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Quality Control in the Healthcare Industry: An Analysis of Surgery Turnover Times

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QUALITY CONTROL IN THE HEALTHCARE INDUSTRY: AN ANALYSIS OF SURGERY TURNOVER TIMES

by

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ABSTRACT

For virtually all hospitals, utilization rates are a critical managerial indicator of efficiency and are determined in part by turnover time. Turnover time is defined as the time elapsed between surgeries, during which the operating room is cleaned and prepared for the next surgery. Lengthier turnover times result in lower utilization rates, thereby hindering hospitals' ability to maximize the numbers of patients that can be attended to. In this thesis, we analyze operating room data from a two year period provided by Evangelical Community Hospital in Lewisburg, Pennsylvania, to understand the variability of the turnover process. From the recorded data provided, we derive our best estimation of turnover time. Recognizing the importance of being able to properly model turnover times in order to improve the accuracy of scheduling, we seek to fit distributions to the set of turnover times. We find that log-normal and log-logistic distributions are well-suited to turnover times, although further research must validate this finding. We propose that the choice of distribution depends on the hospital and, as a result, a hospital must choose whether to use the log-normal or the log-logistic distribution.

Next, we use statistical tests to identify variables that may potentially influence turnover time. We find that there does not appear to be a correlation between surgery

time and turnover time across doctors. However, there are statistically significant differences between the mean turnover times across doctors.

The final component of our research entails analyzing and explaining the benefits of introducing control charts as a quality control mechanism for monitoring turnover times in hospitals. Although widely instituted in other industries, control charts are not widely adopted in healthcare environments, despite their potential benefits. A major component of our work is the development of control charts to monitor the stability of turnover times. These charts can be easily instituted in hospitals to reduce the variability of turnover times.

Overall, our analysis uses operations research techniques to analyze turnover times and identify manners for improvement in lowering the mean turnover time and the variability in turnover times. We provide valuable insight into a component of the surgery process that has received little attention, but can significantly affect utilization rates in hospitals. Most critically, an ability to more accurately predict turnover times and a better understanding of the sources of variability can result in improved scheduling and heightened hospital staff and patient satisfaction. We hope that our findings can apply to many other hospital settings.

1.0 INTRODUCTION

The downtime between surgeries is referred to as turnover time. Essentially, this is the amount of time spent between surgeries, in order to clean and sterilize the room, prepare the next surgery, and so on. The scheduling of surgeries is dependent upon surgery times and turnover times, both of which are variable. By analyzing turnover time and identifying ways of controlling its variability, it could be possible to better schedule surgeries, thereby increasing hospitals' overall utilization rates of their operating rooms.

This research falls under the realm of healthcare operations, a field that is attracting increased attention from operations researchers. The objective of this thesis is to propose answers to some previously unanswered questions dealing with turnover time in operating rooms. Some of these questions are: What theoretical distribution best describes the turnover process? Is there a relationship between the doctor who performs the surgery and the turnover time? Does the turnover process exhibit non-random variability than can be eliminated through better quality control mechanisms? Is there a correlation between the surgery type and the length of turnover? In this thesis, we will closely examine the variables effecting turnover times, seeking ways to cause a reduction in the median turnover time and reduce the variance of times, with an understanding that such reductions would be beneficial to many hospitals.

Due in large part to the increased financial pressures many hospitals are facing, they are scrutinizing their processes and welcoming suggestions for ways to improve efficiency without compromising effectiveness. Evangelical Community Hospital in Lewisburg, Pennsylvania is a non-profit hospital that is just one of the many hospitals finding itself with decreasing operating margins and, therefore, in a position where it would benefit from operations research being used to identify manners of improving its practices.

The inspiration for this study was derived from several sources. The real expressed need of Evangelical Community Hospital was something I decided to research as I have an interest in the healthcare field and, in particular, an interest in the application of operations research methods in a hospital setting that was initially sparked by some of the models studied in my Decision Sciences coursework. My desire to play even a small role in advancing the health care industry was further fueled by the insight into surgery and hospital environments offered by surgeon and author Atul Gawande (2002, 2008, 2009).

The objective of our study is to identify inefficiencies and propose enhancements to the current process, from the scheduling of surgery appointments until the operating room has been cleaned and prepped for the next surgery, which would lead to minimizing the turnover time between surgeries, thus potentially reducing the overtime operating costs, which could lead to significant cost savings. Another important consequence would be that, as the turnover process is kept in control, more operating room capacity can be available, which would lead to an increase in the number of surgeries performed, thus raising the overall service level of the hospital.

This study is based upon deidentified data from Evangelical Community Hospital of historical records of surgeries performed during the two year period from February 2008-January 2010. By studying the implications of operating room scheduling on turnover times at this hospital, conclusions can be drawn that should benefit other hospitals as well.

Our first major contribution is the statistical analysis of fitting turnover times, which has not previously been addressed in the literature. In addition, another major contribution of this work is the development of a quality control chart to monitor turnover variability. Control charts have been previously used in manufacturing processes, but not in hospital environments. The unique dimensions of hospitals require focus on operations research explicitly devoted to hospitals and the issues they face on a daily basis. The amount of money being earmarked for health care is rapidly increasing, demanding an improvement in the efficient use of resources.

This thesis is organized as follows. In Section 2.0, we present an overview of the related literature. Next, we explain the model and design of this empirical study. The subsequent sections detail the statistical findings and the quality control mechanisms we developed. Finally, we present the conclusions derived from our research and offer suggestions for how to utilize them to improve health care efficiency and better understand the variables underlying turnover time.

2.0 LITERATURE REVIEW

There currently exists a vast body of literature covering topics related to our study such as the modeling of surgery times, scheduling approaches, the introduction of technology in hospitals, the effects of long turnover times, and quality control in healthcare.

Appointment scheduling is the science and art of trying to match supply (healthcare provider and equipment/resource availability) with demand (patients requiring care). Gupta and Denton (2008) detail the challenges with healthcare appointment scheduling, focusing on opportunities to apply operations research techniques to improve the methods currently utilized. They outline the necessity to incorporate such techniques as the rising cost of healthcare puts pressure on healthcare providers to improve efficiency. Furthermore, they emphasize that efficiency and timely care, which are largely affected by appointment scheduling, are major determinants in a patient's satisfaction with the care she receives. Strum et al. (1999) define underutilization and overutilization, stating that they are important indicators of operational efficiency and the accuracy of a surgical schedule. If a surgical case begins and ends within the budgeted operating block time, it is classified as budgeted utilization, while unused budgeted time is considered underutilization. Cases beginning or ending outside of the budgeted block time are classified as overutilization. Working to create a schedule with maximum budgeted utilization can have significant cost savings.

Over time many scheduling systems have developed, all seeking to improve upon existing systems. For example, Mount Sinai Hospital used integer programming to devise a schedule in which each department is allocated certain blocks of time on specific days, which they then have the responsibility of apportioning out to different surgeries (Blake and Donald 2002). LaGanga and Lawrence (2007) looked at the viability of applying a practice common in other industries with perishable products, such as the airline industry, to a healthcare environment. They researched the implications of overbooking surgeries in order to account for no-show patients (patients who fail to arrive for scheduled appointments). The conclusion was that overbooking (scheduling more appointments than are able to be accommodated) improved productivity and patient access, but also increased patient waiting time and overtime costs. Overall, the benefit of overbooking is most pronounced in hospitals with large numbers of patients, high no-show rates, and low service variability, although there are benefits to the practice even in settings in which these criteria do not apply.

When creating a surgery schedule, it is imperative that it is designed so that delays are minimized. A patient requiring surgery may face two types of waiting: [1] indirect waiting time, which is the time elapsed from the moment a patient requests an appointment and the time that an appointment is scheduled for; and [2] direct waiting time, which is the time elapse between a patient's appointment time and the time that she is seen by a healthcare provider. Murray and Berwick (2003) focus on ways to minimize delays for patients, thereby improving overall efficiency. Gupta and Denton (2008) also explain that access rules play a major role in determining the length of indirect and direct waiting times, as healthcare providers commonly have to deal with unscheduled appointments due to emergencies.

Surgery times are inherently variable, but an understanding of the variability allows for better scheduling of surgeries. Therefore, attention has been directed at how to best model surgery times. Empirical studies have demonstrated that surgery times are best modeled using a log-normal distribution. For example, Strum, May, and Vargas (2000) illustrated that the log-normal model is superior to the normal model for large sets of surgery times. Consequently, the practice of estimating surgery times based on a log-normal model has been widely adopted. A log-normal distribution has positive support and positive skewedness, which seems apt to surgery times, in which a select few cases may take much longer than average.

Other studies examined turnover times, recognizing the role that prolonged turnovers can play in reducing surgeon satisfaction (Dexter, Epstein, et al. 2005). Using operating room data, they identified turnovers greater than fifteen minutes beyond the mean turnover time. The authors were able to successfully devise manners of estimating the percentage of turnover times that are prolonged and at what times of day they occur. These results can in turn be given to managers, who can benefit from them by targeting their efforts to specific times of the day that have the largest percentages of greater than average turnover times. This study also laid out many of the standards for evaluating turnover times, such as excluding from the analysis turnover times greater than three standard deviations beyond the mean for benchmarking purposes.

A team of doctors researched whether there are in fact measurable benefits to reducing turnover times (Dexter, Abouleish, et al. 2003). They recognized that, in addition to quantitative benefits, there are qualitative benefits, including improved job satisfaction among healthcare personnel and improved patient satisfaction. Yet, their research centered on using information system data to measure the quantitative benefits. Reducing mean turnover time anywhere from three minutes to nineteen minutes was shown to cause a 0.8% to 4.0% reduction in staffing costs. As hospitals increasingly look for ways to cut costs, this research illustrates that reducing turnover times can be a valuable place to begin.

As mentioned, there has been the widespread belief that longer turnover times reduce hospital employee satisfaction. Yet, a recent study shows that surgeons' perceptions of turnover times are not accurately correlated with actual turnover times (Masursky, et al. 2011). Instead, ingrained opinions, such as attitude about the hospital facility and about the activity of the teams responsible for turnover, are believed to influence surgeons' perceptions of turnover times. In general, surgeons tend to overestimate the percentage of longer than average turnovers that occur.

Wright, Roche, and Khoury (2010) studied an initiative to improve timely starts in an operating room. Recognizing the importance of improving efficiency in operating rooms, they evaluated a strategy that strove to improve efficiency by increasing utilization. They identified the most common reasons for delays, which were lack of preparedness of patients and surgeons and anesthesiologists being unavailable. Then, they implemented a strategy which resulted in the occurrence of on-time surgical starts increasing from approximately six percent to sixty percent over the course of nine months. Their approach involved several initiatives and they did lament on the high resistance to change or efforts at improvement in hospital settings, and in operating rooms in particular.

A pair of doctors built a study predicated on the hypothesis that operating room turnover time can be decreased by looking closely at the tasks that routinely occur in an operating room and identifying ways to minimize inefficiencies (Cendán and Good 2006). They looked at the work flow and tasks for each integral member of the operating room team and then redrew each individual's work flow diagram to eliminate many inefficiencies. Furthermore, they paid careful attention to discovering moments in the process that would be improved by briefly adding the assistance of an additional person. Once these changes were implemented in a tertiary care center the turnover time decreased from a mean of 43.7 minutes to 27.7 minutes, allowing for the mean caseload to increase from 1.78 to 2.34 per day.

Rather than focusing on improving existing processes, some researchers have focused on analyzing whether there are benefits to instituting parallel processing in operating rooms (Friedman, et al. 2006). Most hospitals currently utilize a system in which patients progress through the hospital in a sequential fashion, beginning with check-in and culminating with recovery. A study at Massachusetts General Hospital was designed to analyze the benefits of using a parallel processing system, in which an operating room team can work on two patients simultaneously by allowing overlap in the steps (such as one patient being administered anesthesia while another is being moved to recovery). By implementing parallel processing, turnover time and induction time were shortened, thereby improving operating room efficiency and allowing for an increase in the number of cases per day. Furthermore, this was accomplished without significantly increasing costs. Similarly, Marjamaa et al. (2009) demonstrated that parallel workflow models were superior to the traditional sequential ones. All four parallel processing scenarios analyzed yielded reduced nonoperative time. Another team conducted an empirical study looking at the benefits of implementing parallel processing for solely anesthesia induction (Sokolovic, et al. 2002). The study was designed to determine if an increase in anesthesia staff to allow for induction of anesthesia before the previous surgical case ended would lead to increased efficiency. The results were affirmative, with the practice corresponding to significantly decreased time between cases as the next patient had already received anesthesia prior to the conclusion of the preceding surgery.

Harders et al. (2006) also looked at the potential benefits of process redesign, finding similar results. They used a multidisciplinary approach to attempt to lower nonoperative time, which accounts for a large portion of time in operating rooms. They found process-related delays to be common and, therefore, worked to eliminate them, significantly reducing turnover time.

Overdyk et al. (1998) looked more comprehensively at various ways of improving operating room efficiency. They began by analyzing data on delays and the causes of the delays. Next, they implemented plans to minimize delays, which consisted primarily of operating room efficiency awareness education and personal accountability measures. Lastly, Overdyk et al. measured the results of their efforts to improve efficiency and found rather favorable results: first case of the day start time became earlier; surgeons, anesthesiologists, and residents were unavailable much less often; and turnover time decreased by an average of sixteen minutes.

Stepaniak et al. (2010) investigated the effects of scheduling similar cases consecutively and using a fixed operating room team. The results indicated that there were potential benefits to this as preparation and turnover times decreased significantly.

Furthermore, for simple surgeries, procedure times even decreased; however, this effect was not noticed with complex types of surgeries.

Adams et al. (2004) also tried to identify ways of decreasing turnover time, which was supported by surgeons, anesthesiologists, and hospital staff. Their efforts focused on using six sigma initiatives to ultimately lead to process redesign. Their application of six sigma principles yielded a 32% decrease in the mean patient turnaround time, coupled with a 15% decrease in the standard deviation. Similarly, the mean surgeon turnaround time was reduced 32% and the standard deviation was lowered 15%. The authors concluded that the decreased turnover times would allow for at least an additional eleven general surgery cases to be added per month, helping the hospital to sustain an operating margin. Perhaps equally as important, physicians and patients indicated much higher satisfaction with the process and there was a 95% increase in reported teamwork among operating room staff.

A study was done to quantify the staffing costs incurred as a result of longer-than-average surgery times (Abouleish, et al. 2004). Usually the additional revenue generated by longer surgeries is not enough to offset the staffing costs. The researchers looked at the net staffing costs faced by anesthesiology departments when cases are longer than expected and determined that the costs can be very large, with the exact figure depending on compensation levels and payer mix.

One of the primary reasons for research on manners to improve hospital effectiveness and efficiency is the mounting financial pressures facing hospitals. At Texas Children's Hospitals, the introduction of health-care optimization technology helped improved the hospital's financial situation, allowing them to provide better care (Born, et al. 2004). While the technology was designed to optimize contracts with insurers, there are plans to implement similar technology for different purposes as the results have demonstrated the enormous potential benefits of utilizing optimization technology in hospital settings.

Trying to also harness the benefits of technology, a study focused on the implications of utilizing information systems to predict surgery durations (Dexter and Macario 1996). The most accurate estimates were derived from a model that combined the estimates of commercial scheduling software and surgeons' estimates, with the inclusion of patient data shown to have no impact. However, even this model did not produce significantly better time predictions than either the scheduling software or the surgeons' estimates alone, with predictions being only twelve to eighteen percent more accurate.

A computer simulation was done to evaluate the feasibility of fitting in an additional surgical case per day if efforts were taken to make small decreases in the length of each case (Dexter and Macario 1999). The simulation showed that decreasing the duration of cases throughout the day would be unlikely to result in sufficient additional available time to schedule another surgery. As a result, Dexter and Macario suggest that a better approach may be to optimize the scheduling of surgeries. Wright and colleagues (2010) do point out, however, that even if not enough time is gained to fit in an additional case, ending the day earlier could potentially reduce staffing costs as it may reduce the amount of overtime paid.

A major component of our research is understanding how quality control measures can benefit hospitals in regards to reducing turnover time. While quality control has been studied outside the healthcare realm, there is also a vast body of literature examining the role that it can play in healthcare settings. Seim, Andersen, and Sandberg (2006) evaluated the speed with which statistical process control detected reductions in nonoperative time (defined as "the sum of all time spent not performing surgery") when a surgeon performed successive operations in the same room. Furthermore, they analyzed its ability to detect small changes, and concluded that statistical process control is a valuable tool for hospitals as it was able to detect small changes over an extended period of time and was able to detect changes quickly. They mention the importance of having such a tool for detecting both desired and undesired effects, particularly when hospitals are facing enormous financial pressure. The method they used was to monitor changes following the introduction of a new process, thereby evaluating whether the process change had the desired effect. To analyze whether variations were due to chance, in which case the system would be considered stable, or were due to nonrandom assignable causes, in which case the system would be considered unstable, Seim, Andersen, and

Sandberg evaluated the data collected using Western Electric rules. Western Electric rules are one manner of detecting whether a system is out of control using standard statistical process control tools, like control charts.

The study and findings presented in the following chapters will hopefully further the research that has already been done to improve operating room processes and will introduce new ideas regarding how focus on turnover times can have advantageous results for hospitals. The statistical analysis of turnover times and introduction of a quality control tool for identifying non-systematic changes in mean turnover time begin to fill a critical void in the existing body of literature.

3.0 TURNOVER DATA ANALYSIS

3.1 INTRODUCTION

The first step of this empirical study was to analyze the data provided by Evangelical Community Hospital. The data were scrubbed, sorted, and analyzed to test for correlations between doctors and turnover times and to test what distribution best fits the data. The data consisted of deidentified Evangelical Community Hospital patient files with records of surgical cases from February 2008 to January 2010. The files contain data regarding the surgeon, the operating room, the beginning surgery time (defined as "wheels in," or the time a patient is brought into the operating room), and the ending surgery time (defined as "wheels out," or the time a patient is removed from the operating room). The turnover time interval is not explicitly measured by the hospital at this time.

Turnover time was defined as the amount of time elapsed between completion of one surgery ("wheels out") and the beginning of the next surgery ("wheels in") in the same operating room. Essentially, it is the nonoperative time between surgical cases during which the operating room is cleaned and prepared for the next patient. The below figure depicts our definition of turnover. Please note that some researchers include anesthesia in their definitions of turnover time. As we did not have data on anesthesia times this is not included in our definition of turnover.

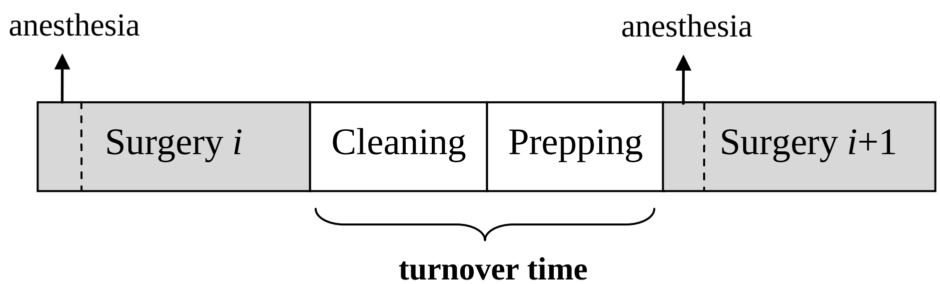


Figure 1. Turnover time identification

Unfortunately, because Evangelical Community Hospital does not keep detailed records that include true turnover time, we were forced to estimate the turnover times. The time elapsed between surgeries may in fact be due to many factors (doctors or nurses arriving late, delays with patient preparation, etc.). However, we have no way of accounting for these factors.

To begin the data analysis, the data first had to be prepared and standardized so that a variety of statistical analysis tools could be applied to draw conclusions. This began with consolidating the data into one large file with a consistent format. The data originally received was in multiple files and was not recorded in a consistent manner. Furthermore, the data had to be cleaned by removing duplicate or incomplete records and correcting misspellings of surgeon's names. In order to calculate and subsequently be able to analyze the turnover times, we sorted the records first by date. Then, the data was sorted by operating room and, finally, by start time of the surgery. The result was a comprehensive list of surgeries in chronological order by operating room.

At the conclusion of this process, the data was organized and we were prepared to calculate turnover time. Yet, there were important factors to consider. First, due to the poor record keeping there were many cases that had incomplete data. If the ending time of the previous surgery or the starting time of the current surgery was not recorded, a turnover time could not be calculated and this data point had to be removed. Next, a turnover time could only be calculated when the operating room for the previous surgery was the same as that for the current surgery. Given these parameters, we created a list of turnover times for applicable cases. The result was a set of 3360 turnover times calculated in minutes from the given time of day surgery start and end times. This data set was reduced to 3346 by eliminating turnover times for doctors who had fewer than five turnover times as we considered these samples to be too small. If we had information regarding the procedures, or types of surgeries, we would separate the data by this variable. However, in the absence of this data, we have chosen to separate the turnover times by doctor. As doctors tend to focus on specific types of surgeries (particularly in a community hospital like Evangelical Hospital), it is our best approximation for surgery types. When the doctors with fewer than five surgeries are eliminated, there are 34 doctors with turnover times remaining in the data set remaining.

In order to arrive at the final data set on which our statistical analysis is based, we did one final step, which was to account for outliers. We considered two approaches - removing outliers and setting outliers to a determined maximum turnover time. After researching both methods, we opted for the former. We believed it was important to adjust our data set to account for the outliers as the circumstances of these cases may be such that there was indeed scheduled to be a break between surgical cases (nonsequential case scheduling) and, therefore, the turnover times are not reflective of the actual time required to clean and prepare the operating rooms (Dexter, Epstein, et al. 2005). However, we believed that capping, or setting all prolonged turnover times to a maximum, would result in an inaccurate cluster of turnover times at that maximum point, thereby distorting distribution fit tests.

Prior to adjusting the outliers, the mean of the turnover times was $\mu = 41.70$ minutes and the standard deviation was $\sigma = 40.37$ minutes. We followed standard practice and eliminated all turnover times greater than the mean plus three standard deviations, calculated to be 162.81 minutes. Chebyshev's Theorem states that at least $1 - \frac{1}{k^2}$ (where $k = \text{number of standard deviations}$) of a data set must lie between the mean and positive or negative k standard deviations. Since we chose $k = 3$, at least

88.89% of all values of our data set lie within three standard deviations of the mean, which is the portion of the data set that we retained.

In other words, any turnover time that exceeded 163 minutes was removed from the data set. This led to the removal of seventy more turnover times (just over two percent of all data points). The summary statistics about the turnover data are provided in the table below.

Table 1. Turnover data summary statistics

N	3276
μ	37.50
σ	27.44
Median	28.00
Minimum	1.00
Maximum	162.00
Range	161.00

The histogram presented below exhibits the characteristics of the data.

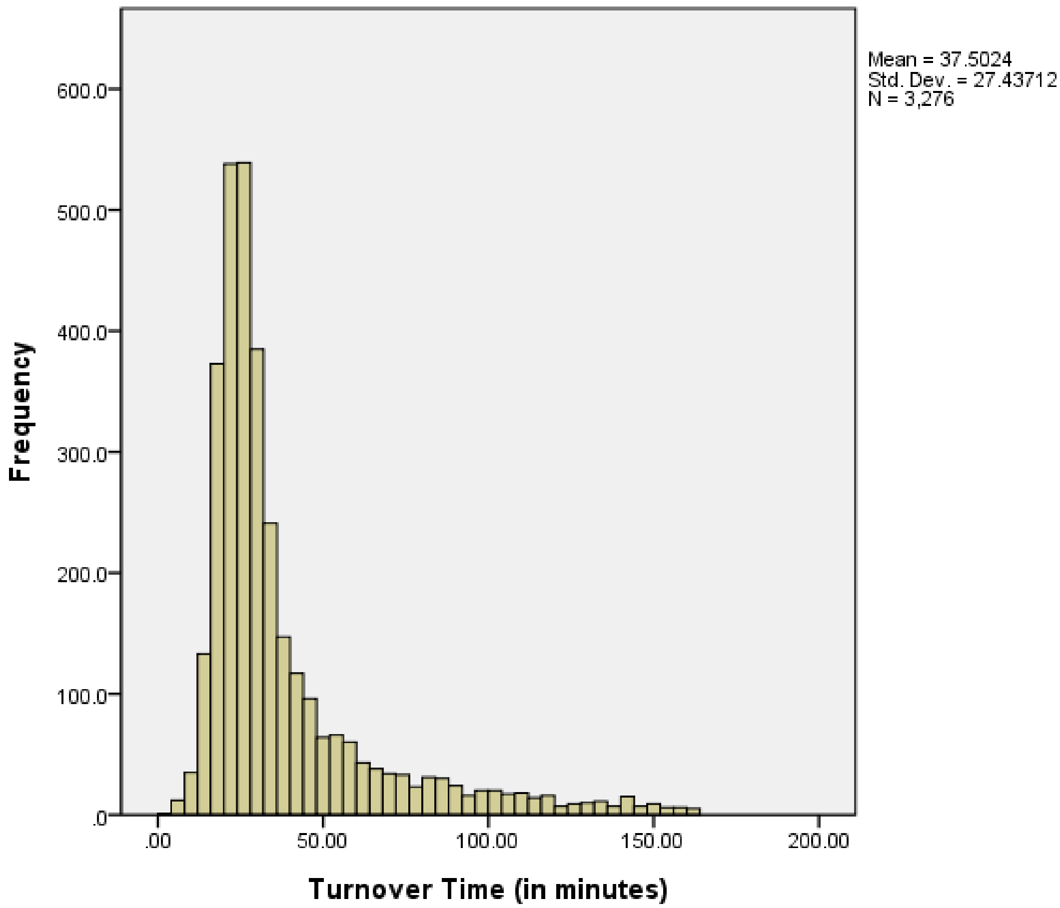


Figure 2. Turnover data histogram

This figure suggests the turnover times are skewed, which led us to analyze whether the data fit a skewed distribution with positive support, like the log-normal or the log-logistic distribution. Our analysis of this follows in Section 3.2.

3.2 DISTRIBUTION ANALYSIS

The distribution analysis component of our research entailed testing our hypothesis that a log-normal or log-logistic curve was better suited to turnover times than a normal curve. Demonstrating what distribution best represents turnover times could be beneficial for better estimating turnover times, resulting in more accurate scheduling and opportunities to reduce costs, improve utilizations, and identify potential outliers (Strum, May and Vargas 2000). Log-normal and log-logistic distributions are both skewed to the right with positive support. A random variable with log-normal distribution has the property that by taking the logarithm of it we obtain a normal distribution. If the data set fits a log-logistic distribution, then the logarithm of the data set fits a logistic distribution. A log-normal distribution differs from a log-logistic distribution in that a log-logistic distribution has a heavier tail.

Let $N(\mu, \sigma^2)$ be a normal distribution, with μ representing the mean and σ^2 being the variance, and let $Logistic(\mu, s)$ be a logistic distribution with mean μ and variance $\frac{\pi^2}{3}(s^2)$. Both distributions have no skewness as shown in the graph below, which depicts a standard normal distribution, $N(0,1)$ and a standard logistic distribution, $Logistic(0,1)$.

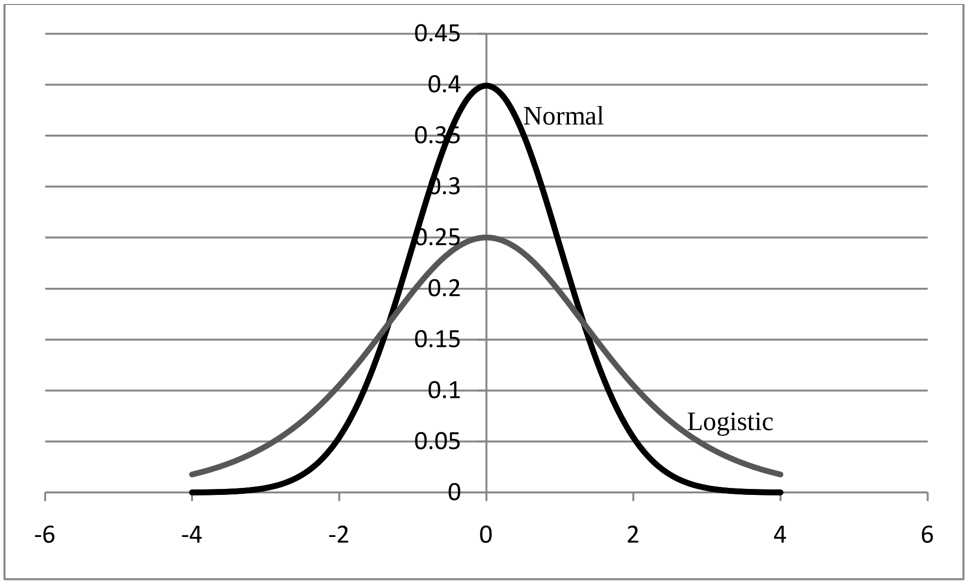


Figure 3. Standard normal and standard log-normal distributions

By taking the anti-logarithm of all values, a normal distribution is transformed into a log-normal distribution and a logistic distribution is transformed into a log-logistic distribution. The resulting log-normal distribution has a mean and a variance described by the following equations:

$$m = e^{\mu + \frac{\sigma^2}{2}}$$

$$s.d.^2 = \left(e^{\sigma^2} - 1\right)e^{2\mu + \sigma^2}$$

The resulting log-logistic distribution has a mean and a variance given by the following equations:

$$m = \frac{\frac{\alpha}{\beta}(\pi)}{\sin\frac{\pi}{\beta}}, \text{for } \beta > 1$$

$$s.d.^2 = \alpha^2 \left(\frac{2\beta}{\sin 2\beta} - \frac{\beta^2}{\sin^2 \beta} \right), \text{ for } \beta > 2$$

where

$\alpha =$ scale parameter
$\beta =$ shape parameter.

The log-normal distribution will be referred to as $LogN(\mu, \sigma)$, with the parameters referring to the underlying normal distribution, while the log-logistic distribution will be referred to as $LL(\alpha, \beta)$. For a standard log-normal distribution $m = \sqrt{e}$ and $s.d.^2 = (e-1)e$; for a standard log-logistic distribution both the mean and the variance are undefined. A standard log-normal distribution and a standard log-logistic distribution are presented below.

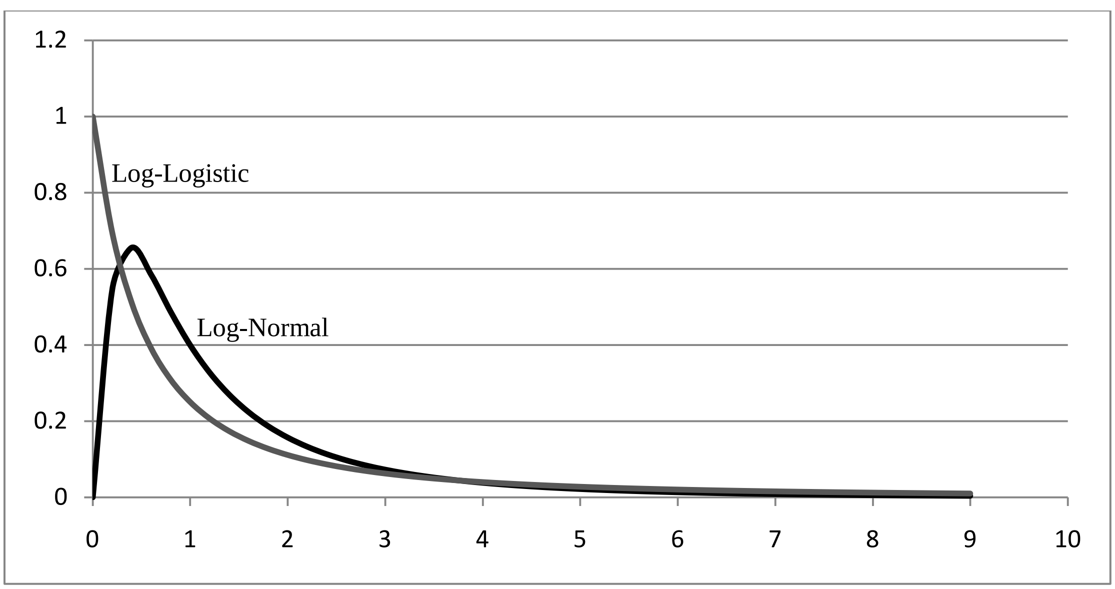


Figure 4. Standard log-normal and standard log-logistic distributions

There are four main parameters used to characterize probability distributions: mean, variance, skewness, and kurtosis. Kurtosis is a description of the shape of the curve. Higher kurtosis indicates that more of the variance of a data set is attributable to extreme deviations, which is seen visibly by higher peaks and heavier tails. Distributions with these attributes are referred to as leptokurtic, whereas distributions with shorter peaks are referred to as platokurtic. Kurtosis is a differentiating feature between the log-normal and log-logistic distributions. The normal distribution is platokurtic; on the other hand, the logistic distribution is leptokurtic. The implications of kurtosis on the fit of a log-normal versus a log-logistic distribution deal primarily with the tails. The log-logistic distribution will fit better if there is greater skewness due to the heavier tails, while the log-normal will prove to be a better fit if the opposite is true.

Another way to study these distributions is to examine their two density functions: the probability density function (pdf), usually denoted by $f(x)$, and the cumulative density function (cdf), usually denoted by $F(x)$. For a normal distribution these two functions are as follows:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$F(x) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{x-\mu}{\sqrt{2\sigma^2}}\right)\right]$$

where

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2}\, dt.$$

On the other hand, the density functions for a log-normal distribution are:

$$f(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}}$$

$$F(x) = \frac{1}{2} + \frac{1}{2}\mathrm{erf}\left[\frac{\ln x - \mu}{\sqrt{2\sigma^2}}\right]$$

For a logistic function the density functions are:

$$f(x) = \frac{e^{\frac{-(x-\mu)}{s}}}{s\left(1 + e^{\frac{-(x-\mu)}{s}}\right)^2}$$

$$F(x) = \frac{1}{1 + e^{\frac{-(x-\mu)}{s}}}$$

Finally, the density functions for a log-logistic function are:

$$f(x) = \frac{\left(\frac{\beta}{\alpha}\right)\left(\frac{x}{\alpha}\right)^{\beta-1}}{\left[1 + \left(\frac{x}{\alpha}\right)^{\beta}\right]^2}$$

$$F(x) = \frac{1}{1 + \left(\frac{x}{\alpha}\right)^{-\beta}}$$

Given the skewedness of log-normal and log-logistic distributions, we believed that they may be apt to describe turnover times since there are often a small number of cases that take much longer than average, thereby increasing the median turnover time.

We tested this hypothesis using graphical methods and statistical tests conducted on our turnover time data.

3.3 RESEARCH MODEL

In order to determine the curve that best fit our sample of turnover times we setup a hypothesis test. The null hypothesis, denoted by H_0, is the theory put forth for testing. The alternative hypothesis, denoted by H_a, is what would be adopted if the null hypothesis were rejected. The null and alternative hypotheses must be mutually exclusive (if one occurs, the other cannot) and collectively exhaustive (together the two hypotheses encompass all possible situations). In our experimental design the null and alternative hypotheses were as follows:

H_0: the turnover times fit a log-normal/log-logistic distribution

H_a: the turnover times do not fit a log-normal/log-logistic distribution

Once these hypotheses are constructed, there are four possible scenarios that can result from our testing as depicted below.

<table>
<tr><td></td><td></td><td colspan="2">DECISION</td></tr>
<tr><td></td><td></td><td>Reject H_0</td><td>Not Reject H_0</td></tr>
<tr><td rowspan="2">REALITY</td><td>H_0</td><td>Type I Error (α)</td><td>Correct Decision</td></tr>
<tr><td>H_a</td><td>Correct Decision</td><td>Type II Error (β)</td></tr>
</table>

Figure 5. Possible hypothesis testing results

A Type I error, or α, is more serious than a Type II error, or β. In the case of our setup, this corresponds to an erroneous rejection of a log-normal or log-logistic distribution (when compared to a normal distribution). Experimental setup can be adjusted to alter the probabilities of α and β occurring. However, when one is lowered, the other decreases. Therefore, minimizing α will result in an increase in β. A confidence level must be determined, from which α is then calculated (as $\alpha = 100 -$ confidence level), or α is fixed and the confidence level becomes $100 - \alpha$.

In order to test our null hypothesis of a log-normal fit, we used the Shapiro-Wilk goodness-of-fit test, which tests whether data fit a normal distribution. Given the property that a logarithmic transformation of log-normal data yields a normal distribution, we took the logarithm of each turnover time and used this as our data set. The Shapiro-Wilk test for normality was chosen as it has been shown to be superior to many other similar tests (such as Kolmogorov-Smirnov or Anderson-Darling) in regards to sensitivity in detecting non-normality, particularly with large sample sizes (Shapiro, Wilk and Chen 1968). The Shapiro-Wilk statistic, denoted by W, is calculated using the following equation:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where

$\bar{x} =$ sample mean
$x_{(i)} =$ order statistics $\left(x_{(1)} < x_{(2)} < x_{(n)}\right)$
$a_i =$ coefficients determined from covariance matrix of ordered statistics.

If the computed Wstatistic exceeds a tabulated critical value, then H_0 must be rejected. Additionally, a P value corresponding to the computed W score can be determined and compared to the chosen α. If the P value is less than α then H_0 is rejected.

Similarly, to test the fit of a log-logistic fit, given that the Shapiro-Wilk test can only be used to test for normality, we employed the Anderson-Darling goodness-of-fit test (Shapiro, Wilk and Chen 1968). This test results in the Cramér-von Mises statistic, or WCM, which is calculated as follows:

$$WCM = n \int_0^1 \frac{\left(F_n(x) - F(x)\right)^2}{F(x)\left(1 - F(x)\right)} dF(x)$$

where

$F_n(x) =$ the empirical distribution function (cdf).

Just as with the W statistic, if the computed WCM exceeds a tabulated critical value, H_o should be rejected. A P value corresponding to the WCM score can also be determined, which is another mechanism for determining if H_o should be rejected.

Our P value results are shown in the following tables, with a large P value indicating acceptance of the null hypothesis. Following the design of the Strum, May, and Vargas study (2000), we decided to differentiate between small (n < 30), medium (30 ≤ n ≤ 100), and large (n > 100) cases.

Table 2. Shapiro-Wilk goodness-of-fit *P* values for the log-normal model

Category	**P < 0.01**	**0.01 ≤ P < 0.10**	**P ≥ 0.10**	**Row Totals**
Small (n < 30)	0 (0.00%)	1 (2.94%)	5 (14.71%)	6 (17.65%)
Medium (30 ≤ n ≤ 100)	9 (26.47%)	1 (2.94%)	2 (5.88%)	12 (35.29%)
Large (n > 100)	16 (47.06%)	0 (0.00%)	0 (0.00%)	16 (47.06%)
Column Totals	25 (73.53%)	2 (5.88%)	7 (20.59%)	34 (100.00%)

Table 3. Anderson-Darling goodness-of-fit *P* values for the log-logistic model

Category	P < 0.01	0.01 ≤ P < 0.10	P ≥ 0.10	Row Totals
Small (n < 30)	0 (0.00%)	2 (5.88%)	4 (11.76%)	6 (17.65%)
Medium (30 ≤ n ≤ 100)	7 (20.59%)	3 (8.82%)	2 (5.88%)	12 (35.29%)
Large (n > 100)	16 (47.06%)	0 (0.00%)	0 (0.00%)	16 (47.06%)
Column Totals	23 (67.65%)	5 (14.71%)	6 (17.65%)	34 (100.00%)

Although these *P* values do not indicate a strong fit to log-normal or log-logistic distributions, they must be interpreted in conjunction with graphical tools such as histograms and probability plots, as the turnover times are distorted by our estimations.

The following histograms show visually the fit of log-normal and log-logistic distributions to our data set.

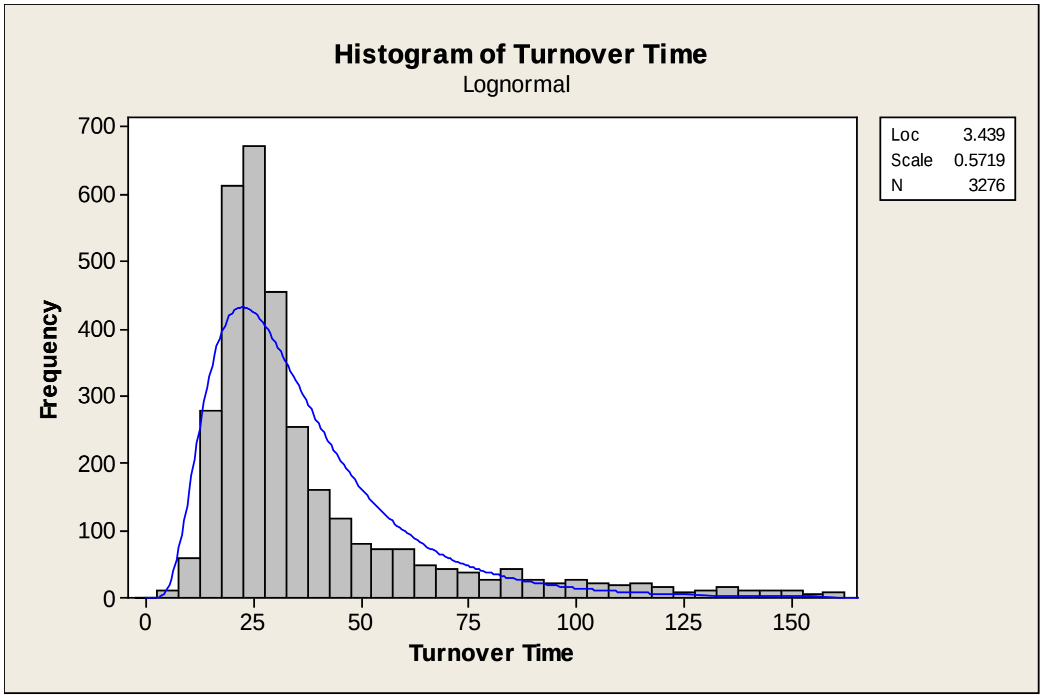


Figure 6. Histogram of turnover data with log-normal distribution fit

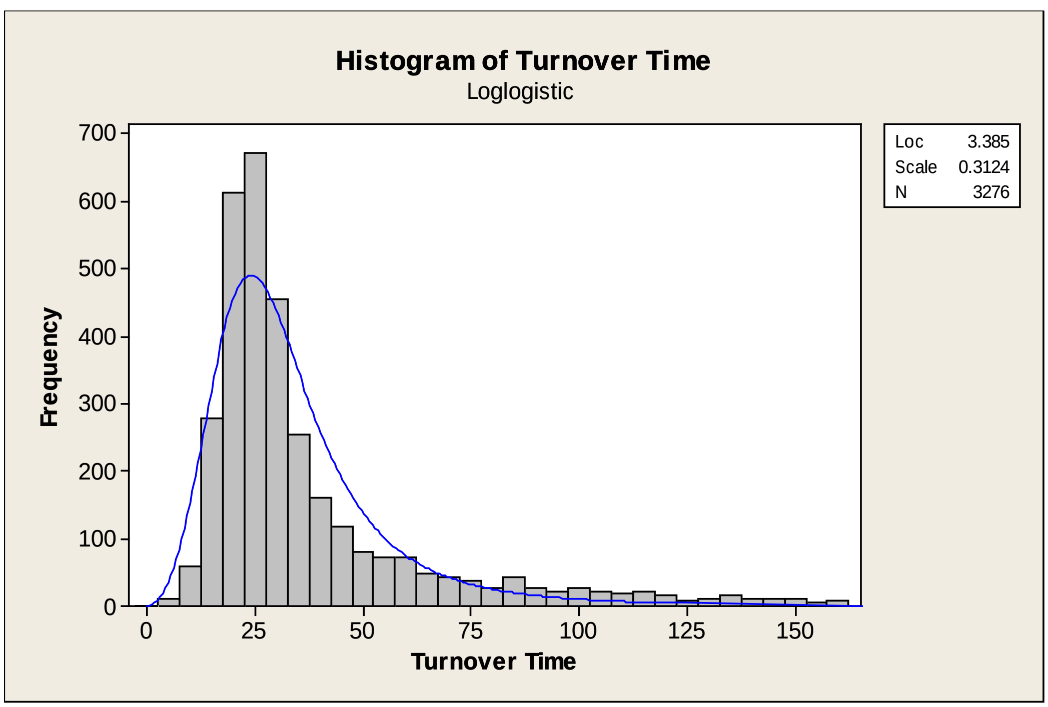


Figure 7. Histogram of turnover data with log-logistic distribution fit

Another graphical tool further illustrating the close fit of the turnover times to a log-normal or log-logistic model is probability plots. In a probability plot, the data set is plotted against its theoretical distribution and goodness-of-fit is shown by the plotted data being clustered along a straight line. The following probability plots show, by doctor, how well the turnover time data corresponds to the two distributions.

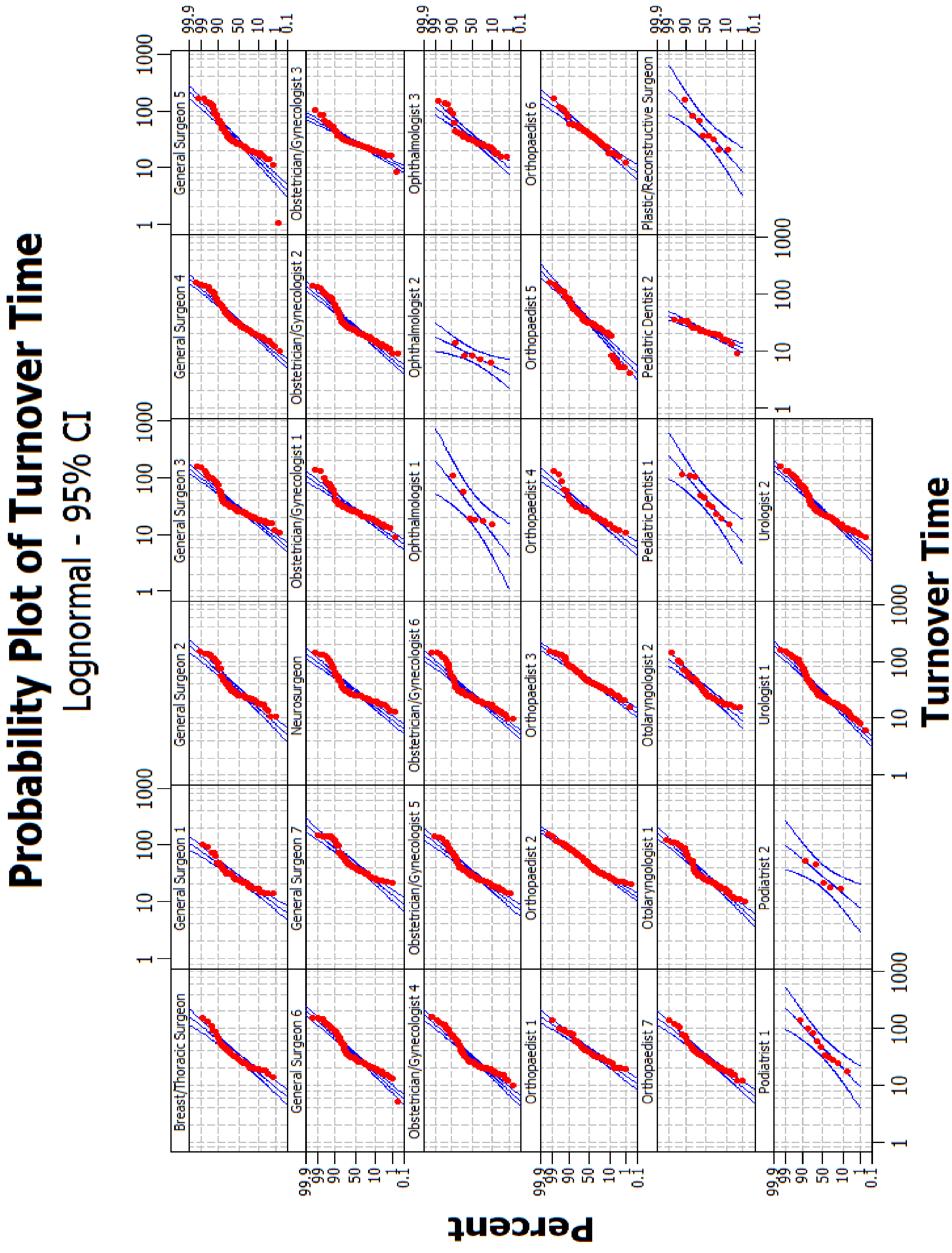


Figure 8. Probability plots by doctor for log-normal distribution

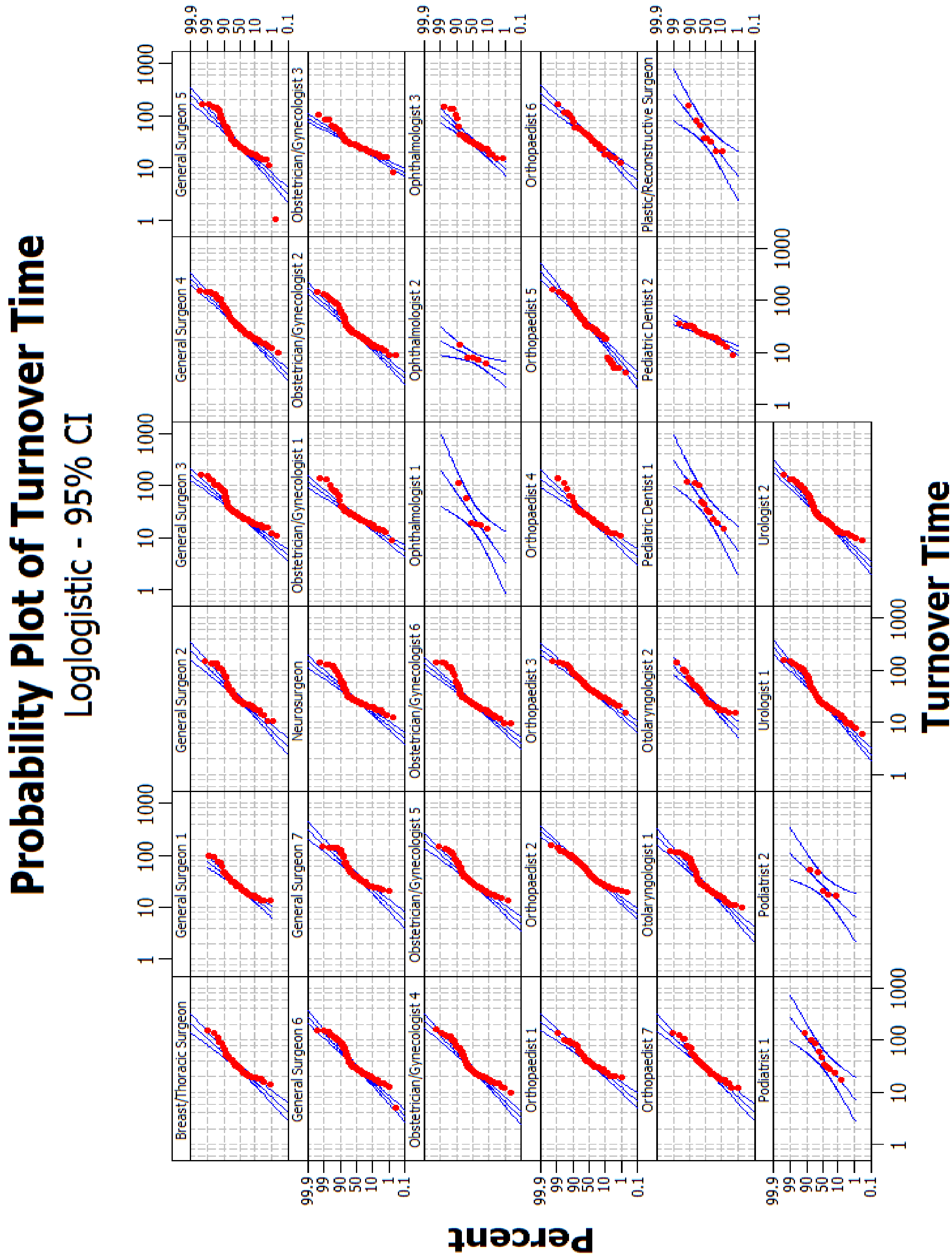


Figure 9. Probability plots by doctor for log-logistic distribution

Each plot should be interpreted separately to understand the fit by doctor of turnover times to a log-normal or log-logistic distribution. As mentioned, a good fit is shown by data points being clustered along the middle straight line. The outer lines are 95% confidence bands; in other words, if all data points fall within these two lines, there is 95% certainty that the data fit the distribution well.

3.4 CORRELATIONS

In continuing our analysis of turnover times, we looked to identify whether certain variables are correlated to turnover time duration. Based on the data that we had, we tested for correlations between length of surgery and length of turnover time and for differences between doctors with respect to the length of turnover time.

We began by analyzing, for each doctor, whether there was a correlation between surgery time (calculated as the difference between the ending surgery time and the beginning surgery time) and turnover time for our data set. As we did not have information on the type of surgery for each record, we grouped and analyzed the data by doctor. Thus, essentially the doctor was used as a proxy for the type of surgery given that doctors generally focus on a specific type of surgery. We chose to analyze this potential correlation due to the thought that longer surgeries may be messier, and, therefore, require more cleanup time. The regression tests were set up with the following hypotheses:

H_0: there is no correlation between turnover time and surgery time

H_a: there is a positive correlation between turnover time and surgery time.

The results of this hypothesis test are presented in the following table.

Table 4. Surgery time and turnover time correlations by doctor

Doctor (represented by surgery type)	n	Pearson Correlation Coefficient	P value
Breast/Thoracic Surgeon	63	0.176	0.084
General Surgeon 1	60	0.098	0.227
General Surgeon 2	97	0.026	0.398
General Surgeon 3	166	-0.008	0.46
General Surgeon 4	189	-0.015	0.421
General Surgeon 5	128	0.031	0.363
General Surgeon 6	178	-0.088	0.121
General Surgeon 7	80	0.211*	0.03
Neurosurgeon	124	-0.029	0.374
Obstetrician/Gynecologist 1	115	0.017	0.43
Obstetrician/Gynecologist 2	182	0.023	0.379
Obstetrician/Gynecologist 3	135	0.145*	0.047
Obstetrician/Gynecologist 4	153	0.013	0.438
Obstetrician/Gynecologist 5	99	0.08	0.216
Obstetrician/Gynecologist 6	146	-0.057	0.247
Ophthalmologist 1	6	0.872*	0.012
Ophthalmologist 2	5	-0.472	0.211
Ophthalmologist 3	48	-0.098	0.254
Otolaryngologist 1	124	0.034	0.354
Otolaryngologist 2	48	0.196	0.091
Orthopaedist 1	69	-0.035	0.387
Orthopaedist 2	169	0.03	0.349
Orthopaedist 3	129	-0.216*	0.007
Orthopaedist 4	65	0.085	0.249
Orthopaedist 5	130	-0.029	0.37
Orthopaedist 6	65	-0.077	0.271
Orthopaedist 7	76	0.122	0.147
Pediatric Dentist 1	10	0.086	0.406
Pediatric Dentist 2	33	-0.039	0.414
Plastic/Reconstructive Surgeon	8	-0.077	0.428
Podiatrist 1	10	-0.385	0.136
Podiatrist 2	5	-0.134	0.415
Urologist 1	184	0.02	0.396
Urologist 2	177	-0.02	0.396

*Indicates that the correlation is significant at the 0.05 level.

The results indicate that there does not appear to be a correlation between surgery time and turnover time across doctors, so the null hypothesis cannot be rejected. We conjecture that there might be two main explanations for this lack of correlation. First, even if longer surgeries are messier, staff may clean up throughout the process so that the chances of infection during surgery are minimized. This results in no extra cleanup being required after the completion of the surgery. Second, our surgery time includes anesthesia time, which may vary, thereby distorting the length of surgery data and not having it represent what we want it to. For the four doctors for whom a significant correlation does exist, we would recommend further investigation to see why this correlation is significant. From a modeling perspective, the insight is that it is reasonably safe to model turnover duration as being independent of the surgery length.

The next analysis we conducted was to identify if there were significant differences in the mean turnover times of various doctors. Our null and alternative hypotheses were the following:

H_0: there is no significant difference in the mean turnover time of the doctors

H_a: there is a significant difference in the mean turnover time of at least one doctor.

The data is represented on the following probability plot and histogram.

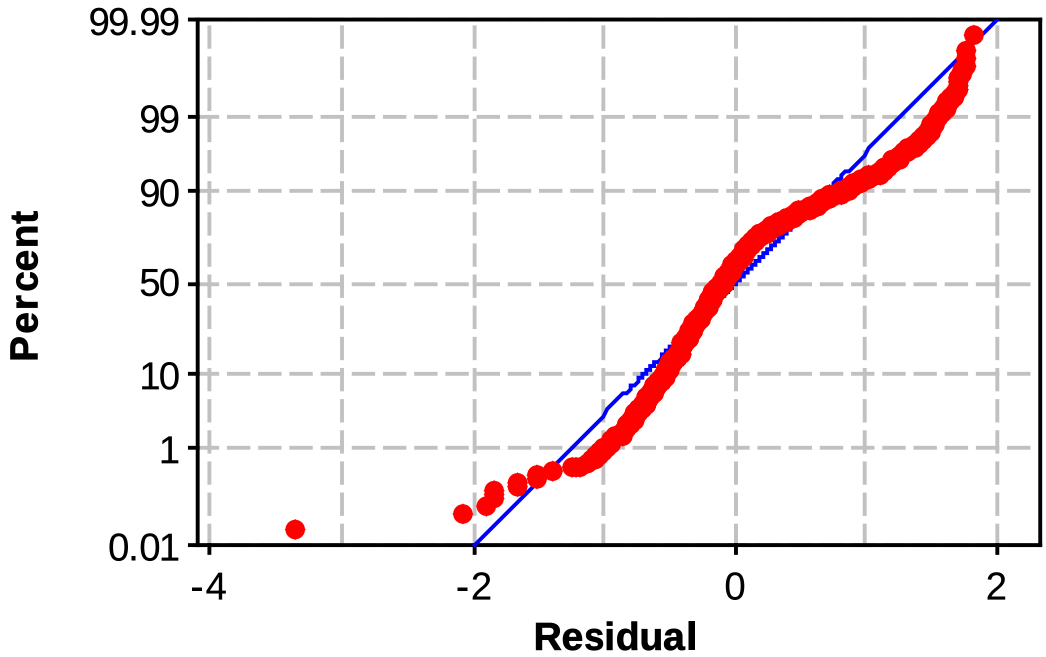


Figure 10. Probability plot of mean logarithm of turnover times

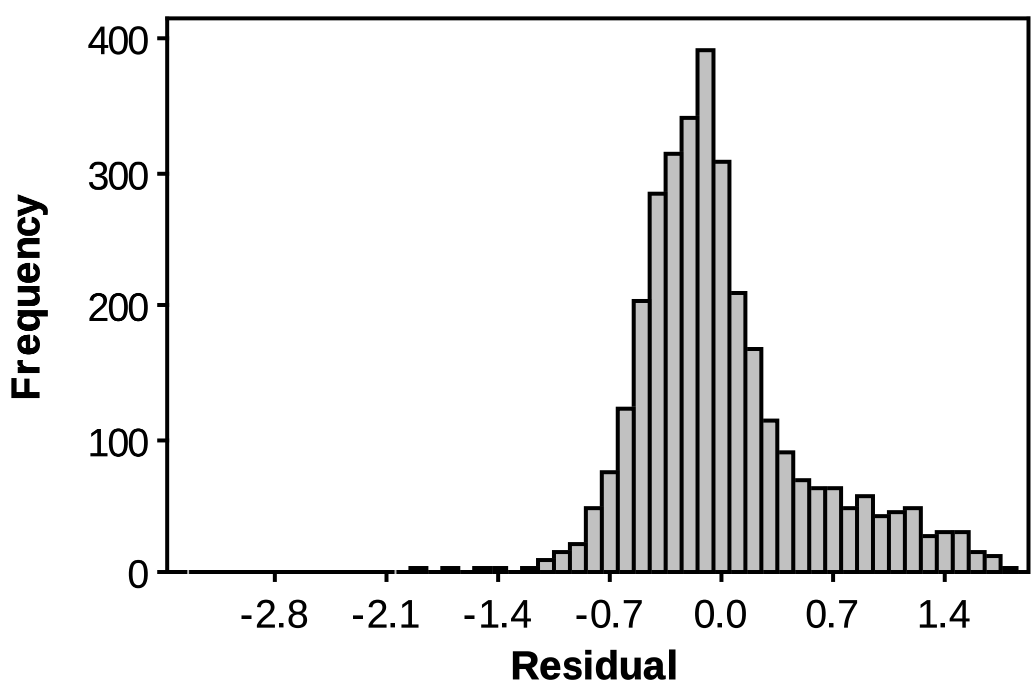


Figure 11. Histogram of logarithm of turnover times

A one-way analysis of variance (ANOVA) was used to test for turnover time differences among the 34 doctors. We found that turnover times differed significantly across these 34 categories, $F(33,3242) = 13.14$, $p < 0.001$. Consequently, we rejected the null hypothesis. Furthermore, using Tukey pairwise comparisons, we were able to identify which pairs of doctors exhibited significantly different average turnover times. The following table indicates groupings for each doctor, where doctors not sharing a group have significantly different mean turnover times.

Table 5. Tukey pairwise comparisons of mean turnover time by doctor

Doctor (represented by surgery type)	*n*	Mean Turnover Time (minutes)	Standard Deviation (minutes)	Tukey Method Grouping
Podiatrist 1	10	56.5	40.2	A B
Plastic/Reconstructive Surgeon	8	55.12	45.5	A B C
Pediatric Dentist 1	10	54.7	40.16	A B C
Orthopaedist 3	129	53.92	27.4	A
Orthopaedist 2	169	52.62	25.85	A
General Surgeon 7	80	52.57	34.97	A B
Orthopaedist 1	69	45.78	23.67	A B C
Orthopaedist 6	65	42.83	25.5	A B C
General Surgeon 6	178	40.66	30.43	B C
Ophthalmologist 1	6	39.67	38.58	A B C
General Surgeon 4	189	39.65	28.14	B C
Orthopaedist 5	130	39.52	28.01	B C
General Surgeon 2	97	39.2	31.25	B C
Ophthalmologist 3	48	38.44	29.51	B C
Obstetrician/Gynecologist 5	99	38.01	26.9	B C
Breast/Thoracic Surgeon	63	37.68	27.34	B C
Otolaryngologist 2	48	37.46	25.61	B C
Orthopaedist 7	76	36.51	24.38	B C
Obstetrician/Gynecologist 4	153	36.29	27.56	B C
General Surgeon 5	128	36	30.46	B C
Neurosurgeon	124	35.26	26.27	B C
General Surgeon 3	166	35.23	26.07	B C
Urologist 1	184	34.79	29.46	B C D
Otolaryngologist 1	124	34.44	25.7	B C
Urologist 2	177	32.37	26.46	B C D
Podiatrist 2	5	31.2	17.36	A B C D
Obstetrician/Gynecologist 6	146	30.8	25.72	B C D
Obstetrician/Gynecologist 2	182	30.49	24.04	B C D
Obstetrician/Gynecologist 1	115	30.31	20.73	B C D
General Surgeon 1	60	30.03	18.1	B C D
Orthopaedist 4	65	29.11	21.41	B C D
Obstetrician/Gynecologist 3	135	28.9	13.1	B C D
Pediatric Dentist 2	33	22.27	5.94	C D
Ophthalmologist 2	5	8.6	3.13	D

Mean turnover times are significantly different between doctors who do not share a letter.

The boxplot shown below graphically depicts the numerical turnover times for each doctor. Overlap in the boxed regions (lower quartile to upper quartile of turnover times) between doctors indicates that there is no significant difference in mean turnover time. However, when there is not overlap, it represents a significant discrepancy in mean turnover time.

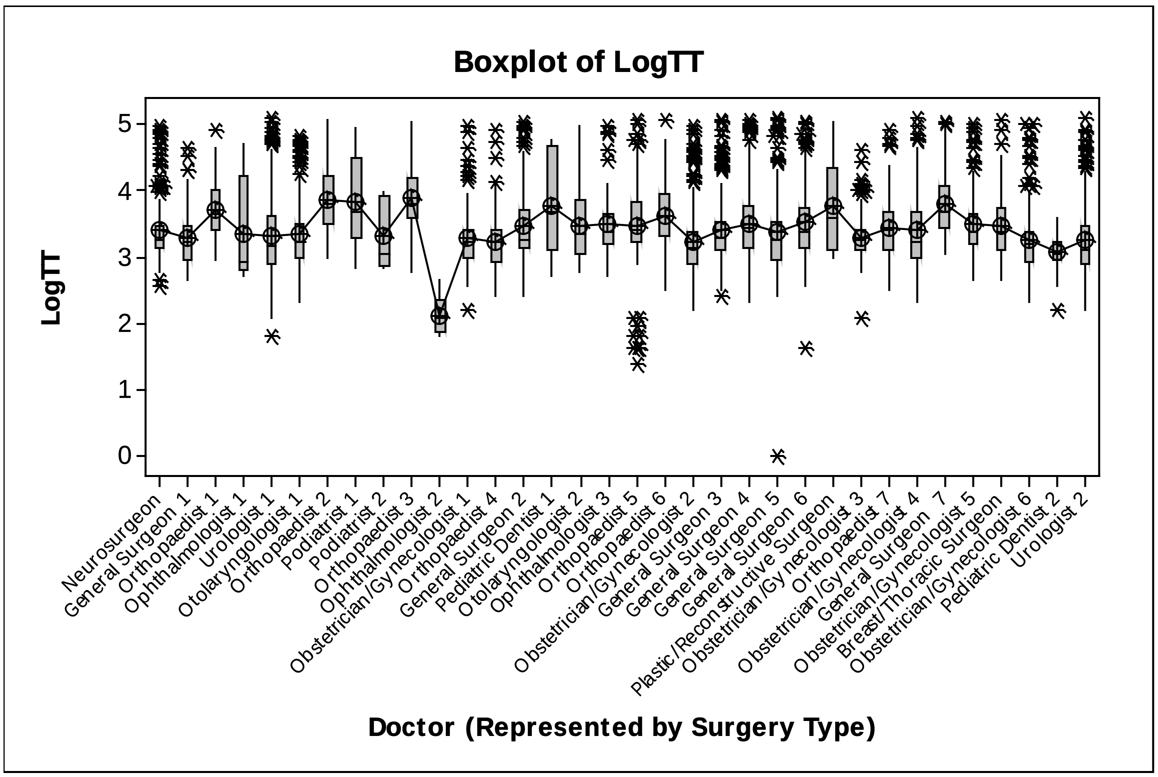


Figure 12. Boxplot of turnover time logarithm by doctor

3.5 CONCLUSIONS

Ideally, we would have had the actual turnover time data and would not have had to estimate turnover times. However, given that sufficient data is not recorded by Evangelical Community Hospital, it was necessary to make such estimations. Consequently, part of our statistical analysis must be based on graphical methods, so that we are not relying solely on quantitative measures. The graphical representations of distribution fits overlaid on histograms of the turnover time data and the probability plots reveal that there appears to be a good fit of turnover times to log-normal and log-logistic distributions.

Because our turnover time estimations likely include time that is not true turnover time (such as staff late arrivals or idle time) as mentioned, our turnover times are overestimated, which is a bias that we must recognize in interpreting our results. A log-logistic distribution has heavier tails than a log-normal distribution, so although our analysis appears to demonstrate that a log-logistic distribution fits better than a log-normal distribution, this may not be the case when analyzing true turnover time (with idle time removed). Both log-normal and log-logistic distributions satisfy the skewed distribution of turnover times. We conjecture that the variability in the number of procedures performed by a hospital effects which distribution is better. A log-normal distribution seems better suited to a hospital that routinely performs many different types of surgeries, whereas a log-logistic distribution is more apt to be the best fit at hospitals that perform a limited number of procedures, such as specialty hospitals. Thus, given that there are reasons to prefer different distributions in different settings and given that we are making conclusions based on turnover time estimations, we have elected to conclude that both distributions should be considered good fits and have not determined which is better. We would advise that hospitals apply the distribution that better fits the offerings of the hospital, as outlined above.

We would recommend that hospitals continue to develop better methods for data recording. Many hospitals have begun to record more useful data, but Evangelical Community Hospital and others fail to record data that allows turnover time to be separated from idle time.

In analyzing correlations between various variables and turnover time, we determined that surgery time does not seem to influence turnover time across doctors. Yet, we discovered that there are doctors whose mean turnover time is statistically significant from other doctors. These findings shed light on variables potentially affecting turnover time.

Based on these results, we will show in Chapter 4.0 how to use quality control measures to improve turnover times.

4.0 CONTROL CHARTS IN HEALTHCARE SETTINGS

4.1 INTRODUCTION

The next component of our research focuses on developing a mechanism to monitor whether the turnover process is in control. If the turnover process is kept in control, more operating room capacity can be available, which would lead to an increase in the number of surgeries performed, thus raising the overall service level of the hospital. Furthermore, it could help monitor and reduce variability, which hopefully would have potential cost savings.

Although quality control charts have been developed to monitor process variability for manufacturing processes, this study serves as the first to provide a framework for instituting a quality control chart in a healthcare setting. A control chart is a tool widely used in quality control, designed to ensure that the process variability stays within specified limits (Krajewski, Ritzman and Malhotra 2010).

Our efforts were focused on designing an easy to implement control chart that would trace the turnover process using standard spreadsheet software. The purpose was to detect abnormal behavior early, so that remedial actions could be considered to bring the process back on track. We chose to monitor the turnover process using control charts as they are the preferred mechanism for continuously monitoring processes (McClave, Benson and Sincich 2008). A process is considered out of control if it exhibits variation that is non-random (even an in control process has variation, but it is of a random nature).

A control chart is developed using three values: (1) the centerline, which reflects the mean of the measured variable; (2) the upper control limit (UCL), which is a specified number of standard deviations above the mean; and (3) the lower control limit (LCL), which is a specified number of standard deviations below the mean. A typical value for this multiplier is three, resulting in UCL and LCL commonly referred to as the three-sigma limits. Under this choice, the Type I error probability (that a point falls beyond this region due to non-random causes) would be 0.0027. In the case of turnover time, lower is better, so the LCL is not as important as the UCL, but we still include the LCL as it is important to identify when there is systematic lowering of turnover time so that it can be replicated in the future.

In order to be able to accurately assess process variability, two control charts are usually constructed when the studied variable can be measured: an $\bar{x}$-chart and an R-chart. An $\bar{x}$-chart plots sample means and is used to identify changes in the process mean. On the other hand, an R-chart plots sample ranges and is therefore used to detect overall changes in process variation. Both charts are constructed using centerlines, UCLs, and LCLs, but the data plotted differs. On the control charts, data are grouped into and plotted by a fixed sample size. The R-chart should first be analyzed to determine if the process variability is stable. If this chart indicates that it is, the $\bar{x}$-chart is next examined to ensure that the process mean is stable. If either chart reveals that the process is not in statistical control, it becomes critical to diagnose the causes of variation. If both charts agree that the process mean and process variation are in control, then the process can simply continue to be monitored.

The following formulas are used to compute the control limits for an R-chart:

$$\mathrm{UCL}_R = D_4\bar{R}$$

$$\mathrm{LCL}_R = D_3\bar{R}$$

where

$\bar{R}$ = center line of the control chart

D_3, D_4 = constants that depend on the sample size.

For the $\bar{x}$-chart, the control limits are computed as follows:

$$\mathrm{UCL}_{\bar{x}} = \bar{\bar{x}} + A_2\bar{R}$$

$$\mathrm{LCL}_{\bar{x}} = \bar{\bar{x}} - A_2\bar{R}$$

where

$\bar{\bar{x}}$ = center line of the control chart

A_2 = constant that depends on the sample size.

The constants for both types of control charts are provided in the table below for normal and for logistic distributions. Traditionally, the control chart constants assume an underlying normal distribution of the process; however, this is not always the case. In particular, our data suggests a possible (log)-logistic distribution, in which case different constants should be used. In their paper, Tadikamalla, Banciu, and Popescu (2008) derive better control chart constants for non-normal processes, which we utilize for the logistic distribution.

Table 6. Constants for control charts for normal and logistic process distributions

		Normal Distribution		Logistic Distribution	
n	A_2	D_3	D_4	D_3	D_4
2	1.880	0.000	3.267	0.002	4.717
3	1.023	0.000	2.575	0.039	3.515
4	0.729	0.000	2.282	0.099	3.066
5	0.577	0.000	2.115	0.156	2.821
6	0.483	0.000	2.004	0.204	2.663
7	0.419	0.076	1.924	0.243	2.550
8	0.373	0.136	1.864	0.276	2.465
9	0.337	0.184	1.816	0.303	2.398
10	0.308	0.223	1.777	0.326	2.343

4.2 DEVELOPMENT METHODOLOGY

Given the potential cost and service benefits of instituting control charts, we worked to create informative, easy to adopt charts. The charts are designed to be easily updated and easily read to determine whether or not the system is in control.

To analyze the stability of the turnover time process, we use the Western Electric rules. These rules are designed to identify non-random changes detected by patterns in the data points. The rules are constructed by dividing a control chart into zones based on standard deviations from the centerline as depicted in the figure below.

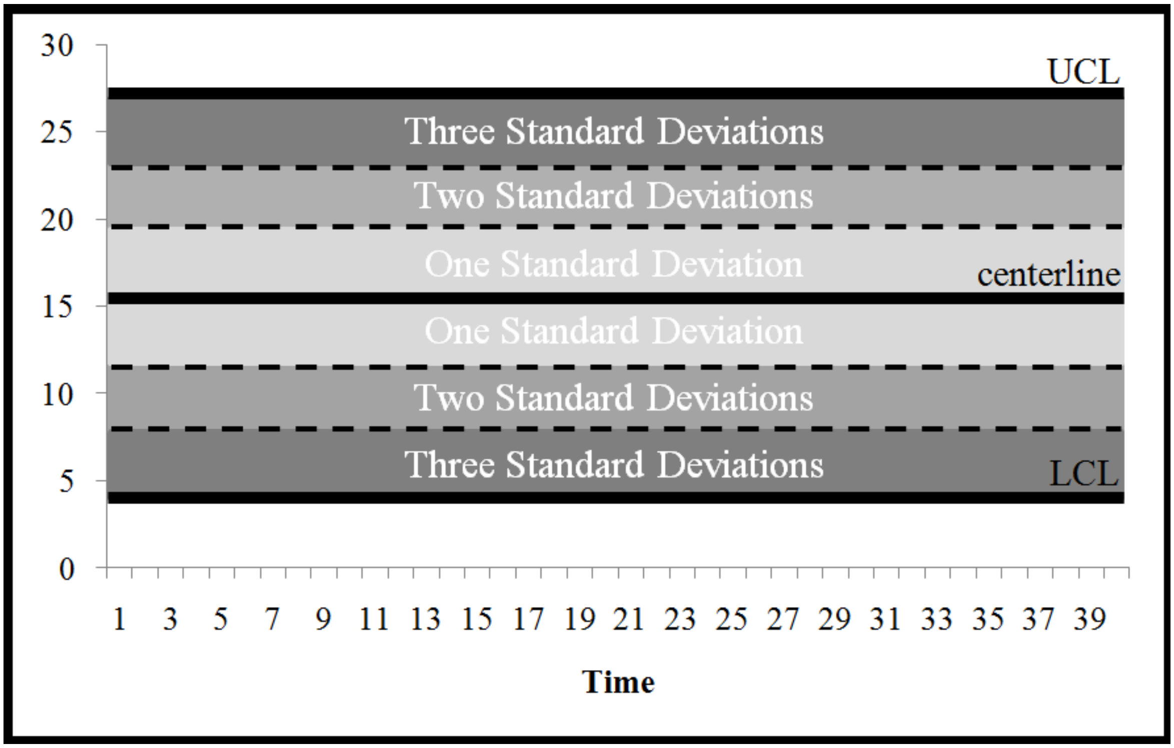


Figure 13. Control chart zones

The following table lists the Western Electric rules.

Table 7. Western Electric control chart rules

Western Electric Rules
One or more points > +/- three standard deviations
Eight consecutive points increasing or decreasing
Fourteen points alternating up and down
Two out of three consecutive points ≥ +/- two standard deviations on one side of centerline
Four out of five points ≥ +/- one standard deviation on one side of centerline
Eight consecutive points on one side of centerline

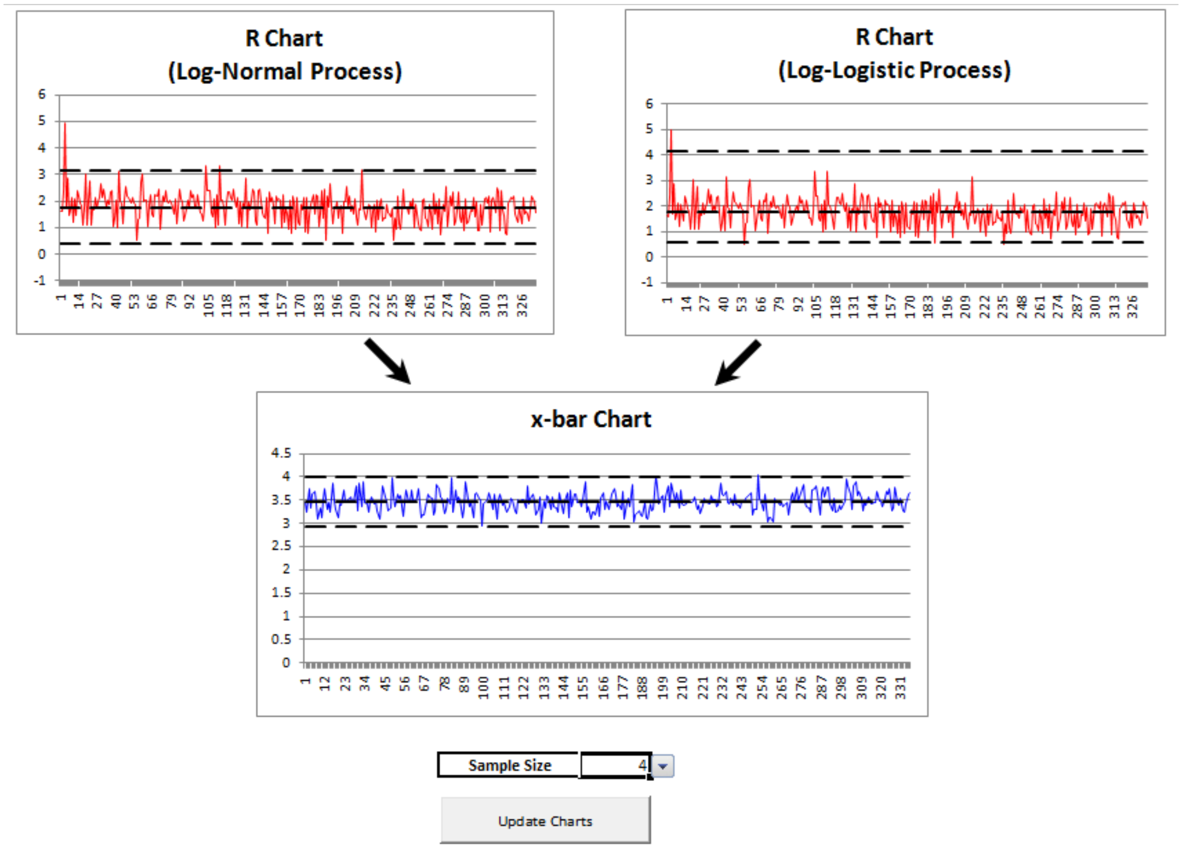
Our control charts, created within Excel using VBA macros, identify when these rules are met. Furthermore, the control charts allow for the sample size to be adjusted. In other words, each data point represents the mean of a specified number of consecutive data points, which can be altered. When the charts are updated, using an easy-to-find button, the new surgery data is plotted. The VBA code is provided in the Appendix.

Given the ease of use of this tool, the enormous benefits it can have, and its accessibility via standard spreadsheet software, we believe that its adoption by the hospital is a simple proposition. Recognizing the impact that it can have, we hope that it will spark the adoption of quality control charts in other hospital settings.

4.3 IMPLEMENTATION

Our spreadsheet with control charts contains three charts: an $\bar{x}$-chart, an R-chart for a log-normal distribution, and an R-chart for a log-logistic distribution. Depending on the hospital and the distribution that better models the hospital's turnover times, the appropriate R-chart can be used in conjunction with the $\bar{x}$-chart.

Presented next are screenshots of the control charts we developed for use by Evangelical Community Hospital.



Process Stability Check	LogN	LL
One or more points beyond +/- three standard deviations	Not OK	Not OK
Eight consecutive points increasing or decreasing	OK	OK
Fourteen points alternating up and down	OK	OK
Two out of three consectuive points at or above +/- two standard deviations on one side of cent	Not OK	Not OK
Four out of five points at or above +/- one standard deviation on one side of centerline	Not OK	Not OK
Eight consecutive points on one side of centerline	Not OK	Not OK

Process Information	
Lower Limit	0
Mean	39.19
Target	25
Upper Limit	40
Sigma	29.89
Cp	0.223
Cpk	0.009
Process is not centered	

Figure 14. Control charts screenshot

The process stability check indicators show that the process is out of control. When the indicator is blue, the $\bar{x}$-chart is the source of the issue, whereas red text indicates that the R-chart is the source of the issue. Since there are both blue and red indicators, the process mean and process variation are both out of control. In other words, there is non-random variation of the turnover time mean and variation. The implication is that the hospital must work to identify the sources of variation and take measures to stabilize the process.

4.4 CONCLUSIONS

The control charts offer a practical, visible way of monitoring turnover time variability and shifts in average turnover time. As the control charts are based in standard spreadsheet software, they are easy to implement in hospitals. The Western Electric rules show whether the process spread and mean are stable or not. If the turnover times are out of control statistically, the hospital can act quickly to identify factors contributing to this and take action to bring the process back under control. Quality control is important for ensuring hospital productivity, staff satisfaction, and patient satisfaction and, therefore, is important to focus on.

Control charts have been successfully implemented in a variety of fields and we believe that healthcare environments should be the next to adopt the useful quality control tool. Not only will the charts help hospitals to identify problems sooner so that they can be addressed earlier, but they will also give hospitals a clear way of monitoring the success of any steps taken to reduce average turnover time.

5.0 CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

Overall, our work is designed to expand upon the current body of literature on hospital effectiveness by analyzing turnover time, a critical component often overlooked. Turnover time is vastly important as lengthier surgery turnover times lead to lower utilization rates and it directly affects scheduling accuracy. Using data provided by Evangelical Community Hospital, we modeled turnover times, analyzed the factors potentially affecting turnover time length, and designed control charts to monitor the variability of turnover times.

Being able to accurately predict turnover times allows for better scheduling, in turn improving hospital efficiency and effectiveness. Thus, our research was designed to identify a distribution that fit turnover times. As outlined, we concluded that the log-normal and log-logistic distributions both appear to be good fits for turnover time. Further research will hopefully build upon this finding by confirming the variables that dictate which distribution is a better fit for a given hospital.

We also sought to identify variables correlated to longer than average turnover times in order to identify factors that may affect turnover time length. Our research showed that there was not a correlation between length of surgery and length of turnover across doctors. When the mean turnover times of the doctors were compared, there did exist statistical differences. Therefore, we suggest continued research of the role, if any, a doctor plays in determining turnover time.

Turnover times are inherently variable, but efforts need to be directed at stabilizing the times. In order to monitor process variability, we designed control charts, a widely used quality control mechanism in other fields, for hospital settings. The control charts allow individual hospitals, such as Evangelical Community Hospital, to identify when turnover times are varying due to non-random causes so that remedial action can be taken.

We believe that the development of applicable control charts, identification of distributions to model turnover times, and analysis of variables potentially correlated to turnover time are important contributions in working to improve hospital effectiveness. As the pressure on hospitals to improve effectiveness in order to boost profitability mounts, tools and findings such as these become critical.

We hope that hospitals that do not already do so will begin to keep more accurate time records so that turnover time can be clearly identified and further studied. Next steps will then entail encouraging implementation of control charts in hospital settings, further researching the variables affecting turnover times, and improving scheduling methods to correspond to findings about turnover times.

APPENDIX A

SOURCE CODE FOR THE CONTROL CHARTS EXCEL SHEET

```
Public Sub cmdUpdateCC_Click()
'These are the arrays that store the control chart constants (2 for R-
chart, 2 for x-bar chart)
Dim D3() As Variant, D4() As Variant, D3LL() As Variant, D4LL() As
Variant, A2() As Variant, A3() As Variant

Dim checkOne As Boolean
Dim checkTwo As Boolean
Dim checkThree As Boolean
Dim checkFour As Boolean
Dim checkFive As Boolean
Dim checkSix As Boolean
Dim checkSeven As Boolean

Dim checkConsecutive As Boolean, blnTrendUp As Boolean, blnTrendDown As
Boolean

Dim sngSampleMean As Single, sngSampleRange As Single
Dim sngTempMin As Single, sngTempMax As Single
Dim AvgDataSeries() As Single, RangeDataSeries() As Single
Dim intIndex As Integer
Dim sngRLCL As Single, sngRUCL As Single, sngRCenter As Single
Dim sngRLCL_LL As Single, sngRUCL_LL As Single
Dim sngxLCL As Single, sngxUCL As Single, sngxCenter As Single
Dim rngTurnoverTime As Range, rngTemp As Range
Dim rngOriginalTimes As Range
Dim intSampleSize As Integer, intSizeOfData As Integer, intCounter As
Integer
Dim intNumPoints As Integer
Dim i As Integer, j As Integer

Dim TestVal(8) As Single

'Initialize the control chart constants arrays
```

```
D3 = Array(0, 0, 0, 0, 0, 0.076, 0.136, 0.184, 0.223, 0.256, 0.283, 0.307, 0.328, 0.347, 0.363, 0.378, 0.391, 0.403, 0.415)
D4 = Array(3.267, 2.574, 2.282, 2.114, 2.004, 1.924, 1.864, 1.816, 1.777, 1.744, 1.717, 1.693, 1.672, 1.653, 1.637, 1.622, 1.608, 1.597, 1.585)
D3LL = Array(0.002, 0.039, 0.099, 0.156, 0.204, 0.243, 0.276, 0.303, 0.326)
D4LL = Array(4.717, 3.515, 3.066, 2.821, 2.663, 2.55, 2.465, 2.398, 2.343)
A2 = Array(1.882, 1.023, 0.729, 0.577, 0.483, 0.419, 0.373, 0.337, 0.308, 0.285, 0.266, 0.249, 0.235, 0.223, 0.212, 0.203, 0.194, 0.187, 0.18)
A3 = Array(2.659, 1.954, 1.628, 1.427, 1.287, 1.182, 1.099, 1.032, 0.975, 0.927, 0.886, 0.85, 0.817, 0.789, 0.763, 0.739, 0.718, 0.698, 0.68)


'Compute the sample means and the sample ranges of the turnover data (logged)
'First, assign the entire log(time) column to a range variable. Remember that this range may contain zeros that need to be stripped later.
Set rngTurnoverTime = Worksheets("Sheet1").Range("LogTurnoverTimes")
Set rngOriginalTimes = Worksheets("Sheet1").Range("updatedSeries")

'Get the sample size (default = 5)
intSampleSize = Worksheets("Control Charts").Range("J35").Value

'Compute the average log(time) for all groups of size intSampleSize
sngSampleMean = 0
intCounter = 0
intIndex = 1
For Each rngTemp In rngTurnoverTime
    If rngTemp.Value <> 0 Then
        sngSampleMean = sngSampleMean + rngTemp.Value
        intCounter = intCounter + 1
        If intCounter Mod intSampleSize = 0 Then
            ReDim Preserve AvgDataSeries(1 To intIndex)
            sngSampleMean = sngSampleMean / intSampleSize
            AvgDataSeries(intIndex) = sngSampleMean
            intIndex = intIndex + 1
            sngSampleMean = 0
        End If
    End If
Next

'Compute the ranges of log(time) for all groups of size intSampleSize
sngSampleRange = 0
sngTempMax = 0
sngTempMin = 1000
intCounter = 0
intIndex = 1
For Each rngTemp In rngTurnoverTime
    If rngTemp.Value <> 0 Then
```

```
        If rngTemp.Value < sngTempMin Then sngTempMin = rngTemp.Value
        If rngTemp.Value > sngTempMax Then sngTempMax = rngTemp.Value
        intCounter = intCounter + 1
        If intCounter Mod intSampleSize = 0 Then
            ReDim Preserve RangeDataSeries(1 To intIndex)
            sngSampleRange = sngTempMax - sngTempMin
            RangeDataSeries(intIndex) = sngSampleRange
            intIndex = intIndex + 1
            sngSampleRange = 0
            sngTempMax = 0
            sngTempMin = 1000
        End If
    End If
Next

intIndex = intIndex - 1 'This now holds the total number of samples of size intSampleSize that we will plot

'At this point, the arrays AvgDataSeries and RangeDataSeries contain the grouped data.
'Now, compute the centerlines (the averages of the values from these two arrays).
sngSampleMean = 0
sngSampleRange = 0
For i = 1 To intIndex
    sngSampleMean = sngSampleMean + AvgDataSeries(i)
    sngSampleRange = sngSampleRange + RangeDataSeries(i)
Next i
sngxCenter = sngSampleMean / intIndex
sngRCenter = sngSampleRange / intIndex

'Compute the LCL and the UCL for the two charts
sngxLCL = sngxCenter - A2(intSampleSize - 1) * sngRCenter
sngxUCL = sngxCenter + A2(intSampleSize - 1) * sngRCenter

sngRLCL = D3(intSampleSize - 1) * sngRCenter
sngRUCL = D4(intSampleSize - 1) * sngRCenter
sngRLCL_LL = D3LL(intSampleSize - 1) * sngRCenter
sngRUCL_LL = D4LL(intSampleSize - 1) * sngRCenter

'Now, the only thing left is plotting the charts! We'll do the R chart first.

'Plot the LCL, UCL, centerline, range data
'We need to create three artificial arrays for the X-axis, LCL and UCL (which basically just repeat themselves)
ReDim XValues(1 To intIndex), LCLArray(1 To intIndex), UCLArray(1 To intIndex), CenterlineArray(1 To intIndex), LCL_LLArray(1 To intIndex), UCL_LLArray(1 To intIndex)

For i = 1 To intIndex
    XValues(i) = i
    LCLArray(i) = sngRLCL
    LCL_LLArray(i) = sngRLCL_LL
```

```
    UCLArray(i) = sngRUCL
    UCL_LLArray(i) = sngRUCL_LL
    CenterlineArray(i) = sngRCenter
Next i

With Worksheets("Control Charts")
    .ChartObjects(1).Activate
    .ChartObjects(1).Chart.HasTitle = True
    .ChartObjects(1).Chart.Axes(xlValue).MinimumScale = -1
    With ActiveChart
        .ChartTitle.Select
        Selection.Characters.Text = "R Chart" & vbCrLf & "(Log-Normal
Process)"
    '.ChartObjects(1).Select
        .ChartArea.Select
        .ChartArea.ClearContents

        .SeriesCollection.NewSeries.Values = RangeDataSeries
        .SeriesCollection(1).XValues = XValues
        .SeriesCollection(1).Name = "Range Data (sample = " &
intSampleSize & ")"

        .SeriesCollection.NewSeries.Values = LCLArray
        .SeriesCollection(2).XValues = XValues
        .SeriesCollection(2).Name = "LCL"

        .SeriesCollection.NewSeries.Values = UCLArray
        .SeriesCollection(3).XValues = XValues
        .SeriesCollection(3).Name = "UCL"

        .SeriesCollection.NewSeries.Values = CenterlineArray
        .SeriesCollection(4).XValues = XValues
        .SeriesCollection(4).Name = "Centerline"

        .SeriesCollection(4).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(2).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(3).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(1).Border.Color = RGB(255, 0, 0)

        .SeriesCollection(1).Border.Weight = xlHairline
        .SeriesCollection(2).Border.Weight = xlMedium
        .SeriesCollection(3).Border.Weight = xlMedium
        .SeriesCollection(4).Border.Weight = xlMedium
        .SeriesCollection(4).Border.LineStyle = xlDash
        .SeriesCollection(2).Border.LineStyle = xlDash
        .SeriesCollection(3).Border.LineStyle = xlDash
    End With
End With

With Worksheets("Control Charts")
    .ChartObjects(3).Activate
    .ChartObjects(3).Chart.HasTitle = True
    .ChartObjects(3).Chart.Axes(xlValue).MinimumScale = -1
    With ActiveChart
```

```
        .ChartTitle.Select
        Selection.Characters.Text = "R Chart" & vbCrLf & "(Log-Logistic
Process)"
    '.ChartObjects(1).Select
        .ChartArea.Select
        .ChartArea.ClearContents

        .SeriesCollection.NewSeries.Values = RangeDataSeries
        .SeriesCollection(1).XValues = XValues
        .SeriesCollection(1).Name = "Range Data (sample = " &
intSampleSize & ")"

        .SeriesCollection.NewSeries.Values = LCL_LLArray
        .SeriesCollection(2).XValues = XValues
        .SeriesCollection(2).Name = "LCL"

        .SeriesCollection.NewSeries.Values = UCL_LLArray
        .SeriesCollection(3).XValues = XValues
        .SeriesCollection(3).Name = "UCL"

        .SeriesCollection.NewSeries.Values = CenterlineArray
        .SeriesCollection(4).XValues = XValues
        .SeriesCollection(4).Name = "Centerline"

        .SeriesCollection(4).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(2).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(3).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(1).Border.Color = RGB(255, 0, 0)

        .SeriesCollection(1).Border.Weight = xlHairline
        .SeriesCollection(2).Border.Weight = xlMedium
        .SeriesCollection(3).Border.Weight = xlMedium
        .SeriesCollection(4).Border.Weight = xlMedium
        .SeriesCollection(4).Border.LineStyle = xlDash
        .SeriesCollection(2).Border.LineStyle = xlDash
        .SeriesCollection(3).Border.LineStyle = xlDash
    End With
End With

'Plot the LCL, UCL, centerline, x-bar data
'We need to create three artificial arrays for the X-axis, LCL and UCL
(which basically just repeat themselves)
ReDim XValues(1 To intIndex), LCLArray(1 To intIndex), UCLArray(1 To
intIndex), CenterlineArray(1 To intIndex)

For i = 1 To intIndex
    XValues(i) = i
    LCLArray(i) = sngxLCL
    UCLArray(i) = sngxUCL
    CenterlineArray(i) = sngxCenter
Next i

With Worksheets("Control Charts")
    .ChartObjects(2).Activate
```

```
    .ChartObjects(2).Chart.HasTitle = True
    With ActiveChart
        .ChartTitle.Select
        Selection.Characters.Text = "x-bar Chart"
    '.ChartObjects(2).Select
        .ChartArea.Select
        .ChartArea.ClearContents

        .SeriesCollection.NewSeries.Values = AvgDataSeries
        .SeriesCollection(1).XValues = XValues
        .SeriesCollection(1).Name  =  "Average  Data  (sample  =  "  &
intSampleSize & ")"

        .SeriesCollection.NewSeries.Values = LCLArray
        .SeriesCollection(2).XValues = XValues
        .SeriesCollection(2).Name = "LCL"

        .SeriesCollection.NewSeries.Values = UCLArray
        .SeriesCollection(3).XValues = XValues
        .SeriesCollection(3).Name = "UCL"

        .SeriesCollection.NewSeries.Values = CenterlineArray
        .SeriesCollection(4).XValues = XValues
        .SeriesCollection(4).Name = "Centerline"

        .SeriesCollection(4).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(2).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(3).Border.Color = RGB(0, 0, 0)
        .SeriesCollection(1).Border.Color = RGB(0, 0, 255)

        .SeriesCollection(1).Border.Weight = xlHairline
        .SeriesCollection(2).Border.Weight = xlMedium
        .SeriesCollection(3).Border.Weight = xlMedium
        .SeriesCollection(4).Border.Weight = xlMedium
        .SeriesCollection(4).Border.LineStyle = xlDash
        .SeriesCollection(2).Border.LineStyle = xlDash
        .SeriesCollection(3).Border.LineStyle = xlDash
    End With
End With


'Write the status of the "beyond 3 sigma" rule
Worksheets("Control Charts").Range("M41").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M41").Value = "OK"
Worksheets("Control Charts").Range("N41").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N41").Value = "OK"

For i = 1 To intIndex
    If  AvgDataSeries(i)  >=  (sngxCenter  +  (A2(intSampleSize  -  1)  *
sngRCenter)) Then
        'checkOne = 1
        'If checkOne = 1 Then
        Worksheets("Control Charts").Range("M41").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M41").Value = "Not OK"
```

```
        Worksheets("Control Charts").Range("N41").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N41").Value = "Not OK"
        Exit For
    End If
Next

For i = 1 To intIndex
    If  AvgDataSeries(i)  <=  (sngxCenter  +  (A2(intSampleSize  -  1)  *
sngRCenter)) Then
        'checkOne = 1
        'If checkOne = 1 Then
        Worksheets("Control Charts").Range("M41").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M41").Value = "Not OK"
        Worksheets("Control Charts").Range("N41").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N41").Value = "Not OK"
        Exit For
    End If
Next

For i = 1 To intIndex
    If RangeDataSeries(i) >= (D4(intSampleSize - 1) * sngRCenter) Then
        'checkOne = 1
        'If checkOne = 1 Then
        Worksheets("Control Charts").Range("M41").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M41").Value = "Not OK"
        Exit For
    End If
    If  RangeDataSeries(i)  >=  (D4LL(intSampleSize  -  1)  *  sngRCenter)
Then
        Worksheets("Control Charts").Range("N41").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("N41").Value = "Not OK"
        Exit For
    End If
Next

For i = 1 To intIndex
    If RangeDataSeries(i) <= (D3(intSampleSize - 1) * sngRCenter) Then
        Worksheets("Control Charts").Range("M41").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M41").Value = "Not OK"
        Exit For
    End If
    If  RangeDataSeries(i)  <=  (D3LL(intSampleSize  -  1)  *  sngRCenter)
Then
        Worksheets("Control Charts").Range("N41").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("N41").Value = "Not OK"
        Exit For
    End If
Next
'End the status report on "beyond 3 sigma" rule

'Eight consecutive points on one side of the centerline
intNumPoints = 1
Worksheets("Control Charts").Range("M46").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M46").Value = "OK"
```

```
Worksheets("Control Charts").Range("N46").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N46").Value = "OK"

For i = 1 To intIndex
    If AvgDataSeries(i) < sngxCenter Then
        TestVal(intNumPoints) = AvgDataSeries(i)
        intNumPoints = intNumPoints + 1
        If intNumPoints > 8 Then
            Worksheets("Control Charts").Range("M46").Font.ColorIndex =
3
            Worksheets("Control Charts").Range("M46").Value = "Not OK"
            Worksheets("Control Charts").Range("N46").Font.ColorIndex =
3
            Worksheets("Control Charts").Range("N46").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 1 To intIndex
    If AvgDataSeries(i) > sngxCenter Then
        TestVal(intNumPoints) = AvgDataSeries(i)
        intNumPoints = intNumPoints + 1
        If intNumPoints > 8 Then
            Worksheets("Control Charts").Range("M46").Font.ColorIndex =
3
            Worksheets("Control Charts").Range("M46").Value = "Not OK"
            Worksheets("Control Charts").Range("N46").Font.ColorIndex =
3
            Worksheets("Control Charts").Range("N46").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 1 To intIndex
    If RangeDataSeries(i) < sngRCenter Then
        TestVal(intNumPoints) = RangeDataSeries(i)
        intNumPoints = intNumPoints + 1
        If intNumPoints > 8 Then
            Worksheets("Control Charts").Range("M46").Font.ColorIndex =
5
            Worksheets("Control Charts").Range("M46").Value = "Not OK"
            Worksheets("Control Charts").Range("N46").Font.ColorIndex =
5
            Worksheets("Control Charts").Range("N46").Value = "Not OK"
            Exit For
        End If
```

```
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 1 To intIndex
    If RangeDataSeries(i) > sngRCenter Then
        TestVal(intNumPoints) = RangeDataSeries(i)
        intNumPoints = intNumPoints + 1
        If intNumPoints > 8 Then
            Worksheets("Control  Charts").Range("M46").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("M46").Value = "Not OK"
            Worksheets("Control  Charts").Range("N46").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("N46").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next
'End of the "eight consecutive points on one side of centerline" rule

'"Eight consecutive points increasing or decreasing" rule
intNumPoints = 1
Worksheets("Control Charts").Range("M42").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M42").Value = "OK"
Worksheets("Control Charts").Range("N42").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N42").Value = "OK"

For i = 2 To intIndex
    If RangeDataSeries(i) > RangeDataSeries(i - 1) Then
        intNumPoints = intNumPoints + 1
        If intNumPoints >= 8 Then
            Worksheets("Control  Charts").Range("M42").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("M42").Value = "Not OK"
            Worksheets("Control  Charts").Range("N42").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("N42").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 2 To intIndex
    If RangeDataSeries(i) < RangeDataSeries(i - 1) Then
        intNumPoints = intNumPoints + 1
        If intNumPoints >= 8 Then
```

```
            Worksheets("Control  Charts").Range("M42").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("M42").Value = "Not OK"
            Worksheets("Control  Charts").Range("N42").Font.ColorIndex  =
5
            Worksheets("Control Charts").Range("N42").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 2 To intIndex
    If AvgDataSeries(i) > AvgDataSeries(i - 1) Then
        intNumPoints = intNumPoints + 1
        If intNumPoints >= 8 Then
            Worksheets("Control  Charts").Range("M42").Font.ColorIndex  =
3
            Worksheets("Control Charts").Range("M42").Value = "Not OK"
            Worksheets("Control  Charts").Range("N42").Font.ColorIndex  =
3
            Worksheets("Control Charts").Range("N42").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next

intNumPoints = 1
For i = 2 To intIndex
    If AvgDataSeries(i) < AvgDataSeries(i - 1) Then
        intNumPoints = intNumPoints + 1
        If intNumPoints >= 8 Then
            Worksheets("Control  Charts").Range("M42").Font.ColorIndex  =
3
            Worksheets("Control Charts").Range("M42").Value = "Not OK"
            Worksheets("Control  Charts").Range("N42").Font.ColorIndex  =
3
            Worksheets("Control Charts").Range("N42").Value = "Not OK"
            Exit For
        End If
    Else
        intNumPoints = 1
    End If
Next
'End "eight consecutive points increasing or decreasing" rule

'"Fourteen points alternating up and down" rule
intNumPoints = 1
blnTrendUp = True
blnTrendDown = True
```

```
Worksheets("Control Charts").Range("M43").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M43").Value = "OK"
Worksheets("Control Charts").Range("N43").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N43").Value = "OK"

For i = 2 To intIndex
    If RangeDataSeries(i) > RangeDataSeries(i - 1) And blnTrendDown
Then
        intNumPoints = intNumPoints + 1
        blnTrendUp = True
        blnTrendDown = False
    Else
        If RangeDataSeries(i) < RangeDataSeries(i - 1) And blnTrendUp
Then
            intNumPoints = intNumPoints + 1
            blnTrendDown = True
            blnTrendUp = False
        Else
            intNumPoints = 1
            blnTrendUp = True
            blnTrendDown = True
        End If
    End If

    If intNumPoints >= 14 Then
        Worksheets("Control Charts").Range("M43").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M43").Value = "Not OK"
        Worksheets("Control Charts").Range("N43").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("N43").Value = "Not OK"
        Exit For
    End If
Next

intNumPoints = 1
blnTrendUp = True
blnTrendDown = True

For i = 2 To intIndex
    If AvgDataSeries(i) > AvgDataSeries(i - 1) And blnTrendDown Then
        intNumPoints = intNumPoints + 1
        blnTrendUp = True
        blnTrendDown = False
    Else
        If AvgDataSeries(i) < AvgDataSeries(i - 1) And blnTrendUp Then
            intNumPoints = intNumPoints + 1
            blnTrendDown = True
            blnTrendUp = False
        Else
            intNumPoints = 1
            blnTrendUp = True
            blnTrendDown = True
        End If
    End If
```

```
    If intNumPoints >= 14 Then
        Worksheets("Control Charts").Range("M43").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M43").Value = "Not OK"
        Worksheets("Control Charts").Range("N43").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N43").Value = "Not OK"
        Exit For
    End If
Next
'End "Fourteen points alternating up and down" rule

'"2 out of 3 consecutive points at or above 2 standard deviations" rule
intNumPoints = 1
Worksheets("Control Charts").Range("M44").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M44").Value = "OK"
Worksheets("Control Charts").Range("N44").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N44").Value = "OK"

For i = 3 To intIndex
    If RangeDataSeries(i - 2) >= (D4(intSampleSize - 1) * sngRCenter) *
2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) >= (D4(intSampleSize - 1) * sngRCenter) *
2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) >= (D4(intSampleSize - 1) * sngRCenter) * 2 /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("M44").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 3 To intIndex
    If RangeDataSeries(i - 2) >= (D4LL(intSampleSize - 1) * sngRCenter)
* 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) >= (D4LL(intSampleSize - 1) * sngRCenter)
* 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) >= (D4LL(intSampleSize - 1) * sngRCenter) * 2
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("N44").Font.ColorIndex = 5
```

```
        Worksheets("Control Charts").Range("N44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 3 To intIndex
    If RangeDataSeries(i - 2) <= (D3(intSampleSize - 1) * sngRCenter) *
2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) <= (D3(intSampleSize - 1) * sngRCenter) *
2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) <= (D3(intSampleSize - 1) * sngRCenter) * 2 /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("M44").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 3 To intIndex
    If RangeDataSeries(i - 2) <= (D3LL(intSampleSize - 1) * sngRCenter)
* 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) <= (D3LL(intSampleSize - 1) * sngRCenter)
* 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) <= (D3LL(intSampleSize - 1) * sngRCenter) * 2
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("N44").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("N44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 3 To intIndex
    If AvgDataSeries(i - 2) >= (sngxCenter + (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
```

```
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i - 1) >= (sngxCenter + (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i) >= (sngxCenter + (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("M44").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M44").Value = "Not OK"
        Worksheets("Control Charts").Range("N44").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 3 To intIndex
    If AvgDataSeries(i - 2) <= (sngxCenter - (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i - 1) <= (sngxCenter - (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i) <= (sngxCenter - (A2(intSampleSize - 1) *
sngRCenter)) * 2 / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 2 Then
        Worksheets("Control Charts").Range("M44").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M44").Value = "Not OK"
        Worksheets("Control Charts").Range("N44").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N44").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next
'End "2 out of 3 consecutive points at or above 2 standard deviations"
rule

'"4 out of 5 consecutive points at or above 1 standard deviation" rule
intNumPoints = 1
Worksheets("Control Charts").Range("M45").Font.ColorIndex = 1
Worksheets("Control Charts").Range("M45").Value = "OK"
Worksheets("Control Charts").Range("N45").Font.ColorIndex = 1
Worksheets("Control Charts").Range("N45").Value = "OK"

For i = 5 To intIndex
```

```
    If RangeDataSeries(i - 4) >= (D4(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 3) >= (D4(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 2) >= (D4(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) >= (D4(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) >= (D4(intSampleSize - 1) * sngRCenter) / 3
Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 4 Then
        Worksheets("Control Charts").Range("M45").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M45").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 5 To intIndex
    If RangeDataSeries(i - 4) >= (D4LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 3) >= (D4LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 2) >= (D4LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) >= (D4LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) >= (D4LL(intSampleSize - 1) * sngRCenter) / 3
Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 4 Then
        Worksheets("Control Charts").Range("N45").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("N45").Value = "Not OK"
        Exit For
```

```
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 5 To intIndex
    If RangeDataSeries(i - 4) <= (D3(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 3) <= (D3(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 2) <= (D3(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) <= (D3(intSampleSize - 1) * sngRCenter) /
3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) <= (D3(intSampleSize - 1) * sngRCenter) / 3
Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 4 Then
        Worksheets("Control Charts").Range("M45").Font.ColorIndex = 5
        Worksheets("Control Charts").Range("M45").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next

intNumPoints = 1
For i = 5 To intIndex
    If RangeDataSeries(i - 4) <= (D3LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 3) <= (D3LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 2) <= (D3LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i - 1) <= (D3LL(intSampleSize - 1) * sngRCenter)
/ 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If RangeDataSeries(i) <= (D3LL(intSampleSize - 1) * sngRCenter) / 3
Then
```

```
            intNumPoints = intNumPoints + 1
        End If
        If intNumPoints >= 4 Then
            Worksheets("Control Charts").Range("N45").Font.ColorIndex = 5
            Worksheets("Control Charts").Range("N45").Value = "Not OK"
            Exit For
        End If
        intNumPoints = 1
    Next

    intNumPoints = 1
    For i = 5 To intIndex
        If AvgDataSeries(i - 4) >= (sngxCenter + (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If AvgDataSeries(i - 3) >= (sngxCenter + (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If AvgDataSeries(i - 2) >= (sngxCenter + (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If AvgDataSeries(i - 1) >= (sngxCenter + (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If  AvgDataSeries(i)  >=  (sngxCenter  +  (A2(intSampleSize  -  1)  *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If intNumPoints >= 4 Then
            Worksheets("Control Charts").Range("M45").Font.ColorIndex = 3
            Worksheets("Control Charts").Range("M45").Value = "Not OK"
            Worksheets("Control Charts").Range("N45").Font.ColorIndex = 3
            Worksheets("Control Charts").Range("N45").Value = "Not OK"
            Exit For
        End If
        intNumPoints = 1
    Next

    intNumPoints = 1
    For i = 5 To intIndex
        If AvgDataSeries(i - 4) <= (sngxCenter - (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If AvgDataSeries(i - 3) <= (sngxCenter - (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
            intNumPoints = intNumPoints + 1
        End If
        If AvgDataSeries(i - 2) <= (sngxCenter - (A2(intSampleSize - 1) *
    sngRCenter)) / 3 Then
```

```
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i - 1) <= (sngxCenter - (A2(intSampleSize - 1) * sngRCenter)) / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If AvgDataSeries(i) <= (sngxCenter - (A2(intSampleSize - 1) * sngRCenter)) / 3 Then
        intNumPoints = intNumPoints + 1
    End If
    If intNumPoints >= 4 Then
        Worksheets("Control Charts").Range("M45").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("M45").Value = "Not OK"
        Worksheets("Control Charts").Range("N45").Font.ColorIndex = 3
        Worksheets("Control Charts").Range("N45").Value = "Not OK"
        Exit For
    End If
    intNumPoints = 1
Next
'End "4 out of 5 consecutive points at or above 1 standard deviation" rule

'Display process information
Worksheets("Control Charts").Range("J50").Value = WorksheetFunction.Average(rngOriginalTimes)
Worksheets("Control Charts").Range("J53").Value = WorksheetFunction.StDev(rngOriginalTimes)
'mean = Application.WorksheetFunction.Average(Range(turnoverTime))
'standardDeviation = Application.WorksheetFunction.StDev(Range(turnoverTime))
'UCL = mean + (3 * standardDeviation)
'LCL = mean - (3 * standardDeviation)

'For Each cell In Range(turnoverTime)
'    If cell.Value > UCL Or cell.Value < LCL Then
'        checkOne = True
'    End If


'If checkOne = False And checkTwo = False And checkThree = False And checkFour = False And checkFive = False And checkSix = False Then
'     result = MsgBox("The process is in control.", vbOKOnly, "Process Stability")
'Else
'      result = MsgBox("The process is out of control.", vbOKOnly, "Process Stability")
'End If
End Sub
```

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