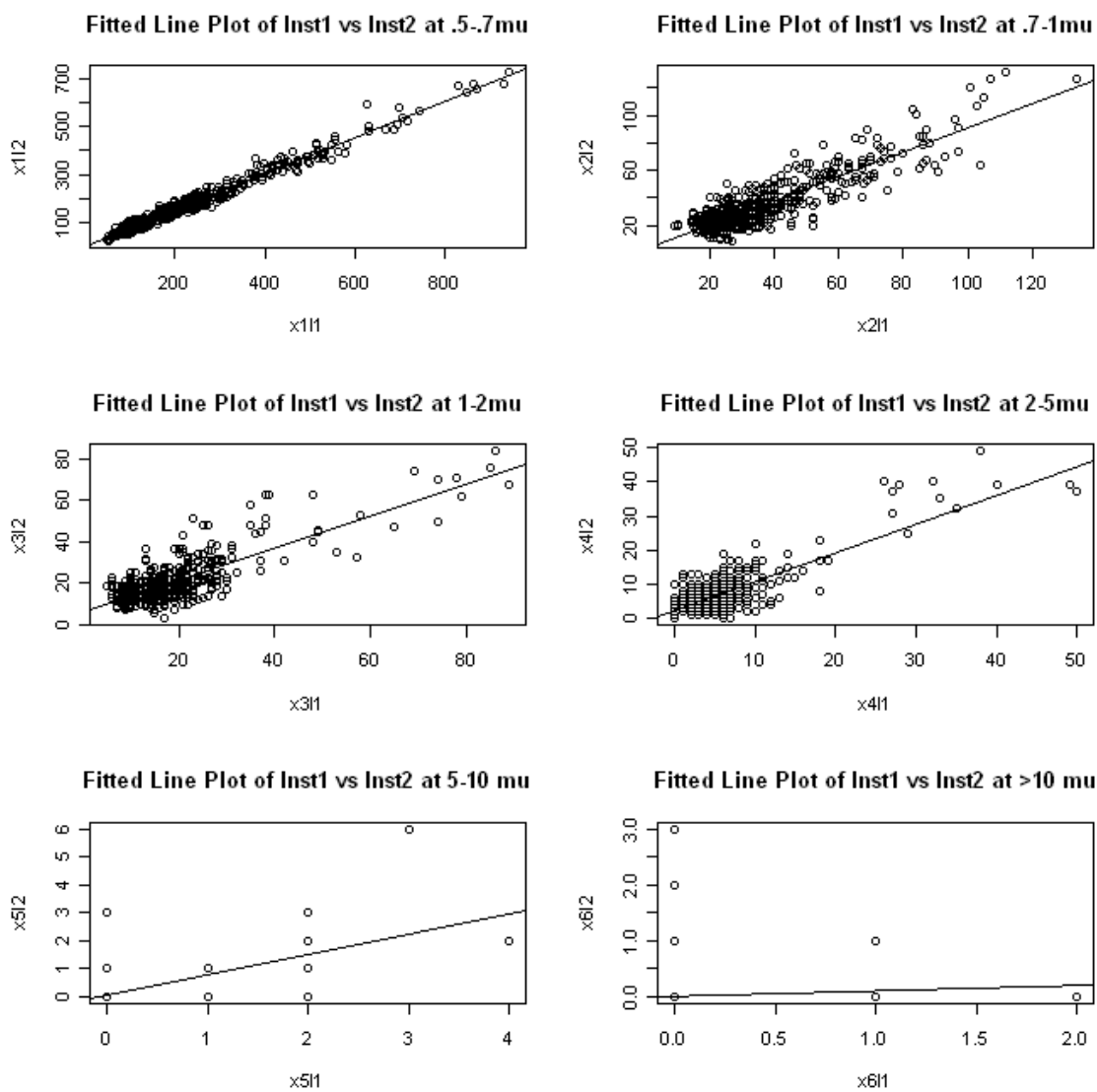
Figure 7, Repeat of Experiment 1: Fitted Linear Plots After Calibration

Figure 8, Particulate Data Skedness

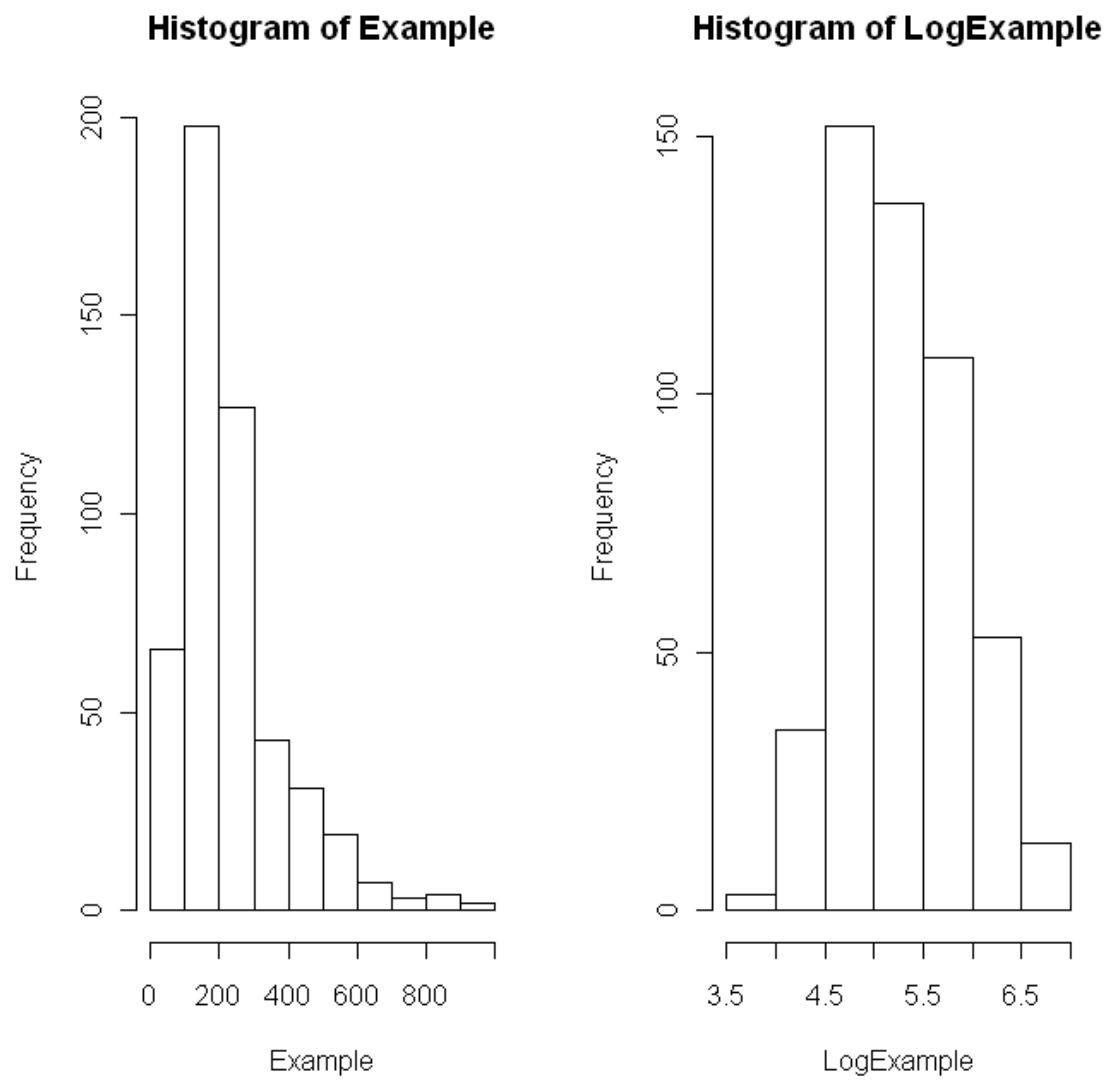


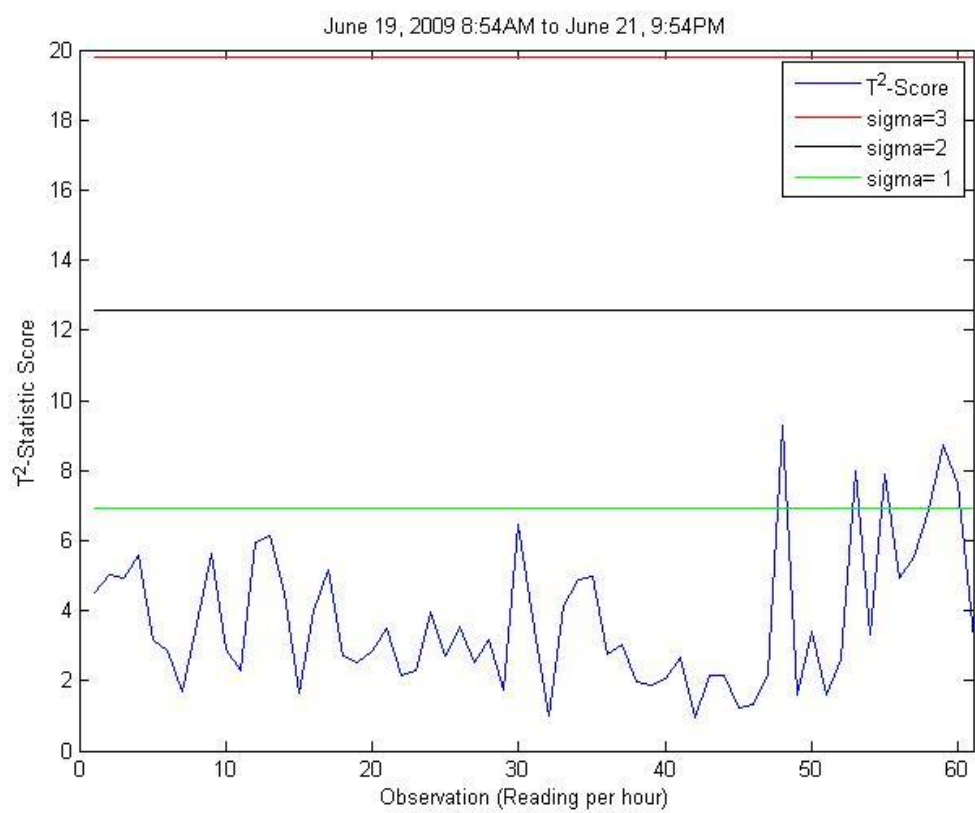
Figure 9, T2-Chart of Area A in Control

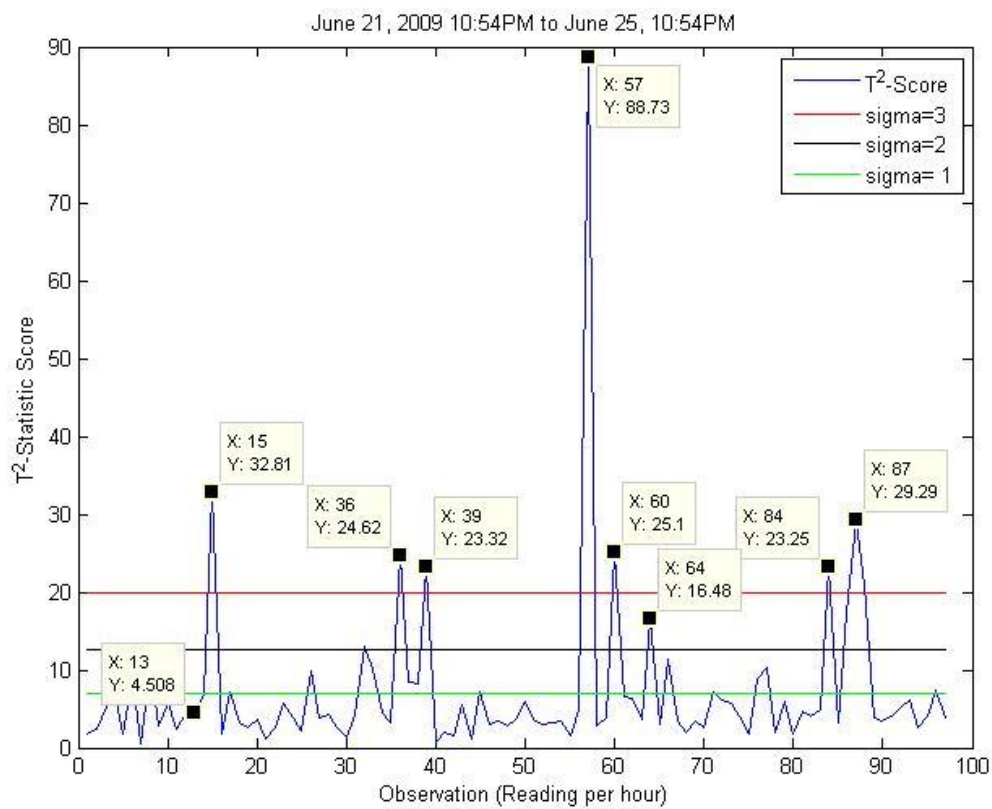
Figure 10, Area A: Out of Control due to Paving Events

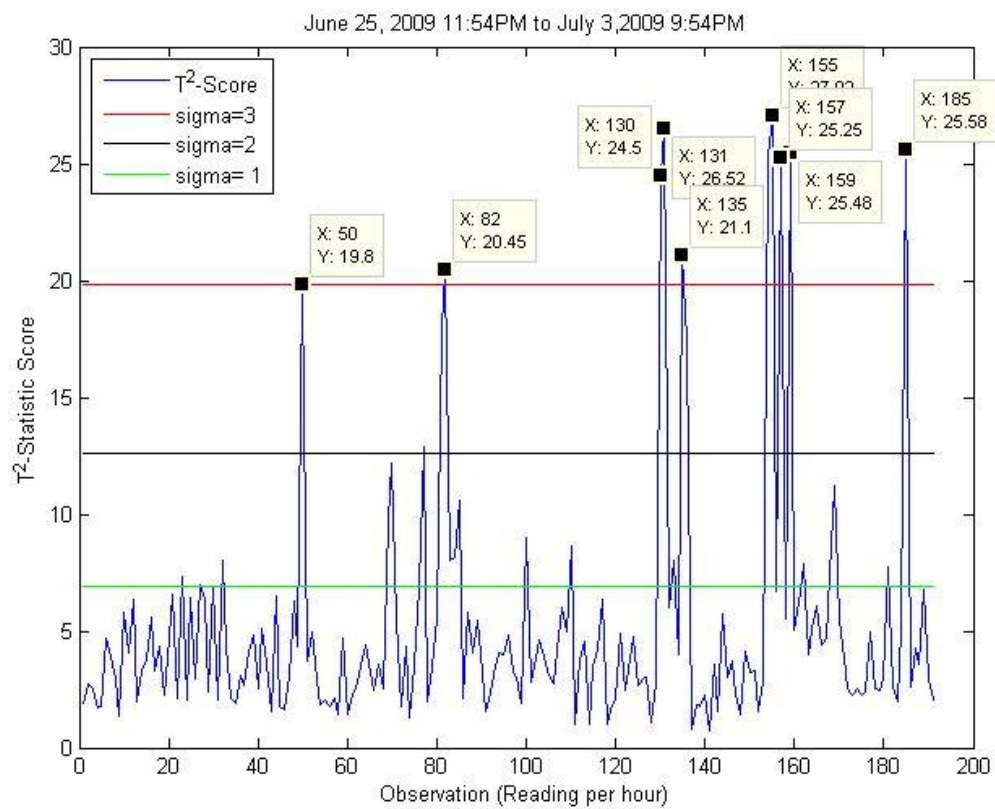
Figure 11, Area A, Out of Control due to Electrical Audit

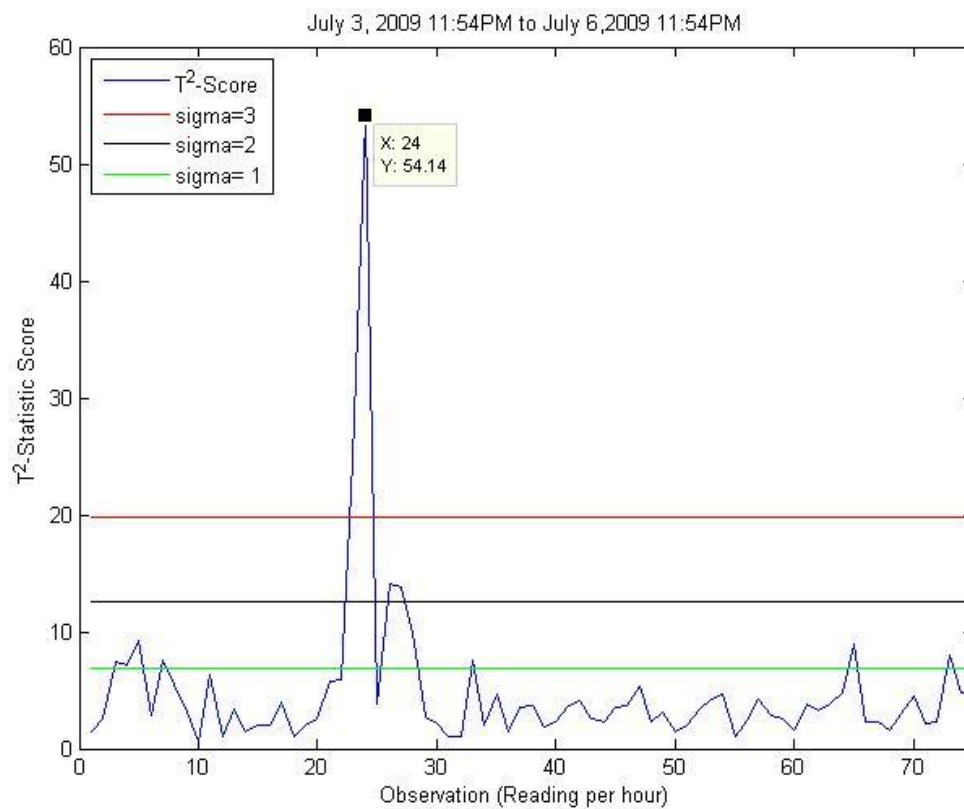
Figure 12, Area A in Control except for July 4th Firework Alarm

Table 1, Regression Results for Pilot Study Experiment

Regression Results $\text{lm}(\text{formula} = \text{xiI2} \sim \text{xiI1})$ where $\text{xi}=(\text{x1} \dots \text{x6})$ for particulate sizes
 Degrees of freedom: $t(416)$, $F(1,416)$

| Coefficients: | Estimate | Std. Erro | t-value | Pr(> t) | Adj. R-squared | F-statistic | p-value |
|----------------------|-----------------|------------------|----------------|--------------------|-----------------------|--------------------|----------------|
| Intercept | 28.3076 | 4.2867 | 6.604 | 1.23e-10 *** | | | |
| x1I1 | 1.01086 | 0.01569 | 64.423 | < 2e-16 *** | | | |
| Total | | 49.15 | | | 0.9087 | 4150 | < 2.2e-16 |
| Intercept | 4.8375 | 1.28133 | 3.775 | 0.000183 *** | | | |
| x2I1 | 1.16294 | 0.03342 | 34.802 | < 2e-16 *** | | | |
| Total | | 14.47 | | | 0.7437 | 1211 | < 2.2e-16 |
| Intercept | -0.2431 | 0.94696 | -0.257 | 0.798 | | | |
| x3I1 | 1.21866 | 0.03804 | 32.04 | <2e-16 *** | | | |
| Total | | 9.503 | | | 0.7109 | 1027 | < 2.2e-16 |
| Intercept | 4.38706 | 0.45285 | 9.688 | <2e-16 *** | | | |
| x4I1 | 0.78872 | 0.04148 | 19.014 | <2e-16 *** | | | |
| Total | | 4.747 | | | 0.4637 | 361.5 | < 2.2e-16 |
| Intercept | 0.16336 | 0.02624 | 6.226 | 1.17e-09 *** | | | |
| x5I1 | 0.47885 | 0.06278 | 7.627 | 1.65e-13 *** | | | |
| Total | | 0.5242 | | | 0.1206 | 58.18 | 1.65E-13 |
| Intercept | 0.01687 | 0.01064 | 1.585 | 0.1137 | | | |
| x6I1 | 0.31647 | 0.12561 | 2.519 | 0.0121 * | | | |
| Total | | 0.2168 | | | 0.01266 | 6.348 | 0.01213 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2, Regression Result for Experiment After Calibration

Regression Results $\text{lm}(\text{formula} = \text{xiI2} \sim \text{xiI1})$ where $\text{xi}=(\text{x1} \dots \text{x6})$ for particulate sizes
 Degrees of freedom: $t(498)$, $F(1,498)$

| Coefficients: Estimate Std. Error t-value Pr(> t) Adj. R-sq F-statistic p-value | | | | | | | |
|--|---------|---------|---------|---------|-----|---------|--------------------|
| Intercept | 6.13753 | 1.4597 | 4.205 | 3.1e-05 | *** | | |
| x1I1 | 0.7495 | 0.00527 | 142.175 | < 2e-16 | *** | | |
| Total | | 18.01 | | | | 0.9759 | 2.02E+04 < 2.2e-16 |
| Intercept | 2.6458 | 0.90824 | 2.913 | 0.00374 | ** | | |
| x2I1 | 0.88518 | 0.02173 | 40.74 | < 2e-16 | *** | | |
| Total | | 9.326 | | | | 0.7687 | 1660 < 2.2e-16 |
| Intercept | 6.1074 | 0.57371 | 10.64 | < 2e-16 | *** | | |
| x3I1 | 0.77692 | 0.02649 | 29.32 | < 2e-16 | *** | | |
| Total | | 6.515 | | | | 0.6325 | 859.9 < 2.2e-16 |
| Intercept | 2.3305 | 0.22675 | 10.28 | < 2e-16 | *** | | |
| x4I1 | 0.83809 | 0.02877 | 29.13 | < 2e-16 | *** | | |
| Total | | 3.632 | | | | 0.6295 | 848.8 < 2.2e-16 |
| Intercept | 0.02389 | 0.01435 | 1.664 | 0.0967 | . | | |
| x5I1 | 0.72893 | 0.03757 | 19.403 | < 2e-16 | *** | | |
| Total | | 0.3162 | | | | 0.4294 | 376.5 < 2.2e-16 |
| Intercept | 0.0146 | 0.00801 | 1.824 | 0.0687 | . | | |
| x6I1 | 0.09975 | 0.05967 | 1.672 | 0.0952 | . | | |
| Total | | 0.178 | | | | 0.00358 | 2.795 0.0952 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Chapter IV

External HVBs during neutron tube Conditioning

The main problem considered in this chapter is high voltage breakdowns that had been occurring during neutron tube conditioning. The task was to link the production data to particulate data. However, internal high voltage breakdowns (IHVBs) and external high voltage breakdowns (EXHVBs) do not occur equally. Even though some IHVBs were expected to occur, EXHVBs, were considered an anomaly. This is because it was postulated that an otherwise flawless tube is scrapped due to external contamination of some kind.

EXHVBs were brought to my attention by an operator from Test (i.e., Conditioning) in August 2008 who had observed a notable increase in the occurrence of EXHVBs. Prior to retiring, a particulate SME, placed two airborne particulate monitors in the Test area. After examining the data logged by the particulate monitors in Test it was found that the particulate monitors had been in place since February 2008. They had been placed there by the SME , when an influx of EXHVBs occurred during the heavy snow season that winter. However, the data collected from Test had many periods of missing data. It appeared as though data was only collected sporadically. This is most likely because the problem with EXHVBs was not consistently severe. Although EXHVBs did not result in consistent losses in Test like IHVBs losses, a pilot study in Test using the occurrence of EXHVBs could reveal much information about the ANNEX that we currently did not understand.

This investigation is based on the assumption that there is no difference between IHVBs and EXHVBs other than the point of initiation. Since there is hypothetically no

difference, then the Test area could serve as a model of what happens when airborne particulates increase in the external environment. This would be analogous to what happens when the parts of the tube are exposed during production to particulates internally, but only looking at one part (i.e. the exterior of the tube). If a relationship arises from this model then it would be reasonable to say particulates increase the likelihood of EXHVBs, then it can be deduced that particulates also increase the likelihood of IHVBs that lead to product losses. However, showing that particulates increase the likelihood of IHVBs would be much more difficult to model, since there are hundreds of piece parts that go into building the tube, leaving hundreds of chances for the exposure to occur. Therefore, one can assume that the findings in Test could be applied to what is going on in the ANNEX.

Generally, HVBs are caused by a particulate placed in a location which attracts current. The particulates could have entered the tube prior to being sealed hence why conditioning is used to “clean up” tubes and why some IHVBs are “expected” since a particulate attracting a current would cause the contaminant to be blown away. EXHVBs were not expected since it was assumed that once the tube has been vacuum sealed particulates are no longer of concern. In Test the tube is placed into flourinert, a critical chemical used in the testing system, and particulates should no longer be attached to the tube, but would now be in the fluid. The idea that particulates were in the flourinert led to the belief that the flourinert was potentially the cause for EXHVBs. The tester itself had also been considered to be the problem since it exceeded its expected lifespan and it over classifies the occurrence of EXHVBs. That is the sensor for “light” and “sound” discussed briefly in chapter 2 is overly sensitive. Despite this issue, it appropriately

indicates EXHVBs when they actually occur in the product. In general, even though the EXHVB indicator is overly sensitive the tester performs its job effectively enough to provide accurate test results.

To best simplify the study, it was assumed that everything else in the system including the tester were not the problem, and the only variables accounted for in the model would be the six particulate sizes recorded by the air monitor and the response variable would be EXHVBs.

4.1 Study using Historical Data

With the little affluence that EXHVBs had on the overall number of product scraps, historical data would have to be used in addition to the data collected at the start of the pilot study. The airborne data starting from February 2008 would mark the start of the retroactive study. From there, the non-conforming report (NCR) data would be retrieved for the Conditioning process and the NCRs caused by EXHVBs would be matched to its particulate data. However, we also wanted to show that reducing particulates would decrease the probability of EXHVBs. Therefore, in addition to simply collecting the airborne data and matching it to the NCRs for past and future tubes, an experiment would be embedded within the data collection.

The purpose of the experiment is to determine if it is necessary and recommendable to increase the level of air purification and air handling systems in the testing area up to clean room standards. The data collected will also help determine if clean room standards should be used in the drawings and design of the potential new test area. Furthermore, it would help determine if clean room standards in Test would reduce or eliminate the occurrence of EXHVBs.

The experiment would consist of several phases in order to use a step-wise approach toward improvements. The multi-phase study would allow us to ascertain the level of cleanliness needed and prevent over-spending on unnecessary clean room standards. The initial phase would include using two to four HEPA Air Purifiers and Air Ionizer products manufactured for residential use. However, there was a slight funding limitation, the Test area is over 2000 square feet and the budget for this study would only allow the purchase of 4 units which were only 99% HEPA-type and covered 80-110 sqft. It was determined that the small units would suffice if they were placed strategically in the area of where the testers were located, *figure 13*. This way a potential clean niche would be created. Additionally it was determined that the Test area usually has low traffic and may be cleaner in air quality than a typical residential household allowing the air purifiers to be used at maximum capability.

Data for Phase I would be collected for a period of 6 months. At the end of the 6 month period an analysis would be conducted to determine if the air purifiers had an effect both statistically on the air quality and operationally in decreasing the EXHVBs. A statistical significance on air quality is expected, however, a decrease in EXHVBs is not. This is because I am assuming that a greater level of intervention is needed beyond the residential air purifiers. At this point Phase II will be proposed. In Phase II, clean room type ceiling tiles would be used and/or a mobile clean room would be created, *figure 14*. The red area represents where the clean room tiles would be placed if it is too costly to replace the ceiling tiles for the entire room. The purple outline represents where the curtain would be placed. The air purifier would model the affects of having a HEPA

filtered air supply. This model set up is not intended to be permanent, but is meant to be used in determining the level of cleanliness required for Test.

To best meet the conditions of Phase II, all of the ceiling tiles would be replaced, and then it would be determined if additional clean requirements were needed. If it was found that EXHVBS were still present then Phase III would be initiated. The clean room curtains to create a mobile clean room will be installed. Frocks, gloves, shoe covers and hair covers would be used in the curtained areas. However, Phases II/III could potentially be proposed together by using the curtains to create a tented area over the testers in order to simulate clean room ceiling tiles.

4.1.1 Experiment Design-Phase I

Method

Participants

The two test operators would continue their work as usual, however they were asked to ensure that the air purifiers and ionizing mechanism remained “on.” They were also asked to inform me if any malfunctions with the air purifiers occurred. A quality assurance employee was involved in assisting in obtaining the Conditioning NCR data and the process engineer for Test assisted in ensuring that the NCR data in model used actually pertained to the EXHVB data.

Materials

Four Honeywell Model 16200 99% HEPA air purifiers were used. This model was selected because each system has a 330 sqft max cleaning capability and accomplishes two air cleaning cycles per hour. The Model 16200 has a 4-stage air filtration system including a washable pre-filter which traps large dust particles. A HEPA

Type filter traps 99% of all allergens and dust down to the 0.3 micron in size. The odor-lock carbon filter removes over 4000 chemical, odors, and cigarette smoke. Finally, the ionizer is a device that provides additional air filtration by creating ions that help remove particles from the air.

Additionally, two Met One HHPC-6's were also used. The HHPC-6's were set to collect a one minute sample (0.1 cubic ft) automatically every 59 minutes. The count mode was set to "Totalize" which is the particle count as it accumulates during the sample period and the count data set to "Differential" which includes particles that are larger than or equal to the particle size selected by smaller than the next greatest particle size. The number of samples was set to "INF," which allows for 500 samples to be collected on the rotating buffer.

Design

The main goal of collecting the airborne particulate data and EXHVB events is to determine if particulates increase the likelihood of defects. Time independent plots for each particulate size level by proportion of failures will be used as the first indicator to determine if there is an obvious trend that shows breakdowns increase as particulates increase. A logistic regression will be conducted to determine if particulate levels matter.

Where in the model, failure means an NCR included EXHVB and it was scrapped,

$$Y_i = \begin{cases} 0 & \text{if } i^{\text{th}} \text{ tube didn't fail} \\ 1 & \text{if } i^{\text{th}} \text{ tube failed} \end{cases}$$

$$P(Y_i = 1) = p_i$$

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_j^p \beta_j X_{j,i}$$

and $X_{j,i}$ = value of the i^{th} observation on j^{th} predictor level

It is likely that since the particulate levels are highly related that a problem with multicollinearity between the different particulate sizes will be encountered. In order to remediate this potential problem principle component regression will be used.

The principle components are derived from conducting a principle component analysis (PCA). A PCA is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables (Johnson & Wichern, 2007, p430). An analysis of PCs often reveals relationships that were not previously suspected and thereby allows interpretation that would not ordinarily result (Johnson & Wichern, 2007, p430). This is why PCA is useful with highly correlated variables. When variables are highly correlated, it is difficult to determine the importance that each variable may reveal and most regression models will become flawed, possibly revealing incorrect information. Since PCs are linear combinations of the variables explained variance-covariance, the characteristic that led to the all of the variables being correlated can be represented in a PC(s). Algebraically, PCs are particular linear combination of the p random variables X_1, X_2, \dots, X_p . Geometrically, these linear combinations represent the selection of a new coordinate system obtained by rotating the original system with X_1, X_2, \dots, X_p as the coordinate axes (Johnson & Wichern, 2007, p430).

This way, the other characteristics of the variables that were masked by the highly correlated data may be represented in the remaining PCs. Therefore, the p variables, and the original data set, consisting of n measurements on p variables, is reduced to a data set

consisting of n measurements on k principle components (Johnson & Wichern, 2007, p430). The coefficients of the PCs can be used as inputs to a regression.

For Phase I of the study the main goal is to show that small, perhaps low-cost improvements are sufficient in making a major impact in decreasing or potentially eliminating EXHVBs. A two-sample t-test will be conducted to determine if the residential air purifiers had an effect on airborne particulate contamination. From this, the level of intervention can be determined. If no difference is found in airborne particulate levels then Phase II will be proposed. If a significant difference in airborne particulate contamination is found, it must be determined if this decrease in particulates had an impact on the occurrence of EXHVBs. This will be done using the logistic regression modeling methods previously discussed. A separate model will be created where

$$Z = \begin{cases} 0 & \text{before} \\ 1 & \text{after} \end{cases}$$

Z is an indicator variable of the experimental conditions used in the regression

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \sum_j^p \beta_j X_{j,i} + Z$$

This will show the proportion of breakdowns before the air purifiers were put into place, then after.

Procedure

The four Honeywell air purifier were set to “ON” at the highest setting, and the air ionizer was also turned on. The air purifiers were placed as set in *figure 13*. The particulate data would be manually downloaded every 21 days in order to prevent data loss, for the upcoming tubes to be tested.

Other than manually downloading the data, the multi-phase study would require little human interaction. However, creating a data set from the historical data required tedious data cleaning. The NCR and actual test date data were found in two different databases, in different formats. Additionally, the NCR data was not available immediately after a tube was NCR'd so it was data that was difficult to obtain. Because of the delay in obtaining the NCR results, the study would have to be considered a "retro-active" study. Once a tube was NCR'd we used the NCR data to find when the tube had been tested. Each tube is typically tested in a lot of eight, so the tubes tested in the lot were also included in the data set as non-NCR tubes. The exact time could not be obtained for tubes that were exposed to the air in the Test room, so the average particulate count for the day would be used. Since the goal is to look specifically for NCRs pertaining to EXHVBS and it's a condition that the tester has a tendency to over specify EXHVBS, the test process engineer verified that the data qualified as accounting for actual NCRs due to EXHVBS and not false indications. This data would be collected until the completion of Phase I in March 2009.

4.1.2 Experiment Results

During the winter shutdown, the four air purifiers had to be moved because they were plugged into electrical outlets located on the testers, and the testers were going to be powered down for the shut down. The 4 units as well as the HHPC-6's were moved on top of 4 nearby cabinets. Upon return from the winter shutdown, an operator noted a clicking/snapping sound. Upon investigation, they discovered that the clicking was a result of a cyclical sparking that was coming from the air purifiers. When the ionizer was set to "ON" mode, a charge was building on the cabinets causing a static dispersion. It

was believed that this problem was not seen before because they were sitting on the testers and the testers are grounded. The multi-phase experiment was cancelled and the 4 units were returned to the manufacturer as defective.

The six particulate levels were each categorized into ten groups ranked by the particulate count. This grouping was used just to make six plots that display the proportion of failures i.e. EXHVBs, per particulate level as the number of particulates in that level increases, *see figures 15-18*. 95% Confidence Intervals were added to the plots and represented by the “-“marks in the plots using R.

From *figure 15*, it appears that EXHVBs occur at a fairly constant level regardless of the increase in particulates of sizes 0.5-0.7 μ . Most likely, there is no effect as particulate count increase or decrease for this size. In *figure 16*, almost appears to have an even distribution of proportion of failures across the different particulate counts. No real relationship between particulates of size 0.7-1 μ increasing and proportion of failures appears to be present. In *figures 17 & 18*, the proportion of failures by rank appears to only be random scatter. In *figure 17*, it almost appears as if more EXHVBs occur at lower particulate count rates of sizes 1-2 μ . In *figure 19*, an apparent relationship between proportion of failures and increase in particulates of sizes 5-10 μ is present. Similarly, in *figure 20*, the relationship also appears to be present in particulates >10 μ .

A logistic regression model would be flawed without PCA because of the multicollinearity. The multicollinearity is visible in *figure 21*. Clearly, groups 1 through 4 are correlated, and it appears that groups 5 and 6 are also correlated. This problem was going to be resolved using PCA therefore further modeling was conducted.

4.2 Results and Models

Additional data was collected to complete the historical data analysis. The particulate and tube conditioning data ranged from February 18, 2008 to February 6, 2009. There were a total of 1,020 commercial use tubes tested during this period. However, due to missing particulate data only 742 were included (N=742). There were 57 EXHVB events which resulted in NCRs. However, 28 of the 57 EXHVB events were scrapped, labeled as response variable B1. The analysis was conducted using R.

The PCA was conducted using the Correlation Matrix by using a standardized version of the data set. The standardized values were used to eliminate problems with magnitudes of the data counts obtained. Using the princomp command on the standardized values in R we can enter “cor=False.” The PC loadings are then obtained and can be multiplied by the standardized values. This is useful because when new observations are obtained they can be scaled by the obtained means and standard deviations’ multiplied by the loadings, then fed into the resulting regression model to make predictions.

$$X_{standardized} = (X_{new[,j]} - \frac{\bar{X}_{[j]}}{\sigma_{[j]}}) \times \begin{pmatrix} & Comp1 & Comp2 & Comp3 & Comp4 & Comp5 & Comp6 \\ grp1 & -0.47856976 & 0.04302757 & 0.7237686 & -0.11008694 & 70.46161997 & 0.14165615 \\ grp2 & -0.50771960 & -0.09981588 & 0.1681167 & 0.00674705 & 70.62633281 & -0.55826164 \\ grp3 & -0.50798877 & -0.06988655 & -0.2672139 & 0.13857367 & 50.30893584 & 0.74230453 \\ grp4 & -0.48991305 & 0.06196647 & -0.5742232 & 0.14754500 & 60.53768551 & -0.33990853 \\ grp5 & -0.12248272 & 0.68811995 & -0.1025677 & -0.70183588 & 90.08196532 & 0.04094940 \\ grp6 & 0.01106312 & 0.71130329 & 0.1903682 & 0.67401004 & 0.05786918 & -0.00684142 \end{pmatrix}$$

Typically, in PCA only the first few components are used where a Scree plot, *figure 4.11*, can show the variance explained by each component. Once the line is horizontal or flat then only those components are selected. However, as seen in *figure 22*, most of the variance seems to be explained by component 1 (Comp.1) and Comp.2, but the plot line does not appear to level out. Therefore, it was determined that the Scree plot would not be the best variable selection method. Additionally, little is understood about the particulate data and perhaps another component containing less of the explained variance may include the necessary information to predict EXHVBs. For this reason a stepwise selection method was used.

The first Logistic Regression model using the PC variables and $B1=(EXHVB \text{ Scrap})$, *table 3*, shows that Comp.1, Comp.3, and Comp.4 are significant at $\alpha=0.10$ set as the cut-off. However, Comp.6 has a $p=0.1249$, perhaps if the non-significant components are removed and Comp.6 is held in it will be significant. The logistic regression was repeated, *table 4*, however, Comp.6 was not significant at $\alpha=0.10$ cut-off and was also removed. The final model (Model 1), *table 5*, includes Comp.1, Comp.3 and Comp.4 and was significant at $\alpha=0.10$. Model 1, was used to determine the probability of an EXHVB that will result in a scrapped tube.

To validate the logistic model predictive qualities the leave-one-out cross-validation (LOOCV) method and the area under the receiver operation characteristic (ROC) curve were used. The LOOCV method was used to avoid an overly optimistic area under the curve (AUC) for the ROC, since we re-fit the logistic regression model each time we remove a point to get a better measure of the entire variability involved in the prediction process.

The ROC x-axis is labeled as false positive rate (FPR) which is the percentage of tubes the model incorrectly predicts to have an EXHVB resulting in a scrap and is equivalent to (1-specificity). The ROC y-axis measures the true positive rate (TPR) which is the percentage of tubes the model correctly predicts an EXHVB resulting in a scrap will occur and is equivalent to sensitivity. The sensitivity defines how sensitive the model is to the outcome of interest, in this case EXHVBS that result in a scrap. On the other hand the FPR, or (1-specificity), is defined as, how well the model can specify or distinguish between a true positive (TP) and a false positive (FP). In this case the model will either correctly or incorrectly predict that an EXHVB that results in a scrap will occur.

The TPR and FPR thresholds range from (0, 1). We select the thresholds using the obtained $\Pr(\text{failure})$ values from the PCA logistic regression LOOCV where $\Pr(\text{failure})$ is the probability that an EXHVB will occur given the particulate levels. In order to determine what level to set the cut-off threshold we find when the ROC Curve is furthest from the diagonal line, and closest to the upper left corner of the graph.

The ROC curve, *figure 23*, for Model 1 was obtained. The AUC=0.563, meaning that overall it can distinguish a true positive (TP) from a false (FP) 56.3% of the time, which is slightly better than the line of discrimination which is the diagonal line from the left bottom corner to the right top corner. In order to decrease the probability of a FP, the specificity can be increased. However, when this is done, there is a reduction in the ability to identify a TP and a failure may go through. For this reason the thresholds can be varied, depending on the trade-offs that the product can take.

In our case, it is better to incorrectly classify a tube as a FP, than allow a TP to go through. In the *figure 23*, it can be observed that the model could account for approximately 90% of the TPR, if we considered decreasing the specificity and allowed FPR to be approximately 60%. To achieve 90% detection of TPs we would set the threshold at $\Pr(\text{failure}) = 0.032$. Therefore, we would only test when $\Pr(\text{failure}) < 0.032$. The model with a $\text{TPR} \cong 0.90$ would produce the outcomes in *table 6*. From the classification table, we can calculate:

Overall Percentage of Tubes Classified Correctly by the Model

$$\frac{TP + TN}{Total} = \frac{25 + 372}{742} = 53.6\%$$

The False Positive Rate

$$\frac{FP}{(FP + TN)} = \frac{342}{714} = 47.89\%$$

The False Negative Rate

$$\frac{FN}{(FN + TP)} = \frac{3}{28} = 0.107\%$$

Sensitivity

$$\frac{TP}{(TP + FN)} = \frac{25}{28} = 89.21\%$$

Specificity

$$\frac{TN}{(FP + TN)} = \frac{372}{714} = 52.1\%$$

Model 1 does very well at identifying EXHVBs that result in scraps and it can be used to indicate when it is best to test tubes. Even though it over-classifies the occurrence of EXHVBs, the correct detection of 90% of all failures ensures that on days that testing

was delayed until airborne particle conditions improve are actually preventing losses. Over the 1 year period that this data was collected a total of 87 test days were included in the model. Although, only 87 days were included in the model during that one year period testing only occurred on 123 days. This is because testing occurs on a queue so we only test if product is available to test. The EXHVBs that resulted in scraps occurred in 22 of the 87 days testing occurred. The model correctly identified 19 of those days, meaning that if we were willing to test only on the days the model allowed we would be able to test 64% of the 87 days and detect 90% of all failures. There is no penalty (i.e. product loss) in not testing; the only penalty to not testing when tubes are in the queue would be the inconvenience of scheduled testing. Since we only test 123 days in a year there is a lot of flexibility in scheduling testing. These are quite remarkable results.

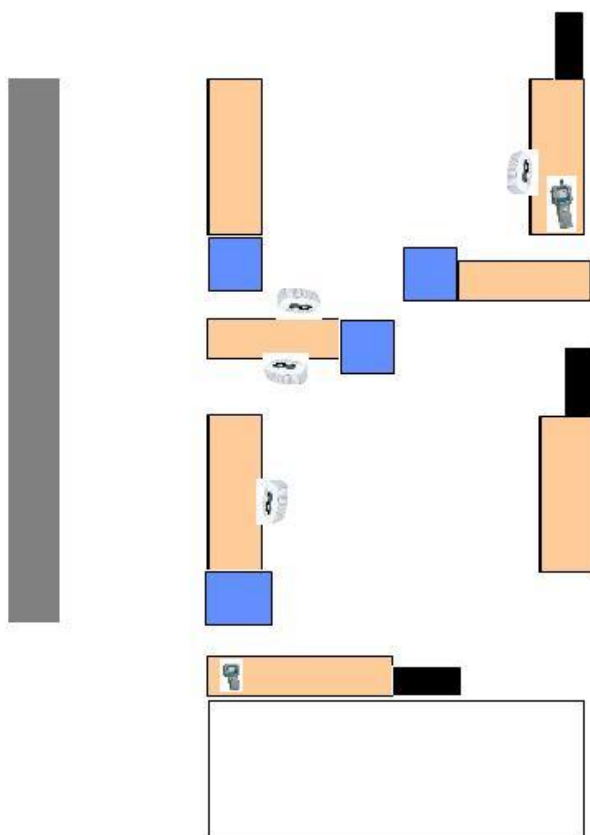
Figure 13, Phase I Experiment Layout

Figure 14, Phase II Experiment Layout

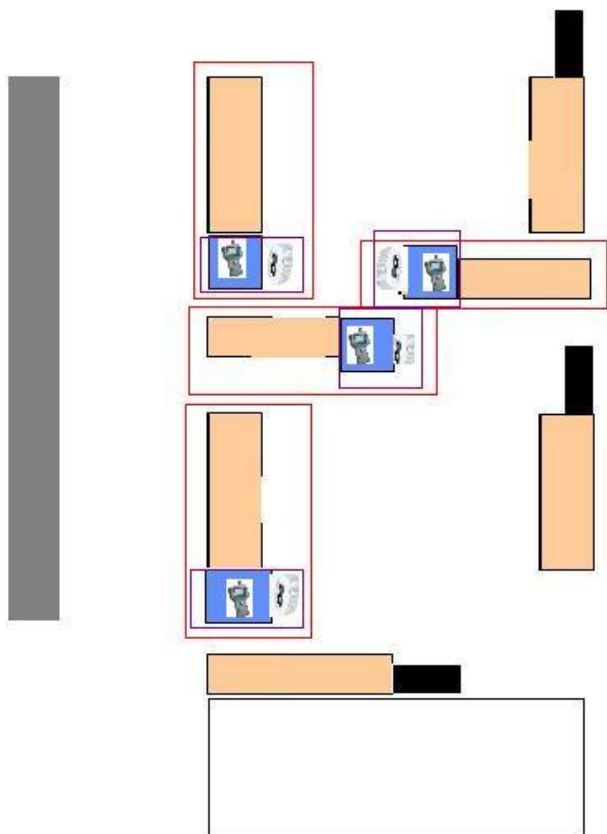


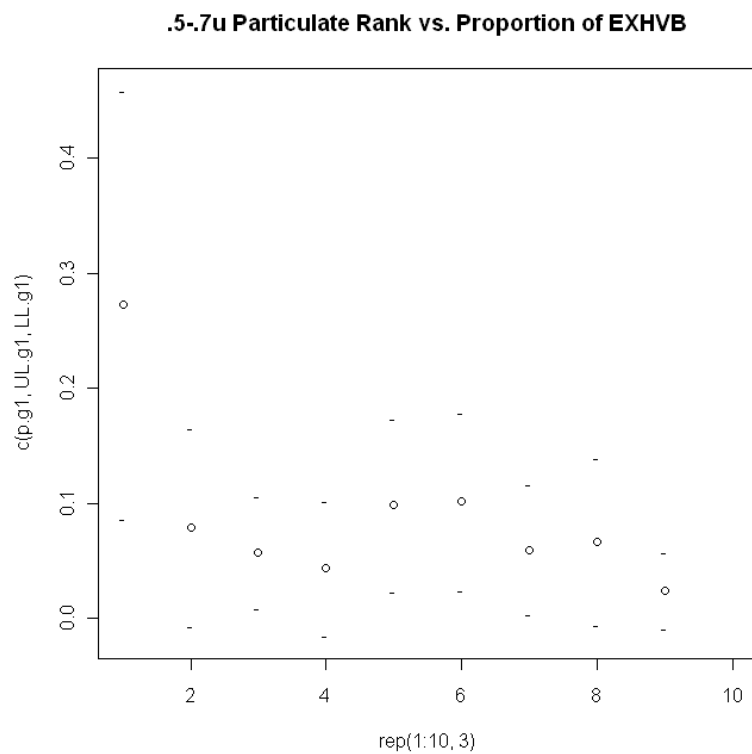
Figure 15, .5-.7 μ Particulate Rank vs. Proportion of EXHVBs

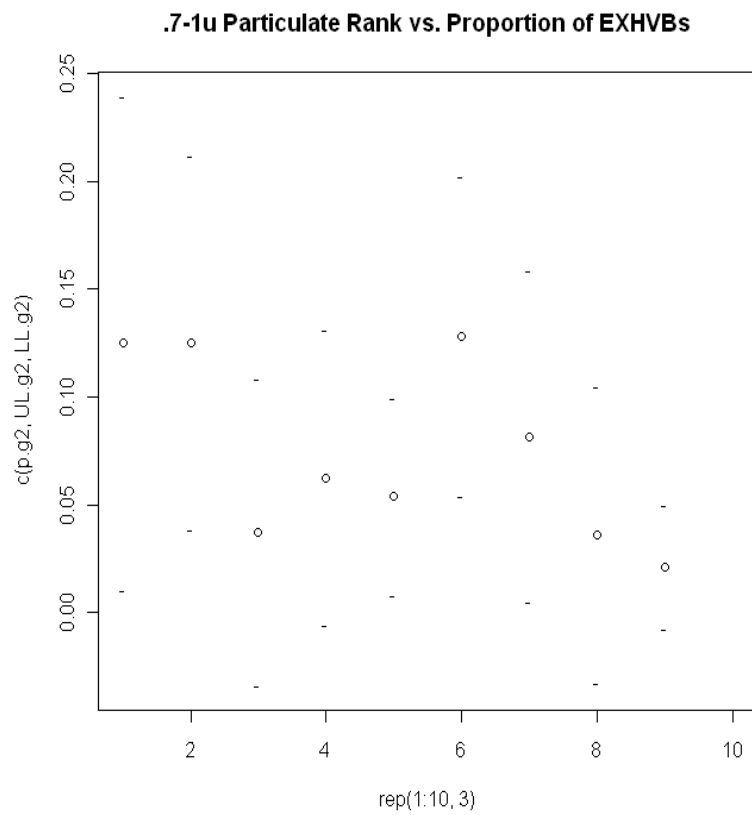
Figure 16, .7-1 μ Particulate Rank vs. Proportion of EXHVBs

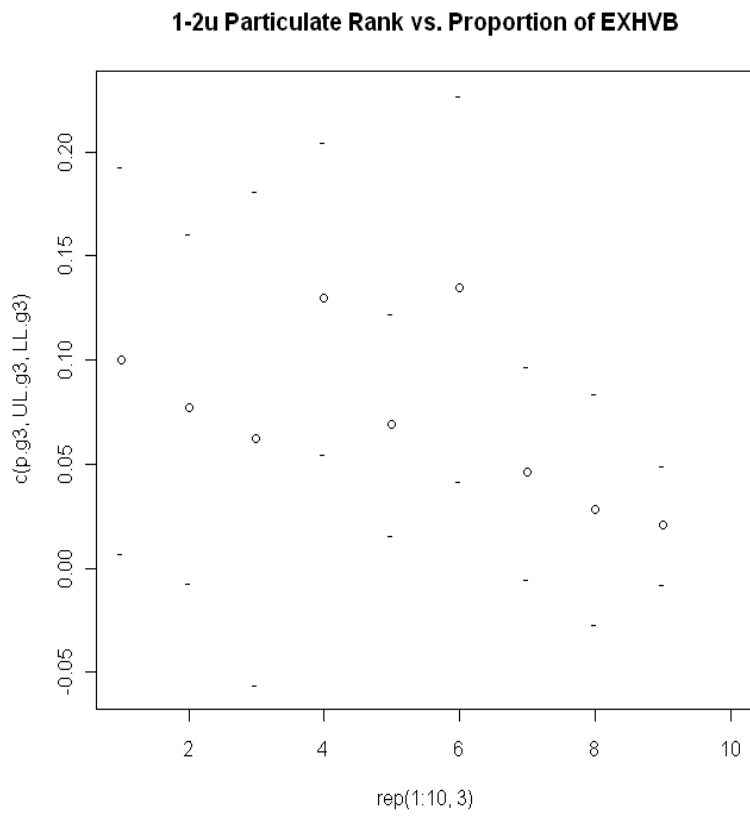
Figure 17, 1-2 μ Particulate Rank vs. Proportion of EXHVBs

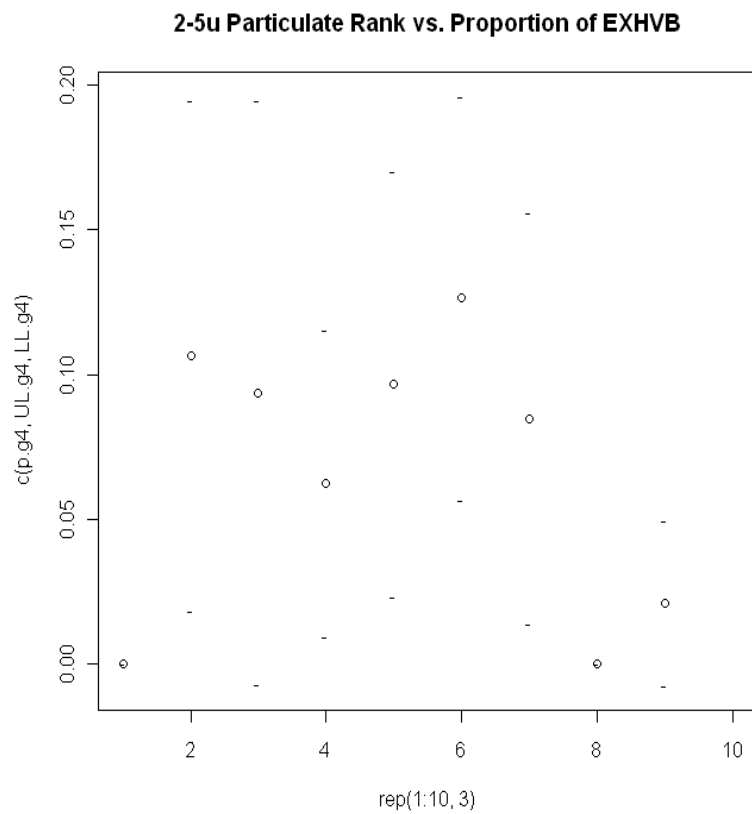
Figure 18, 2-5 μ Particulate Rank vs. Proportion of EXHVBs

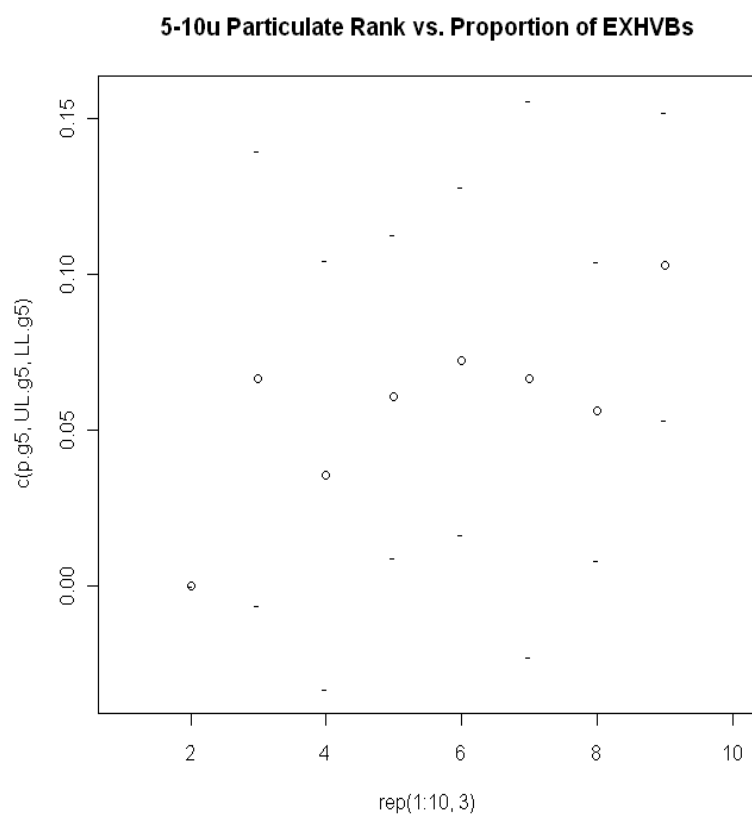
Figure 19, 5-10 μ Particulate Rank vs. Proportion of EXHVBs

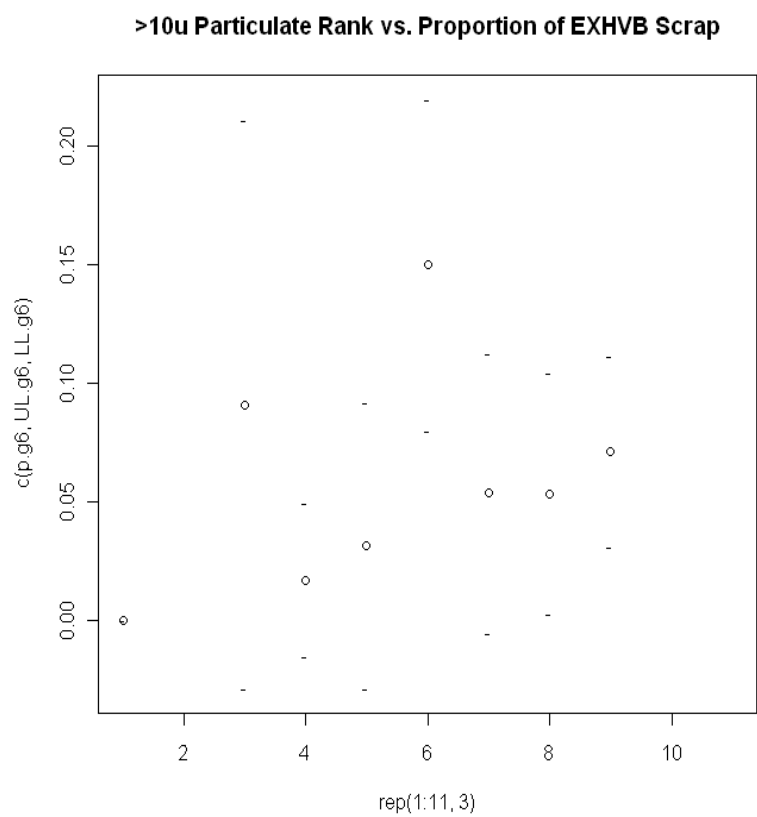
Figure 20, >10 μ Particulate Rank vs. Proportion of EXHVBs

Figure 21, Scatterplot Matrix of Predictors

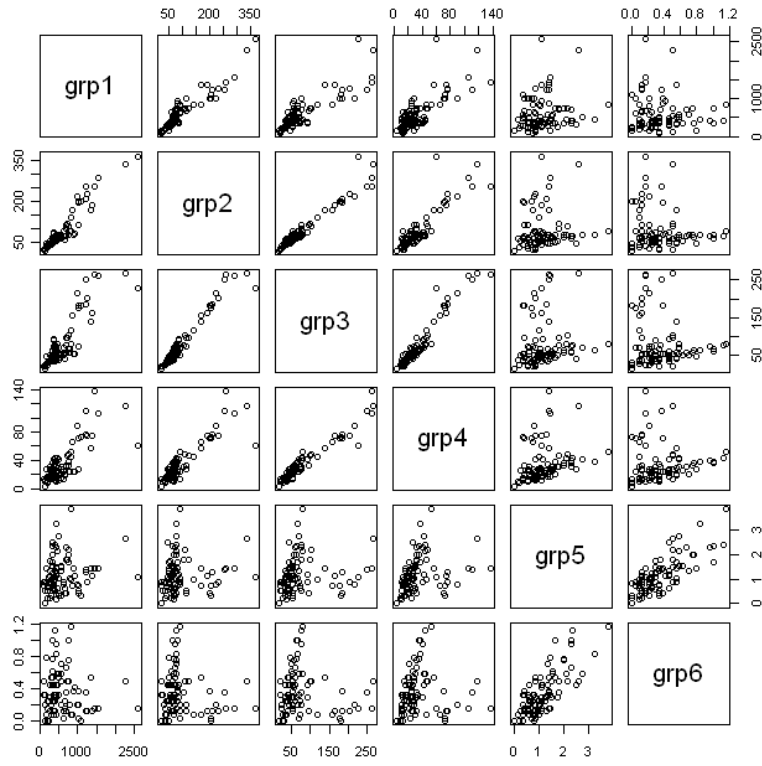


Figure 22, Screeplot

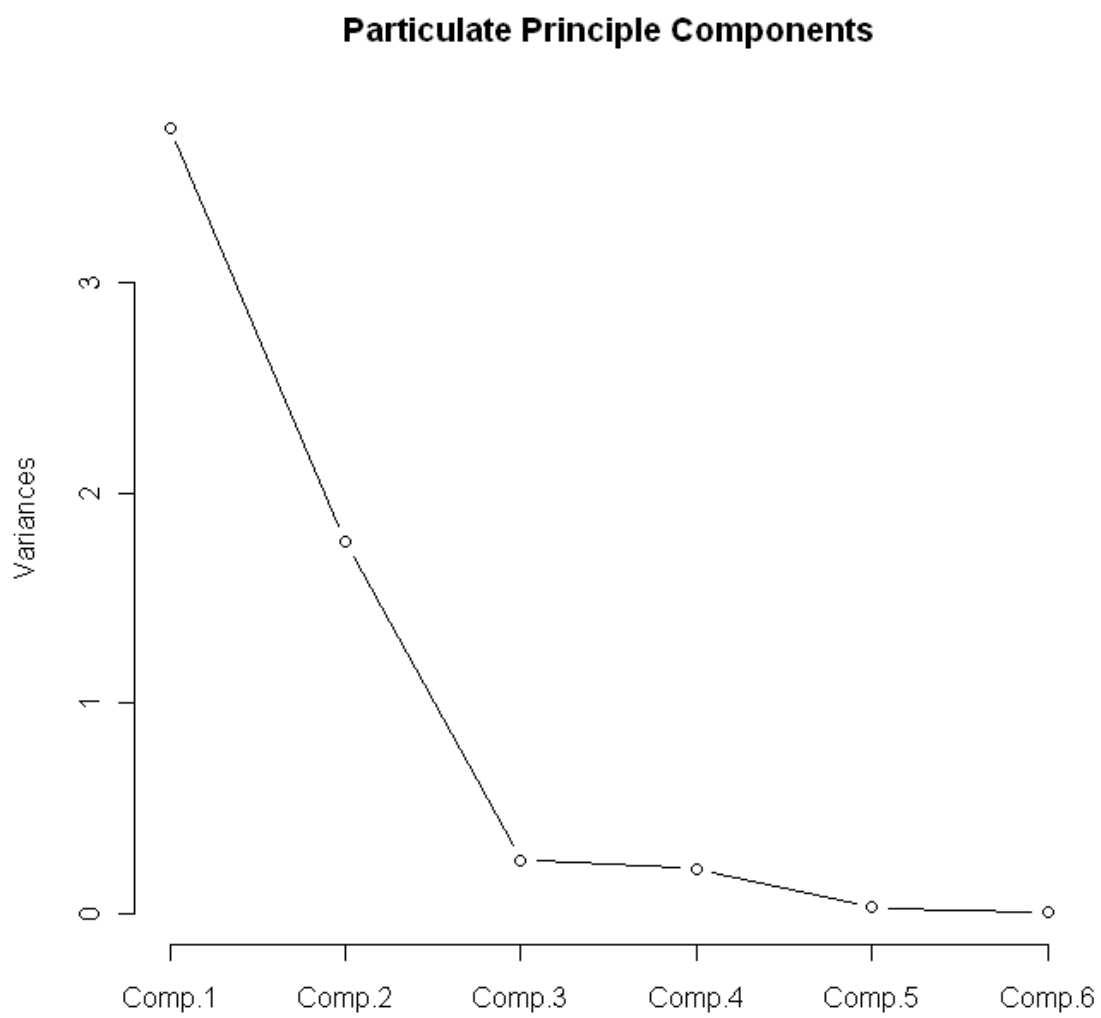
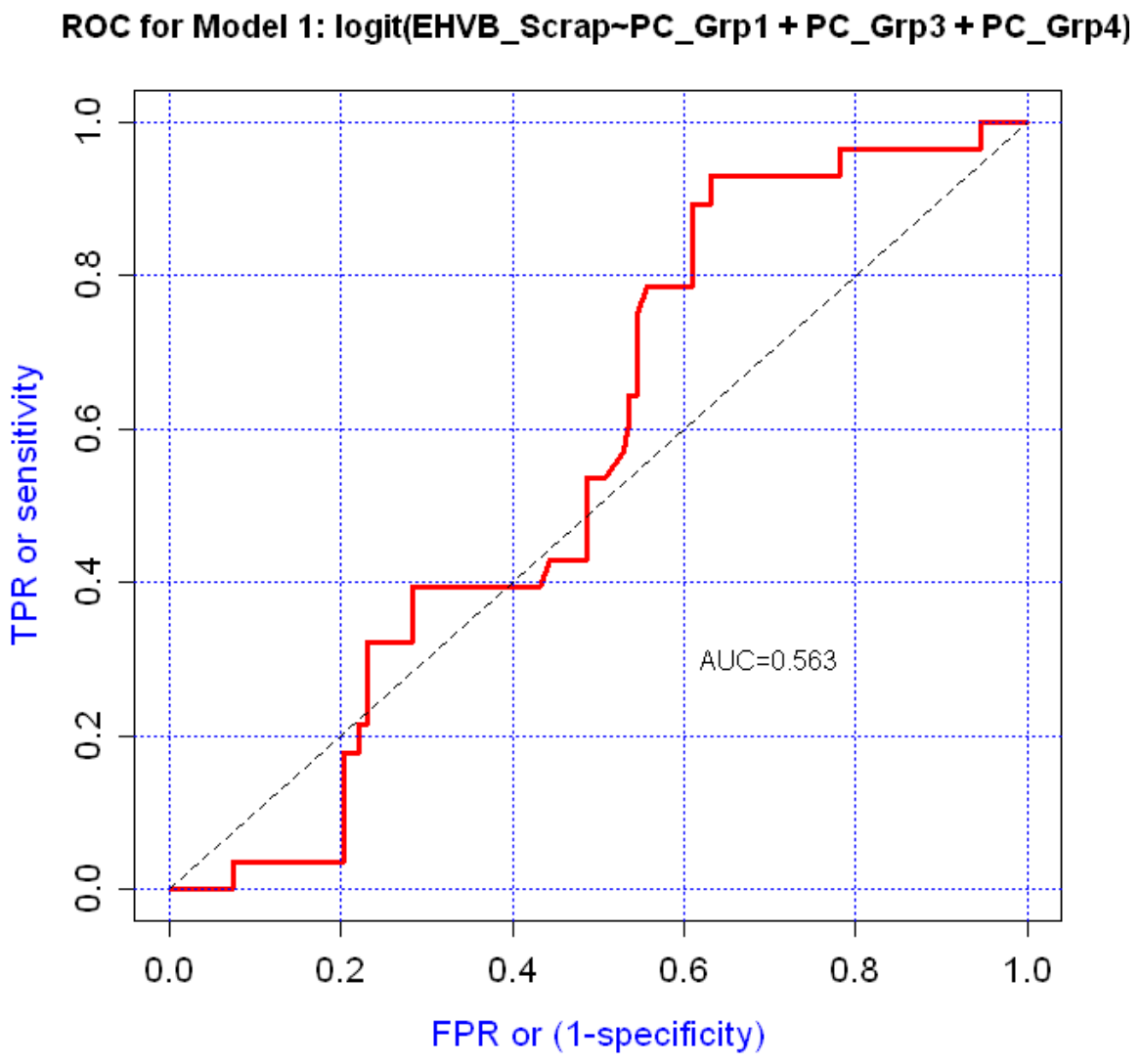


Figure 23, ROC Curve for Model 1



***Note:** The scale for this graph is coarse and was generated using 500 iterations of potential cut-off points.

Table 3, PCA Logistic Regression Step 1

Call:

```
glm(formula = B1 ~ Comp.1 + Comp.2 + Comp.3 + Comp.4 + Comp.5 +
     Comp.6, family = binomial("logit"), data = reg.data)
```

Deviance Residuals:

```
   Min      1Q  Median      3Q      Max
-0.4978 -0.3202 -0.2803 -0.1638  2.8154
```

Coefficients:

| | Estimate | Std. Error | z value | Pr(> z) |
|-------------|----------|------------|---------|------------|
| (Intercept) | -3.66482 | 0.31219 | -11.739 | <2e-16 *** |
| Comp.1 | 0.44472 | 0.22013 | 2.020 | 0.0434 * |
| Comp.2 | 0.06191 | 0.17261 | 0.359 | 0.7198 |
| Comp.3 | 1.11818 | 0.59339 | 1.884 | 0.0595 . |
| Comp.4 | -1.21085 | 0.51401 | -2.356 | 0.0185 * |
| Comp.5 | -1.13890 | 1.51467 | -0.752 | 0.4521 |
| Comp.6 | -8.44880 | 5.50550 | -1.535 | 0.1249 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 238.45 on 741 degrees of freedom
 Residual deviance: 224.25 on 735 degrees of freedom
 AIC: 238.25

Number of Fisher Scoring iterations: 8

Table 4, PCA Logistic Regression Step 2

```
glm(formula = B1 ~ Comp.1 + Comp.3 + Comp.4 + Comp.6, family = binomial("logit"),
    data = reg.data)
```

Deviance Residuals:

| Min | 1Q | Median | 3Q | Max |
|---------|---------|---------|---------|--------|
| -0.5004 | -0.3140 | -0.2718 | -0.1675 | 2.7446 |

Coefficients:

| | Estimate | Std. Error | z value | Pr(> z) |
|-------------|----------|------------|---------|------------|
| (Intercept) | -3.6132 | 0.2890 | -12.501 | <2e-16 *** |
| Comp.1 | 0.4229 | 0.1967 | 2.150 | 0.0316 * |
| Comp.3 | 1.0129 | 0.5330 | 1.901 | 0.0574 . |
| Comp.4 | -1.1182 | 0.4931 | -2.268 | 0.0234 * |
| Comp.6 | -6.4429 | 4.8463 | -1.329 | 0.1837 |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 238.45 on 741 degrees of freedom
 Residual deviance: 224.95 on 737 degrees of freedom
 AIC: 234.95

Number of Fisher Scoring iterations: 7

Table 5, PCA Logistic Regression Step 3 Final

Call:

```
glm(formula = B1 ~ Comp.1 + Comp.3 + Comp.4, family = binomial("logit"),
    data = reg.data)
```

Deviance Residuals:

| Min | 1Q | Median | 3Q | Max |
|---------|---------|---------|---------|--------|
| -0.4310 | -0.3317 | -0.2757 | -0.1905 | 2.7827 |

Coefficients:

| | Estimate | Std. Error | z value | Pr(> z) |
|-------------|----------|------------|---------|------------|
| (Intercept) | -3.5736 | 0.2818 | -12.680 | <2e-16 *** |
| Comp.1 | 0.4266 | 0.2027 | 2.104 | 0.0354 * |
| Comp.3 | 0.9924 | 0.5355 | 1.853 | 0.0638 . |
| Comp.4 | -1.0830 | 0.4940 | -2.192 | 0.0283 * |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 238.45 on 741 degrees of freedom
 Residual deviance: 226.77 on 738 degrees of freedom
 AIC: 234.77

Number of Fisher Scoring iterations: 7

Table 6, PCA Logistic Regression Model 1 Classification Table

Classification Table

| | | Actual | | Total |
|------------------|------------------|---------------|------------------|--------------|
| | | EXHVB | Not EXHVB | |
| Predicted | EXHVB | 25 | 37 | 62 |
| | Not EXHVB | 3 | 677 | 680 |
| Total | | 28 | 714 | 742 |

Chapter V

Internal High Voltage Breakdowns

Although we now had a model to illustrate the problem with external HVBs, the lack of understanding on what and where the problem of internal HVBs was originating still existed. By analyzing the historical data, a better understanding of the production process was now in place. We needed a way to track the particulates in the ANNEX on all of the unserialized parts as they were built up to a tube. However, with the hundreds of pieces used to manufacture the final product, this was going to be extremely difficult. With planning and assistance from some core operators, an observational study was designed.

5.1 Experiment Design for Investigation of IHVBs

Method

Participants

The participant demographics were not collected for confidentiality purposes. Additionally, the study will be ignoring the operator factor and will only be considering the airborne particulate data the parts in the study are exposed too. Operators from the ANNEX participated in this study. In *figure 24*, a lay out of the ANNEX and other production floor areas is available to help understand where production takes place. Additionally, three operators from the welding process (room W), two from vacuum sealing (room X), two from final marking (room M), and one operator from conditioning (room T) participated in the study. The study was running under a limitation that the operators are in a trades union which protects them from having to conduct work not

already clearly outlined in their job descriptions. Therefore, forced participation was prohibited. They were informed that work on these tracked observational units was to be conducted as they process any normal product, adhering to their normal work instructions.

Parts

A total of nine jobs of three part types were selected to be tracked. The parts are manufactured by jobs that lead to the following parts: Frame, Insulator, and Screen. Basically, the pieces that go into building the parts could not necessarily be tracked, but we could track the particle exposure as the parts were being put together. These parts would later result in two other parts: the final frame and the final header. These two pieces would then be welded in a class 1000 clean room (room W) not located in the ANNEX, and at this point it is considered a tube job, which will be constantly referred to in this study as a “lot.” The tube job contains 8 tubes. However, the three jobs that lead to the final lot may contain additional parts to build more tubes, but this information was neglected due to administrative limitations of the study, and only the lots of 8 were considered. The nine jobs resulted in 3 lots of tubes. That is 24 total tubes were tracked during the study.

Only allowing a total of 3 lots to be part of the study was a limitation set by materials availability. Therefore, the jobs were not selected randomly. The manufacturing piece parts become available to release to start a new job, once the “Super Market” supply is close to depleted.

Materials

To protect the integrity of the product, the specific materials used in production are not listed. The key tool for this study was the 14 HHPC-6 DAPCs. The HHPC-6's were set to collect a one minute sample (0.1 cubic ft) automatically every 29 minutes. The count mode was set to "Totalize" which is the particle count as it accumulates during the sample period and the count data set to "Differential" which includes particles that are larger than or equal to the particle size selected by smaller than the next greatest particle size. The number of samples was set to "INF," which allows for 500 samples to be collected on the rotating buffer. Forms were designed for this study, *see figure 25*. Notable items that were useful in this study, however, already part of the production process included totes, ORACLE, and special clean environment cabinets.

Design

Frame, Insulator and Screen were selected as the observational study parts because this ensured that we collected data from all areas of the ANNEX, *see figure 24*. The parts were built either uniformly in parallel or in series, where some parts entered all locations while others did not. These three parts not only enter most or all locations at any given point in the build but they also go through every process that takes place in the ANNEX when observed cumulatively. In this way we know we have the best coverage that can be obtained by an observational study.

Unlike, in the EXHVB study, the entire purpose of recording what time and date the parts are exposed to location air is to quantify the effect of the total time exposed. With the air sampling taking place every 29 minutes the airborne conditions are available on that time grid. However, the exact time the parts are exposed may not necessarily

occur during the exact time the reading was collected. Therefore, a method to approximate air particulate exposure was developed. Additionally, the exposure may take place between time intervals for instance 08:15 and 10:20, while the DAPC may have readings for the top of the hour (i.e. 08:00, 09:00,...) so this had to be accounted for.

An algorithm was created to calculate the unit Particulate Minute (PM), so that we could quantify the level of airborne exposure a part is subjected to. This method of multiplying the airborne particulate read at a certain time, by the time parts are exposed to came from Don Lifke, who worked for EMCORE Corporation in the past and said this was standard practice there (personal communication, 2009). This idea appeared to be ideal for the purpose of determining which area/location has the greatest affect on the piece parts during production in the ANNEX toward HVBS. The general calculation goes as follows for air sampling times $(t_1, \dots, t_m) \in [a, b]$ then

$$PM = (t_1 - a)P_{t_0} + (t_2 - t_1)P_{t_1} + \dots + (b - t_m)P_{t_m}$$

Where P_{t_i} = the particle count at a time (t) given by the interval [a,b]. In order to get the time something was exposed to P_{t_i} we multiply it by the difference, which is equal to the total time exposed. In order to repeat this for the data collected, a function was written using MATLAB. This function allowed any time interval to be valid by taking into consideration the possible cases in the data.

The rooms in the ANNEX and the other areas the parts travel through are the covariates and they are measured by the HHPC-6 DAPCs. However, each room consists of 6 covariates because the HHPC-6 reports the six sizes, which are labeled as 1=(0.5-0.7 μ), 2=(0.7-1 μ), 3= (1-2 μ), 4= (2-5 μ), 5= (5-10 μ), and 6= (>10 μ). If we were to consider all of the 14 rooms six particulate levels we would have 84 covariates. However,

a variable selection method cannot be used to reduce the number of variables in the Poisson Regression. This is because of the study limitation of 3 lots, which essentially, resulted in 3 design points with 8 replicates. That is the covariates (particle counts) are the same for all 8 tubes in each lot.

The Poisson distribution can be used for outcomes that result in count data, $(Y_i = 0,1,2,\dots,N)$, with mean λ_i , where a large count or frequency being a rare event. In the Poisson regression model the probability of observing Y_i is as follows:

$$\Pr(Y_i) = \frac{e^{-\lambda_i} \lambda_i^{Y_i}}{Y_i!}, \quad i = 1, \dots, n$$

where the logarithm of the mean λ is the linked linear function of the explanatory variables such that:

$$\log(\lambda_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \dots + \beta_k X_{ki}$$

where, X_1, \dots, X_{p-1} are a set of predictor variables.

The Poisson is a reasonable model for this data because the tubes go through a total of 32 tests during conditioning, where combinations of static and dynamic tests are conducted. Each test marks for an opportunity for an HVB to occur. The response variable is given by sum of HVBs, (i.e. the number of failures). Where, "0", indicates zero failures. However, a tube will never have 32 failed conditioning tests. This is because the tester is designed to stop if a tube has >5 HVBs. The tester considers this rule in regards to a single type of test (static or dynamic). Hypothetically, 11 would be the maximum amount of HVBs seen, although rare, more HVBs in one tube can occur to due tester anomalies. Although, the tester will not stop testing a tube until there are >5

breakdowns in a single type of test, operationally, a tube is scrapped when >5 HVBs occur whether the tester stopped or not.

There is a case where if a tube fails the first three tests, the tester automatically stops and considers this tube a failure. This is notable, because a tube that fails 3 tests in general (i.e. has 3 HVBs), is different from a tube that fails the first 3 tests, since 3 general HVBs would be considered acceptable, while the second case would not. If we simply used the sum of the HVBs (i.e. total number of failed tests), these two cases would both be labeled “3” and they are not the same. Therefore, it was determined that a label for the response variable would be needed in order to consider these different situations. A scoring system was developed by using this equation so the response variable is:

$$Y = (\text{Total Number of Tests} - \text{Number Tests Passed}).$$

In this way, if a tube fails 3 tests, but passes the rest, then it would receive a score of

$$Y = (32 - 29) = 3$$

While a tube that fails the first 3 static tests would receive a score of 28, because in this case it only passed its first 4 dynamic tests. There are many other cases not discussed where simply giving the response a total count of HVBs would result in misrepresenting the data.

This model will not rely on the outcome scrap or non-scrap as in Ch 4, but instead only using the breakdown data. With this model we would be able to calculate $P(Y = 0)$ or $P(Y > 5)$ etc. given the *PM* data for each area. This model could be beneficial in that if the *PM* data can predict the number of breakdowns, then we will be able to determine which areas potentially contribute to the occurrence of HVBs in the

tubes. However, this is an exploratory analysis, and these preliminary indications may not be definite.

Procedure

The three jobs were selected to form lot 1 as they became available. Using ORACLE the controller placed hold points in the jobs selected so that they could not be moved to their next process without notifying the controller when work was completed. This was done in order to ensure that the new job was to be matched to the other remaining two jobs. Once all three jobs to build the lot were released the controller placed holds, as an additional check point so that the operator could not move a job to the next process unless the other jobs that were matching it were also ready to be moved to the next process.

Once the jobs were selected forms were attached to the lid of the tote the job parts were placed into. The forms were designed to follow the parts through their processes so that the operator would only be required to fill in a blank.

An operator was designated as the lead for this study and was to know where the three jobs would be located and to re-brief the operators prior to beginning work on the study parts. After being briefed about what to do the operator would complete that process. Once the parts were ready for welding the parts were bagged, and the totes were picked up by the operators from weld. The lid is then removed and the parts were placed into a nitrogen cabinet until the parts were going to be welded together. After the parts became a tube, the hold points were no longer required and the operators were able to just note when they moved the tubes out of the nitrogen cabinets to then complete a vacuum sealed tube. Once the tubes were vacuum sealed they were placed in a different kind of

tote made to hold the tubes. The tubes were then moved to the room M where the “dirty processes” described in Ch 2 take place, and placed into plastic vials designed to hold the tubes individually.

Finally, they were moved to Conditioning where they were tested. The operator in test was asked to note when the tubes were exposed, and once placed in the tester, to note the results of the tests the tubes go through. The results were verified using the data provided by the tester. Although this does not complete the tube manufacturing the study concludes at “condition” since this is the point when the product yields are affected. This process was repeated 3 times for a total of 3 lots and 24 tubes.

5.2 IHVB Experiment Results

Results

The eight tubes per lot were replicates from a design point. There were not enough degrees of freedom to fit a model with the 84 covariates or to use model selection methods. Therefore, these are preliminary results mainly exploratory to attempt to get a handle on what covariates can affect the tube. These are not definite results; they may give some indication of what is going on. Enough data was rendered from rooms A, E, G, J, M and T to be included in the study. In *Appendix D* some details on the constraints which eliminated the other rooms from the study are discussed. It was decided that 36 Poisson regressions would be fit individually, to look at one factor main effects at a time as an exploratory analysis. Although this would not present definitive evidence, the analysis might be able to narrow down the areas that are most likely to have an influence for a HVB to occur.

Since different parts of the tube visited the same rooms at different points in the build sequence, it was determined the cumulative impact of each room would be used to see which room and particulate size is most influential on HVB rate. Therefore the sum of the *PM* for each piece part per room included in the data set was used as the variable in the Poisson regressions for each particulate size.

A plot of the performance of each tube in lots 1, 2 and 3 by Number of breakdowns, can be seen in *figure 26*. Lots 1 and 2 performed similarly in terms of breakdowns, while lot 3 had the least amount of breakdowns occur per tube. A histogram of the breakdown data for all of the lots was made to show the distribution of the data, *figure 27*. By the histogram of the breakdown data we can see that the Poisson distribution assumption fits.

The Poisson regressions for the exploratory analysis of all the rooms included in this study were conducted using R. Since the *PM* unit was extremely large the original *PM* data had to be multiplied by 1×10^{-6} in order to complete the analysis. This was done for all of the covariates in this study. Therefore the coefficients are based on the transformed *PM* units. For room A, the Poisson regressions show that all particulate sizes of the *PM* were significant at $p < 0.10$, *see table 7*. The results show that as the *PM* for each particulate size in room A increases, then the probability of an HVB increases. These preliminary results show that room A appears to contribute to the HVB problem.

The Poisson regressions for the exploratory analysis of room E were conducted. All of the all particulate sizes of the *PM* were significant at $p < 0.001$, *see table 8*. However, all of the coefficients were negative in this room. Therefore, the results show that as the *PM* for each particulate size increases, the probability of a HVB decreases.

This result was contradicting to what was expected especially in room E, particulate levels seem to always be out of control and it was believed to definitely be a culprit room. However, the work on the piece parts to the tube is conducted under a clean air flow lab bench. At the completion of each build in room E, the parts are sealed into plastic bags and placed in a nitrogen cabinet. Therefore, it was determined that increasing particulate levels in room E did not necessarily decrease the probability of a HVB. Instead, it was reasonable to believe that the methodology used to protect the product from particulate contamination was sufficient, and room E did not contribute to the HVB problem, positively or negatively; at least based on these preliminary results.

The Poisson regressions for the exploratory analysis of room G were conducted. Some of the *PM* particulate sizes were significant *see table 9*. Since this is an exploratory analysis used to determine a potential influence, G1 can be considered a contributing factor with a $p=0.105$. G2 had a low a non-significant p-value as well; however, it is small enough to show that there may be a relationship. G3 was significant a $p<0.10$, but G4 was not significant. G6 was significant with a $p<0.10$. The Poisson regressions show that as the *PM* levels in this room increase then the probability of a HVB increases. The results for room G most likely have confounding issues, since all of the particulates are related. Unfortunately, because only the main effects of each variable can only be analyzed individually it is difficult to remediate the multicollinearity in this model. It may be reasonable to assume that room G *PM* levels contribute to the occurrence of HVBS in the tube. However, because of the nature of this exploratory analysis the effects from room G may be due to chance alone.

The Poisson regressions for the exploratory analysis of room J were conducted. All of the *PM* particulate sizes were significant except for the largest *PM*, J6, *see table 10*. The J1...J4 variables had positive coefficients showing that as the *PM* increased, then the probability of a HVB increased. However, for J5 and J6 the coefficients were negative. After a careful analysis of the data, it was clear that this happened because of the change in the HHPC-6 settings, discussed in *Appendix D*. Room J had low airborne particle levels and HHPC-6 was reading zeros for J5 and J6 during the time that Lot 1 and Lot 2 were worked on in the production sequence. However, for Lot 3, the HHPC-6 had readings greater than zero. Therefore, it appeared that airborne conditions worsened for Lot 3 but there were less HVBs. When in reality the conditions most likely did not worsen. Previously, due to the small and short sampling period the HHPC-6 was not detecting these particles.

The response variable for room M and T were slightly different than for the other Poisson regressions for the exploratory analysis of the other rooms. This is because in rooms M and T the tube is vacuum sealed and the interior is no longer exposed or considered vulnerable to internal contamination. For these rooms, only EXHVBs were counted. The raw count or the sum of total number of EXHVBs for each observation was used as the response variable. The Poisson regressions for room M were not significant, except in the case of M5, *see table 11*. No real explanation could be resolved onto why this was the case. M5 being significant may have been a chance occurrence. Perhaps, more data needs to be collected before it is determined that room M is a contributing factor to increased probability of EXHVBs. However, because of the nature of this exploratory analysis, this result may be negligible.

For room T the Poisson regressions were significant for all of the *PM* levels with $p < .001$, *table 11*. The coefficients were all positive showing that as the *PM* increases then the probability of an EXHVB increases. Based on the results in Ch4 and this study, room T has continued to have an effect on EXHVBs, even though this analysis is considered purely exploratory, this result will most likely not change with further studies.

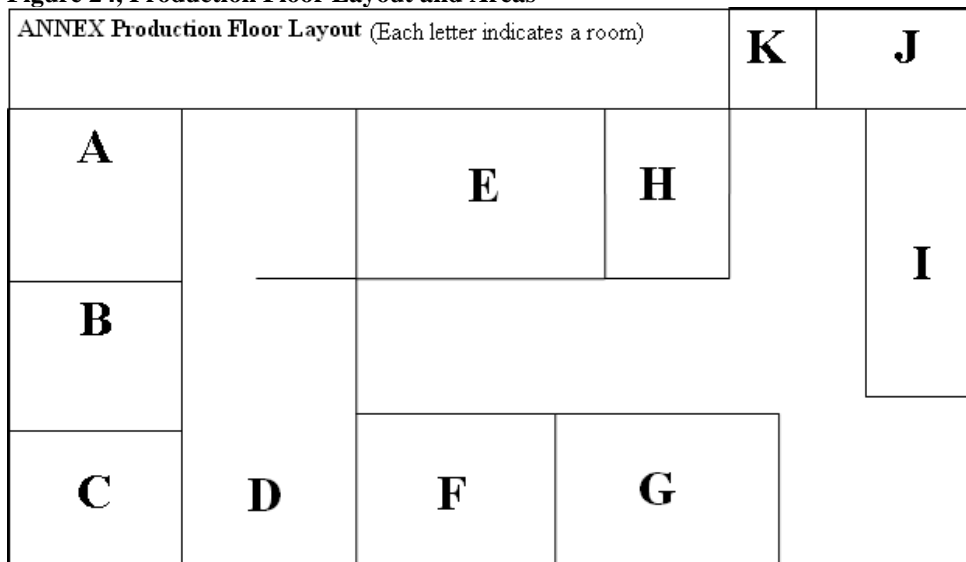
5.3 Conclusion

Due to the results obtained in this study it was determined that an automated airborne particulate monitoring system would be installed in the ANNEX. The system is a unit similar to the HHPC-6. However, it is a permanent wall mounted fixture, rather than a hand-held unit. This system is server based and the data downloads will occur automatically, removing any of the human factors involved in the data acquisition, which were a major limitation in this study, as discussed in *Appendix D*. Additionally, the data will be available for review in as close to real time as currently possible and has software and a network fully supported by the manufacturer, eliminating the difficulties seen with HHPC-6 even after network communications were developed, (not discussed in this thesis).

This decision was made because the tube production management and engineering teams felt that this study needed to be repeated and continued, but some of the challenges of the study (i.e. data acquisition) needed to be eliminated. Once the new airborne monitoring system is obtained, this study will be repeated as part of the “routine-work” for a period of at least 6-months. This decision was made by management in order to meet union requirements that operators are not obligated to conduct work not already outlined in their standard procedure. Therefore this study will be standard procedure for

the data collection period. In a 6-month period at least a total of 125 Lots will be included and therefore, there will be approximately 1000 observations to fit the model on. This will allow for a better fit that will take into account confounding issues, and allow for the analysis of interaction effect. This study was beneficial by showing that the ANNEX had an effect on production yields, even though this analysis was purely exploratory.

Therefore, the tube production team was able to procure the funds to obtain an automated particle monitoring system in order to fully understand the problem, to improve and reduce tube loss; thereby improving product yields.

Figure 24, Production Floor Layout and Areas

Other Areas (These areas are in separate locations from the ANNEX and each other)

| | | | |
|------------------------|-------------------------|------------------------------|--------------------------|
| Class 1000 W | Class 10000 X | "Dirty"Processes M | Conditioning T |
|------------------------|-------------------------|------------------------------|--------------------------|

Figure 25, Example of ANNEX study Form Used

| Particulate Tracking | | Note: Please use a new line per Room Change, tick marks ' ' ok for repeat dates | | |
|---|-------------|--|-----------------|--------------------------------|
| If you have any questions please contact Armida Carbajal 867-5309 | | | | |
| EXAMPLE*This Sheet is for Frame Processed*EXAMPLE | | | | |
| Date | Room Letter | Time | Time | (If Applicable) |
| | | Parts Exposed | Parts Unexposed | Notes ie: furnace, concerns |
| Example: | | | | |
| 8/16/09 | I | 9:50 AM | 10:45 AM | Clean & Etch |
| 8/17/09 | A | 9:02 AM | 11:00 AM | ScreenPrint/Oven |
| " " | A | 1:00 PM | 1:10 PM | From Oven to cart |
| " " | D | 1:11 PM | 1:12 PM | Transport to furnace |
| 8/18/09 | H | 1:12 PM | 1:17 PM | Load ScnPrnt Furn |
| 8/19/09 | H | 8:40AM | 8:45 AM | Unload ScnPrnt Furn |
| " " | D | 8:45 AM | 8:46 AM | Transport |
| " " | A | 8:46 AM | 9:37 AM | inspect/bag |
| 8/20/09 | K | 1:35 PM | 2:10 PM | Quasi |
| | | | | |
| | | | | |
| | | | | |

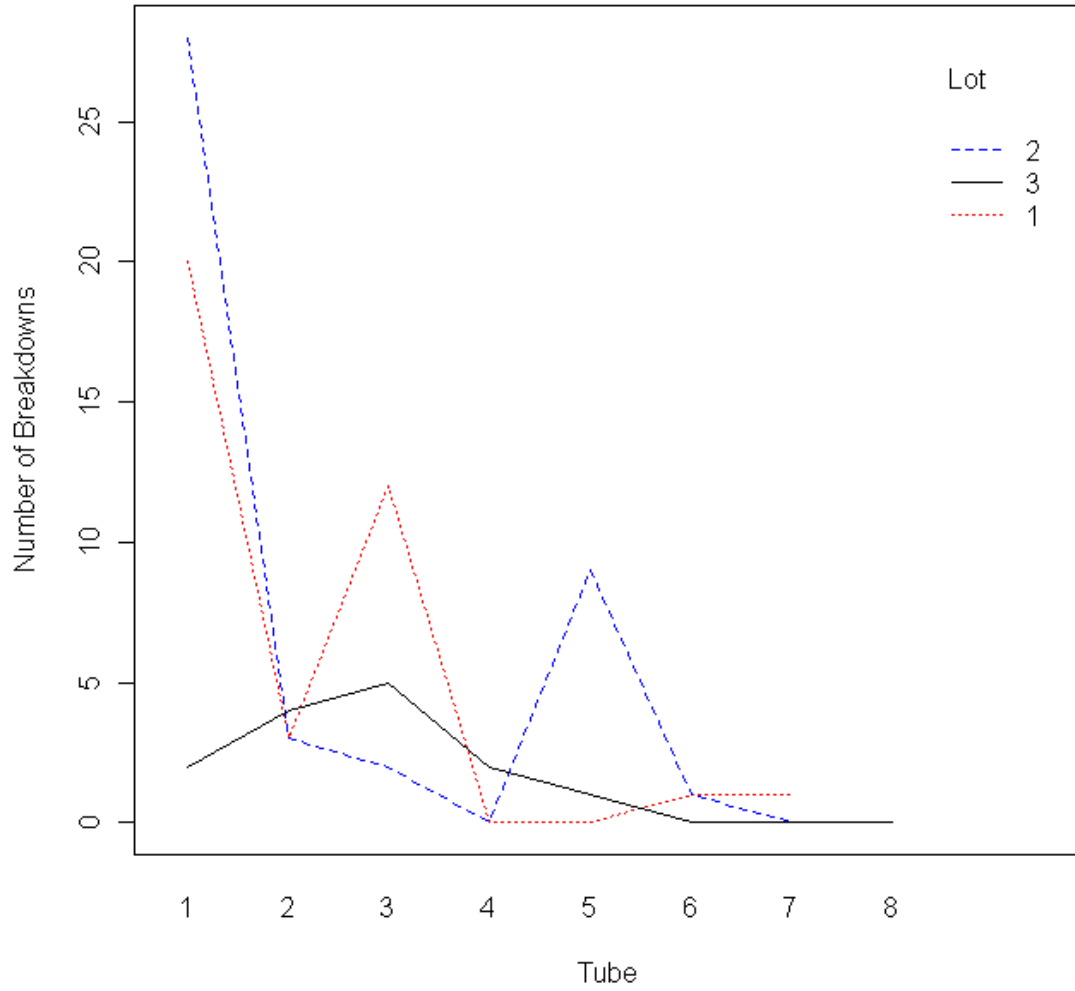
Figure 26, Lot Performance: Tube by Number of Breakdowns

Figure 27, Histogram of Breakdown Data for All Lots

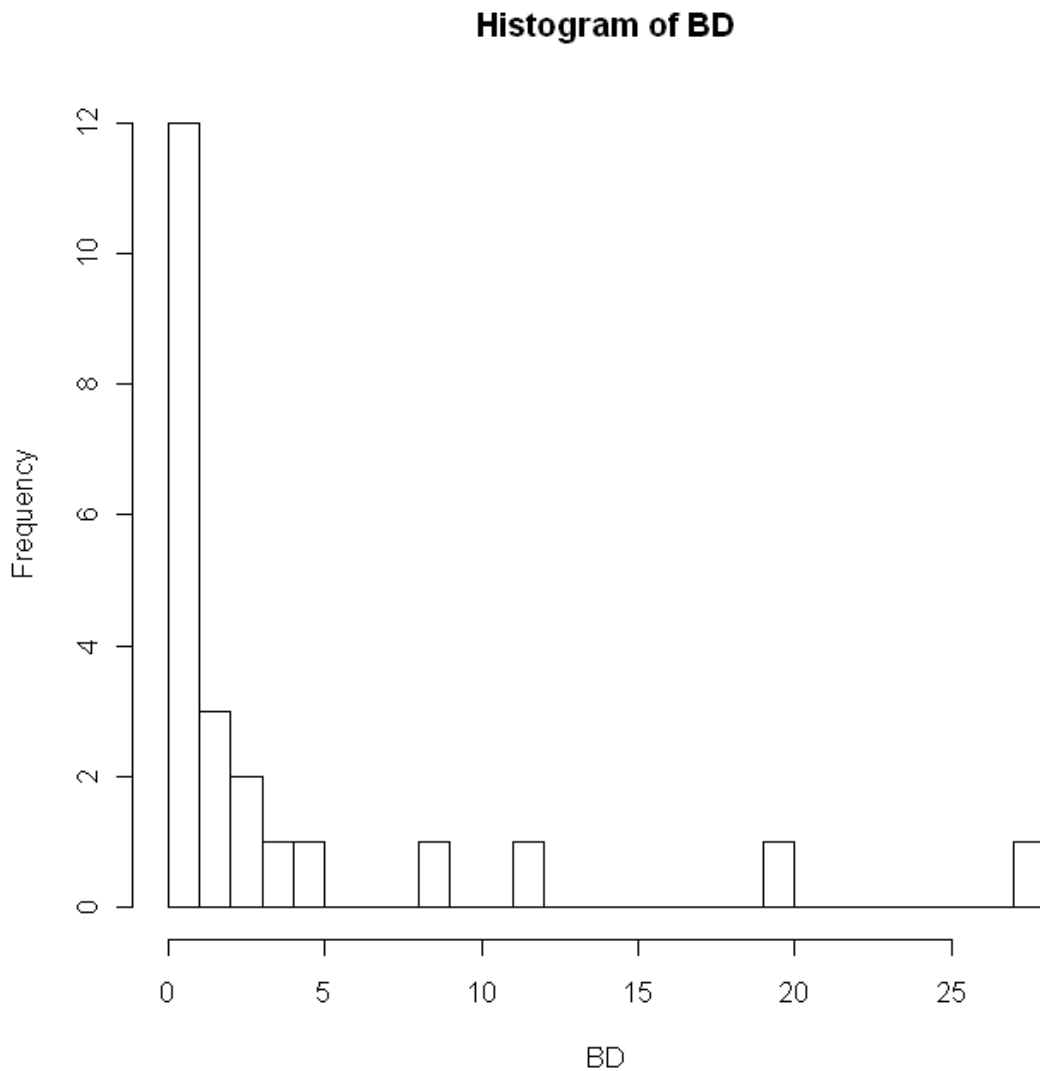


Table 7, Poisson Regression Results for Room A

Poisson Regression Results glm(formula = BD ~ Ai, family = poisson) where Ai=(A1...A6) PM levels

| Coefficients: | Estimate | | z value | Pr(> z) | Null | | Residual | | AIC: |
|---------------|----------|---------|---------|--------------|-----------|----|-----------|----|--------|
| | Std. | Error | | | deviance: | df | deviance: | df | |
| (Intercept) | 1.2526 | 0.1437 | 8.716 | <2e-16 *** | 189.64 | 22 | 186.84 | 21 | 237.82 |
| A1 | 1.0417 | 0.6127 | 1.7 | 0.0891 . | | | | | |
| (Intercept) | 1.2321 | 0.1496 | 8.238 | <2e-16 *** | 189.64 | 22 | 186.6 | 21 | 237.58 |
| A2 | 4.4552 | 2.5151 | 1.771 | 0.0765 . | | | | | |
| (Intercept) | 1.2263 | 0.1572 | 7.803 | 6.06e-15 *** | 189.64 | 22 | 187.01 | 21 | 237.98 |
| A3 | 4.7385 | 2.8741 | 1.649 | 0.0992 . | | | | | |
| (Intercept) | 1.2274 | 0.1487 | 8.253 | <2e-16 *** | 189.64 | 22 | 186.34 | 21 | 237.32 |
| A 4 | 4.9606 | 2.6853 | 1.847 | 0.0647 . | | | | | |
| (Intercept) | 1.207 | 0.148 | 8.154 | 3.52e-16 *** | 189.64 | 22 | 185.34 | 21 | 236.32 |
| A5 | 38.414 | 18.209 | 2.11 | 0.0349 * | | | | | |
| (Intercept) | 1.1796 | 0.1485 | 7.946 | 1.93e-15 *** | 189.64 | 22 | 183.97 | 21 | 234.95 |
| A6 | 128.2843 | 53.0126 | 2.42 | 0.0155 * | | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Table 8, Poisson Regression Results for Room E

 Poisson Regression Results glm(formula = BD ~ Ei, family = poisson) where i=(1...6) PM levels

| Coefficients: | Estimate | Std. Error | z value | Pr(> z) | Null deviance: | df | Residual deviance: | df | AIC: |
|---------------|-----------|------------|---------|--------------|----------------|----|--------------------|----|--------|
| (Intercept) | 2.3196 | 0.2394 | 9.691 | < 2e-16 *** | 189.64 | 22 | 172.71 | 21 | 223.69 |
| E1 | -1.6804 | 0.4417 | -3.804 | 0.000142 *** | | | | | |
| (Intercept) | 2.7896 | 0.3502 | 7.966 | 1.64e-15 *** | 189.64 | 22 | 171.6 | 21 | 222.58 |
| E2 | -6.7351 | 1.7529 | -3.842 | 0.000122 *** | | | | | |
| (Intercept) | 2.838 | 0.3615 | 7.85 | 4.15e-15 *** | 189.64 | 22 | 170.98 | 21 | 221.96 |
| E3 | -6.623 | 1.7242 | -3.841 | 0.000122 *** | | | | | |
| (Intercept) | 2.6688 | 0.3207 | 8.322 | < 2e-16 *** | 189.64 | 22 | 171.37 | 21 | 222.35 |
| E4 | -10.4059 | 2.715 | -3.833 | 0.000127 *** | | | | | |
| (Intercept) | 1.8162 | 0.1382 | 13.139 | < 2e-16 *** | 189.64 | 22 | 175.42 | 21 | 226.4 |
| E5 | -211.5141 | 58.5001 | -3.616 | 0.000300 *** | | | | | |
| (Intercept) | 1.7394 | 0.1198 | 14.516 | < 2e-16 *** | 189.64 | 22 | 171.27 | 21 | 222.25 |
| E6 | -503.6521 | 131.33 | -3.835 | 0.000126 *** | | | | | |

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Table 9, Poisson Regression Results for Room G

| Poisson Regression Results glm(formula = BD ~ Gi, family = poisson) where i=(1...6) PM levels | | | | | | | | | | |
|---|----------|---------|-------|---------|--------------|----------------|----|--------------------|----|--------|
| Coefficients: | Estimate | Std. | Error | z value | Pr(> z) | Null deviance: | df | Residual deviance: | df | AIC: |
| (Intercept) | 1.1929 | 0.1746 | | 6.834 | 8.28e-12 *** | 189.64 | 22 | 187.09 | 21 | 238.07 |
| G1 | 26.3545 | 16.2411 | | 1.623 | 0.105 | | | | | |
| (Intercept) | 1.1436 | 0.2268 | | 5.043 | 4.59e-07 *** | 189.64 | 22 | 187.85 | 21 | 238.83 |
| G2 | 0.7136 | 0.5265 | | 1.355 | 0.175 | | | | | |
| (Intercept) | 1.2173 | 0.1556 | | 7.821 | 5.22e-15 *** | 189.64 | 22 | 186.6 | 21 | 237.57 |
| G3 | 0.3173 | 0.1789 | | 1.774 | 0.0761 . | | | | | |
| (Intercept) | 1.2853 | 0.1563 | | 8.222 | <2e-16 *** | 189.64 | 22 | 188.46 | 21 | 239.44 |
| G4 | 0.319 | 0.291 | | 1.096 | 0.273 | | | | | |
| (Intercept) | 1.2907 | 0.1409 | | 9.159 | <2e-16 *** | 189.64 | 22 | 187.96 | 21 | 238.94 |
| G5 | 2.4787 | 1.8884 | | 1.313 | 0.189 | | | | | |
| (Intercept) | 1.2705 | 0.1325 | | 9.592 | <2e-16 *** | 189.64 | 22 | 186.26 | 21 | 237.24 |
| G6 | 6.0699 | 3.248 | | 1.869 | 0.0616 . | | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Table 10, Poisson Regression Results for Room J

| Poisson Regression Results glm(formula = BD ~ Ji, family = poisson) where i=(1...6) PM levels | | | | | | | | | |
|---|-----------|------------|---------|--------------|----------------|----|--------------------|----|--------|
| Coefficients: | Estimate | Std. Error | z value | Pr(> z) | Null deviance: | df | Residual deviance: | df | AIC: |
| (Intercept) | 1.0813 | 0.1674 | 6.459 | 1.05e-10 *** | 189.64 | 22 | 181.97 | 21 | 232.95 |
| J1 | 26.5555 | 9.5345 | 2.785 | 0.00535 ** | | | | | |
| (Intercept) | 0.07219 | 0.38984 | 0.185 | 0.853081 | 189.64 | 22 | 173.06 | 21 | 224.04 |
| J2 | 412.45816 | 108.9108 | 3.787 | 0.000152 *** | | | | | |
| (Intercept) | 1.2136 | 0.1461 | 8.304 | <2e-16 *** | 189.64 | 22 | 185.34 | 21 | 236.31 |
| J3 | 63.3332 | 30.201 | 2.097 | 0.036 * | | | | | |
| (Intercept) | 1.2308 | 0.1469 | 8.378 | <2e-16 *** | 189.64 | 22 | 186.23 | 21 | 237.21 |
| J4 | 202.7038 | 108.6541 | 1.866 | 0.0621 . | | | | | |
| (Intercept) | 1.674 | 0.1118 | 14.973 | < 2e-16 *** | 189.64 | 22 | 170.8 | 21 | 221.78 |
| J5 | -2422.523 | 629.7919 | -3.847 | 0.000120 *** | | | | | |
| (Intercept) | 1.534 | 0.172 | 8.915 | <2e-16 *** | 189.64 | 22 | 188.87 | 21 | 239.85 |
| J6 | -692.478 | 782.13 | -0.885 | 0.376 | | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Table 11, Poisson Regression Results for Room M

Poisson Regression Results glm(formula = BD ~ Mi, family = poisson) where i=(1...6) PM levels

| Coefficients: | Estimate | Std. Error | z value | Pr(> z) | Null deviance: | df | Residual deviance: | df | AIC: |
|----------------------|-----------------|-------------------|----------------|--------------------|-----------------------|-----------|---------------------------|-----------|-------------|
| (Intercept) | -0.7724 | 0.6249 | -1.236 | 0.216 | 60.527 | 22 | 59.947 | 21 | 77.606 |
| M1 | 0.6596 | 0.8833 | 0.747 | 0.455 | | | | | |
| (Intercept) | -0.4842 | 0.5049 | -0.959 | 0.338 | 60.527 | 22 | 60.447 | 21 | 78.106 |
| M2 | 0.7817 | 2.7693 | 0.282 | 0.778 | | | | | |
| (Intercept) | -0.4188 | 0.4538 | -0.923 | 0.356 | 60.527 | 22 | 60.505 | 21 | 78.164 |
| M3 | 0.4134 | 2.7657 | 0.149 | 0.881 | | | | | |
| (Intercept) | -0.5212 | 0.4529 | -1.151 | 0.25 | 60.527 | 22 | 60.336 | 21 | 77.995 |
| M4 | 1.1923 | 2.7407 | 0.435 | 0.664 | | | | | |
| (Intercept) | -1.5734 | 0.5519 | -2.851 | 0.004363 ** | 60.527 | 22 | 47.195 | 21 | 64.854 |
| M5 | 10.1889 | 3.0813 | 3.307 | 0.000944 *** | | | | | |
| (Intercept) | -1.094 | 0.6283 | -1.741 | 0.0816 . | 60.527 | 22 | 58.239 | 21 | 75.898 |
| M6 | 61.3714 | 44.0748 | 1.392 | 0.1638 | | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Table 12, Poisson Regression Results for Room T

| Poisson Regression Results glm(formula = BD ~ Ti, family = poisson) where i=(1...6) PM levels | | | | | | | | | |
|---|-----------|----------|---------|--------------|-----------|------|-----------|----|--------|
| Coefficients: | Estimate | | | | | Null | Residual | | AIC: |
| | Std. | Error | z value | Pr(> z) | deviance: | df | deviance: | df | |
| (Intercept) | -1.4229 | 0.5096 | -2.792 | 0.005237 ** | 60.527 | 22 | 47.074 | 21 | 64.733 |
| T1 | 0.6448 | 0.1934 | 3.334 | 0.000857 *** | | | | | |
| (Intercept) | -1.4112 | 0.5065 | -2.786 | 0.005336 ** | 60.527 | 22 | 47.071 | 21 | 64.73 |
| T2 | 2.49 | 0.7468 | 3.334 | 0.000855 *** | | | | | |
| (Intercept) | -1.4079 | 0.5056 | -2.784 | 0.005364 ** | 60.527 | 22 | 47.07 | 21 | 64.73 |
| T3 | 2.9934 | 0.8978 | 3.334 | 0.000855 *** | | | | | |
| (Intercept) | -1.4262 | 0.5105 | -2.794 | 0.005210 ** | 60.527 | 22 | 47.075 | 21 | 64.734 |
| T4 | 11.0716 | 3.3214 | 3.333 | 0.000858 *** | | | | | |
| (Intercept) | -1.6905 | 0.5851 | -2.889 | 0.003862 ** | 60.527 | 22 | 47.254 | 21 | 64.913 |
| T5 | 480.8347 | 145.9878 | 3.294 | 0.000989 *** | | | | | |
| (Intercept) | -1.6917 | 0.5862 | -2.886 | 0.00391 ** | 60.527 | 22 | 47.288 | 21 | 64.947 |
| T6 | 1057.6654 | 321.8617 | 3.286 | 0.00102 ** | | | | | |

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Number of Fisher Scoring iterations: 6

Appendices

Appendix A: Particulate Metrology Literature

Peacock, S.L., Accomazzo, M.A, and Grant D.C. (1986) developed a precise calibration technique to generate count calibration data for light-scattering instruments. Peacock et al, (1986) describe the function of optical particle counters as measuring the light scattered by individual particles passing through a small sensing volume. The photo detector then collects the scattered light and converts it into an electrical pulse which is processed by counter electronics. The amplitude of the pulse generated depends on particle size with larger pulses indicative of larger particles. The electrical pulses are counted and measured by the electronics on a circuit board or threshold circuitry, a microprocessor, and communications circuitry. The microprocessor then displays the count on the front panel as total particulate count in specified size ranges (Henderson, p.2, 1999).

Peacock, et al. (1986) measured the performance of the particle counters in terms of particle count *efficiency*, defined as the ratio of indicated concentration to actual concentration. Efficiency is a function of concentration and particle size assuming a constant flow rate. As particle concentration increases, particle coincidence and electronic circuit saturation effects affect efficiency (Peacock, et al. 1986).

Particle *coincidence* is defined as the simultaneous presence of more than one particle within the discrete airborne particle counter (DAPC) optically defined sensing zone at any time (ASTM, 2003). A combined signal from several particles may be reported as arising from a single larger particle by the instrument. These instruments all

have a particle concentration limit. If the particle concentration in the DAPC becomes excessive, then the probability of more than one particle being present in the sensing volume at any time may become significant. In that situation, several small particles simultaneously present in the volume will be reported as larger and fewer particles than those actually present in the [air sample] being measured (ASTM, 2003).

Particle counters were meant to be placed in low level airborne contamination areas. Otherwise the probability of coincidence increases and the output the DAPC is given with less precision. ASTM (2003) recommends relying on the manufacturer's specifications when it comes to the DAPC capabilities. In order to maintain instrument capability recalibration should be part of the maintenance plan. The particle counters for this research will need to be used in a non-clean environment, and the high counts that affect a DAPC function present a problem. Examination of the DAPC calibration is required to ensure best practices in the study.

Standard practice for the calibration of a DAPC uses near-mono-disperse sphere particles as approved by ASTM International (2003). Mono-dispersed particles are Polystyrene latex (PSL) particles that are qualified and used by National Institute of Standards and Technology (NIST) suitable metrology laboratories. During a routine field calibration the inlet flow rate, zero count level and particle sizing are checked and tuned if necessary. PSL particles allow the resolution and counting accuracy to be defined for each size threshold. If repairs or modifications are needed then they are sent to a full metrology facility for complete calibrations.

In theory, DAPCs functionality is affected by the air it samples.

Appendix B: Particulate Studies Literature

At the Laser Interferometer Gravitational Wave Observatory (LIGO), the hardware is extremely sensitive to optical scattering by particle contamination (Henderson, 1999). In order to reduce particulate levels Met One model 227 DAPCs were placed in 11 rooms in order to observe the trends. The monitors provided readings in particles greater than 0.3 microns. The Met One 227 monitors were set on automatic mode on a cycle of one minute sample and a 29 minute holding period. Since the monitors have one cubic foot per minute pump, the data points were multiplied by ten to give particles per cubic foot. Henderson (1999) then added the integer one to generate semi-log plots.

The major trend they noticed was that the particles would rise during working hours and falls at night, during weekends and holidays (Henderson, 1999). No tests were conducted to investigate why this was the case but the data found was consistent with the idea that airborne particles are brought in by people, fibers from clothes, dust on items etc (Henderson, p5, 1999). The other possibility discussed in Henderson (1999) was that perhaps the particles in the area were initially at rest on surfaces and that air currents created by movement sent the particles into the air. Henderson (1999) discovered that one of their rooms was constantly over 10,000 particles greater than 0.3 microns per cubic foot. They thought perhaps one of the problems was that there was only one fresh air supply and no return air supply. When Henderson (1999) discovered the extreme particulate levels in that area, the room was vacuumed with a High Efficiency Particle Arrestor (HEPA) vacuum and caps and frocks in addition to the previously required shoe covers became required clothing. The particle levels dropped to between 5,000 and 1,000

particles greater than 0.3 microns after these improvements were made (Henderson, 1999). The Met One Model 227 was useful and reliable in the case of the LIGO clean facility and provided the necessary data to make improvements.

The second study uses DAPCs in the extreme case of an outdoor example. This study reveals that DAPCs can be of practical use to measure particulates in non-clean room environments. In a study on outdoor tobacco smoke (OTS) five different real-time particle sensing instruments were used to pinpoint and understand transient elevations in OTS pollution (Klepeis, N.E, Ott, W.R., & Switzer, P., 2007). Klepeis et al (2007) found that airborne particle concentrations are common practice for use in indicating the presence of second hand smoke (SHS). Therefore, they felt it applicable to OTS studies since airborne particles comprise a significant portion of sidestream and mainstream mass emissions from burning cigarettes and indoor particle concentrations associated with SHS are substantial (Klepeis et al., 2007). Additionally, the size range for SHS particles are 0.02-2 microns and this fine particulate matter can be measured using portable continuous monitors (Klepeis et al., 2007).

Klepeis et al., (2007) simultaneously used multiple monitors of the same type and different types in order to achieve a high level of confidence in measured OTS. They conducted 14 experiments indoors during the testing phase. Klepeis et al., (2007) found good consistency for intra-instrument and inter-instrument comparisons, with the bulk of errors <10-20%. They conducted 10 outdoor experiments and were able to observe the difference between indoor and outdoor smoke behavior. They found that OTS disappears almost instantly when the tobacco sources are extinguished, while indoor levels persist at high levels and with slow decay for hours until doors are opened to ventilate the house.

Most importantly Klepeis et al., (2007) found that real-time particle instruments, especially those based on light scattering, are useful in characterizing OTS levels. Additionally the different particle detection instruments used provided consistent findings.

Appendix C: HVB in Vacuum Systems Literature

In SF₆ gas vacuum system high voltage breakdown studies, it was found that dust and conduction particles were a serious limitation for practical applications (Maller, V.N. & Naidu, M.S., 1981). The insulation strength of compressed gases can be greatly reduced by the presence of contamination in the form of conducting particles, (Maller, V.N. & Naidu, M.S., 1981, pg.46). Along with dust and conducting particles, metallic particles present in SF₆ gas when voltage is applied electrostatic forces cause the particles to levitate perpendicular to the electrode surfaces resulting in reduced insulation strength of the design (Maller, V.N. & Naidu, M.S., 1981). Maller & Naidu (1981), recognized that the presence of these particles was inevitable and therefore other methods must be developed in order to control these particles.

Under certain conditions, particles have been observed to become wedged or welded onto the cathode and then emit charged particles until eventually a spark destroys them or until they are otherwise removed (Maller, V.N. & Naidu, M.S., 1981, pg.49). When breakdowns occur, the initiation point of the breakdown is often destroyed, (Mehrhoff, 1981). Brainard and Reidel (1976), observed nothing at the initiation site of a HVB in a neutron tube except the substrate, the flaw or contaminant was blown or evaporated away. Conditioning decreases the probability of breakdowns in subsequent test pulses as found in Mehrhoff (1981), however, it also reduces the ability to detect and identify culprit particles.

There were a couple of cases when K and Si were found in high concentrations at the initiation site by Brainard and Reidel (1976). These particles were believed to be a form of mica which is a dielectric, (Brainard, J.P & Reidel, A.A., 1976). Dielectric [i.e.

insulator] particles charge to breakdown fields during ion bombardment, creating enough plasma upon discharge to initiate a full inter-electrode breakdown (Brainard, J.P. & Reidel, A.A., 1976). The particle size is what determines the energy available for the plasma generation and it was hypothesized that there is a limiting particle size at which breakdowns are not initiated. In a simulation study conducted by Brainard and Reidel (1976) an aqueous sodium chloride solution was evaporated on a target and created crystallites of NaCl between 10 to 50 microns which adhered to the target. It was found that the larger particles produced an inter-electrode breakdown every time during ion bombardment. The smallest particles occasionally caused a breakdown. The small particles were most likely at the limit of the energy required to initiate a complete inter-electrode breakdown, since the particle capacitance is proportional to the particle volume, (Brainard, J.P. & Reidel, A.A., 1976).

Appendix D: Data Limitations for Chapter 5

During the experiment there were several events that occurred in which resulted in lost airborne particulate data. The first event occurred when the individual responsible for downloading the data informed me that due to unforeseen demands they forgot to download the data, and uploaded the data two days after the scheduled due date. After this information was received the HHPC-6 was set back to 59 minute count time intervals, in order to conduct the in situ data downloads. However, during the lapse in time the data for rooms was lost. In the case of room C, D, and K the data lost resulted in an inability to include the rooms in the study.

Additionally, it was discovered that the operators did not fully understand what was meant when they were asked to note what time the parts were “exposed” to room air, this resulted in complete data loss for room B and H. As a result of this event more detailed briefings and examples of what they were to do in the data collection were provided. Furthermore, the HHPC-6 in room K malfunctioned and had to be shipped out for repairs, which resulted in a missing monitor for a one month period. The HHPC-6 in room X was moved to room K. It was determined that the HHPC-6 from room W would be moved with the study lots. However, there were overlaps in the production sequences so great in rooms W and X and the HHPC-6 could only be in one location at a time that W and X particulate data was missing to the extent that they could not be included in the study. These events all occurred during the data collection for Lot 1, and the effect of these events was not seen until the study was completed. Additionally, 1 tube from Lot 1 was scrapped prior to Conditioning. Therefore, lot 1 only contained 7 tubes.

During Lot 2 and Lot 3 build of the study, all of the HHPC-6's were due for calibration. Pre-planning for this event was conducted in order to prevent any loss of airborne particulate data. However, during a discussion with the DAPC service engineer, I was informed that the most accurate way to collect data with the HHPC-6 is by setting the monitor for collection of 1 cubic foot of air. This air sample would be collected during a ten minute period and would give the best estimate of what was really in the air rather than collecting a 1 minute air sample and multiplying the result by 10. Although, I was aware that this would add some variability to the data between the particulate counts for lot 1 and portions of lot 2, I assumed that this would result in less variability within the particulate data since this would achieve increased accuracy. The main difference noted at the end of the study was that with the increased accuracy, certain rooms during the original settings were showing zero counts for particulate sizes of 5μ or greater. However, with the 10 minute sampling period these particle sizes were no longer zero.

Room I was eliminated from the study because the airborne particulate counts were always zero even with increased accuracy of the HHPC-6. With counts always being zero in room I, there was clearly no particulate effect from that room. This study showed that the ANNEX airborne particulate levels in rooms A, G, and J were contributing factors in the increasing probability of HVBs. However, rooms B, C, D, H and K were not analyzed due to missing data and this data needs to be collected in order to determine the true effect that the ANNEX has on the occurrence of HVBs.

Additionally, this study although significant, is only an exploratory analysis and not to be used to base final decisions on. This study may only point towards what is causing the problems.

Appendix E: List of Abbreviations

ANNEX: Not an abbreviation, just the name for the piece part and assemblies neutron tube production floor

ASTM: originally known as American Society for Testing and Materials now known as ASTM-International

AUC: Area under the curve

DAPC: discrete airborne particulate counter

EXHVB: External high voltage breakdown

FPR: false positive rate

HEPA: high efficiency particulate absorbing/arresting

HHPC-6: Handheld particulate counter

HVB: High voltage breakdown

IHVB: Internal high voltage breakdown

LOOCV: leave-one-out cross-validation

NCR: non-conforming report, also a name for a failed tube

NG: neutron generator

PCA: principle component analysis

PC(s): principle component(s)

PM: particulate minute, unit developed for Ch5

ROC: receiver operating characteristic

SME: subject matter expert

SNL: Sandia National Laboratories

TPR: true positive rate

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