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## CASE STUDIES

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# Reducing Start Time Delays in Operating Rooms

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**Problem:** Health care today is facing serious problems: quality of care does not meet patients' needs and costs are exploding. Inefficient utilization of expensive operating rooms is one of the major problems in many hospitals worldwide. A benchmark study of 13 hospitals in the Netherlands and Belgium showed that, for a variety of reasons, surgery consistently started too late.

**Approach:** For a short and a somewhat longer period, two selected hospitals from the benchmark study agreed to record the start times of the first operation each day for each of their operating rooms. In addition to start times, the improvement team also recorded potential influence factors (covariates, or X's). Statistical techniques used during the project were statistical graphics, Pareto charts, histograms, box plots, time-series plots, Box-Cox transformations, and ANOVA to determine possible influential factors.

**Results:** It is shown that anesthesia technique and specialty are influence factors. However, the poor planning and scheduling process turned out to be the most important factor in the delay of start times. After introducing a new planning process, the hospitals involved were able to gain substantial cost savings, increased efficiency, and substantial reductions of the delay in start times for surgery.

Key Words: ANOVA; Box-Cox transformation; Health Care Quality; Lean Six Sigma; Pareto Charts.

## Process Description

**H**EALTH CARE worldwide is facing serious problems. Costs are escalating and quality of care often fails to meet expectations, see, e.g., Institute of Medicine (2001). Improving quality while reducing costs is, or should be, a major strategic priority for health care organizations. It may strike the uninitiated as a contradiction, but quality improvement projects applied to health care processes can simultaneously produce reductions in costs while increasing quality. This study provides an example of this empirical finding.

In this case study, we describe how Six Sigma projects carried out at two hospitals helped to improve the efficiency of operating rooms (see the brief introduction of Six Sigma in the Appendix). The first hospital was the Red Cross Hospital (RCH) in Beverwijk, the Netherlands, a 384-bed medium size hospital with a staff of 1,250 and a yearly budget of \$95 million. In addition to being a general hospital, the RCH is also the site of a national burn care center with 25 beds that provides specialized services to all of the Netherlands. The RCH introduced Six Sigma in 2002 and five groups, each of about 15 green belts (GBs), were trained during the first 3 years; see Van den Heuvel et al. (2005). The second hospital was the Canisius Wilhemina Hospital (CWH) in Nijmegen, the Netherlands. This is a much larger hospital, with 653 beds, employing 3,200, with a yearly budget of \$185 million. The CWH started to implement Six Sigma in early 2005. The introduction of Six Sigma at CWH was guided by the same leadership team previously responsible for the implementation at the RCH. Initially, two groups of 20 GBs were trained. In 2006, a second wave of GBs were trained; see Van den Heuvel et al. (2006). At both hospitals, the GB

training included instructions in the use of the statistical software package Minitab. Thus, the statistical analyses and graphs shown below are all prepared with Minitab.

Operating rooms are expensive and capacity limiting facilities in hospitals. Their optimal utilization is key to efficient hospital management. The RCH and the CWH have 9 and 13 operating rooms, respectively. To illustrate the business case for focusing on operating rooms, suppose the official start time is 8:00 am but the actual average start time is 8:40 am. An average of 40 minutes may not sound extraordinary, but for a hospital with 13 operating rooms and an average of 250 days in a year, this adds up to about 2,150 lost hours or 270 full days that could be used for productive work. In the Netherlands, the cost of an operating room is estimated to be approximately \$1,500 per hour. Hence, 2,150 lost hours is equivalent to \$3.2 million per year and more than the full capacity of one entire operating room. Furthermore, operating rooms in modern hospitals are capital intensive units, staffed by highly skilled and expensive staff. Starting too late means considerable wait time for staff and patients. Waste and inefficiency on such a scale when there are waiting lists for surgery ought not be tolerated.

For those reasons, both hospitals decided to improve the efficiency of their operating rooms. In the following, we mainly report on the statistical aspects of the project at the RCH without dwelling on details that otherwise may be relevant for discussing a Six Sigma case or for more general issues related to the application of Six Sigma in health care.

One of the first steps in an improvement project is to describe the process with a process map or flow chart. Figure 1 shows a much simplified process map describing the major process steps a typical patient undergoing surgery goes through.

Note that an operation is defined here to start after anesthesia. Hence, the operational definition of start time is at the time of the incision.

## Data Collection

The measure phase starts with the selection of critical-to-quality (CTQ) characteristics; see, e.g., De Mast et al. (2006). A commonly used tool to guide a team from the project definition to specific and measurable CTQs is the CTQ flow down (CTQF); see, e.g., De Koning and De Mast (2007). The CTQF helps structure the logic underlying a project. Fur-

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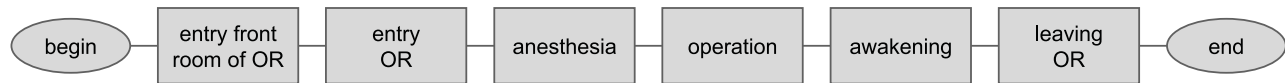


FIGURE 1. Overview Process Map for a Surgical Procedure.

thermore, it shows how CTQs relate to higher level goals, such as performance indicators, and helps the team align the project with the organization's strategic goals. At a lower level of the hierarchy, it shows how the CTQs are related to measurements. Figure 2 shows the CTQF for this project.

The primary stakeholder in this case is the hospital and the strategic goal is the overall reduction of the cost of running the hospital. Further, the CTQF shows that efficiency (i.e., the key performance indicator, KPI) can be divided into the number of operations and the amount of unused time of an operating room; in Figure 2, we denote these quantities by PI (performance indicators). The PI "amount of unused time" is related to two one-dimensional measurements (the CTQs). In the present project, the CTQs "start time of the first operation" and "changing time of operations" are used. In what follows, we focus on the start time of the first operation.

The next step of the measure phase is to develop a precise description of the measurement plan. For each operation, we collected a number of time stamps and important characteristics (covariates, or  $X$ 's), such as type of anesthesia technique and type of specialty. For each operating room and for each first operation, we recorded the following:

1. Official start time (i.e. the target time of the incision).
2. Time of arrival at the front door of the operating room of the first patient.
3. Time of arrival in the operating room of the first patient.
4. Time anesthesia starts.
5. Time incision starts.
6. Time surgery ends.
7. Time patient leaves operating room.

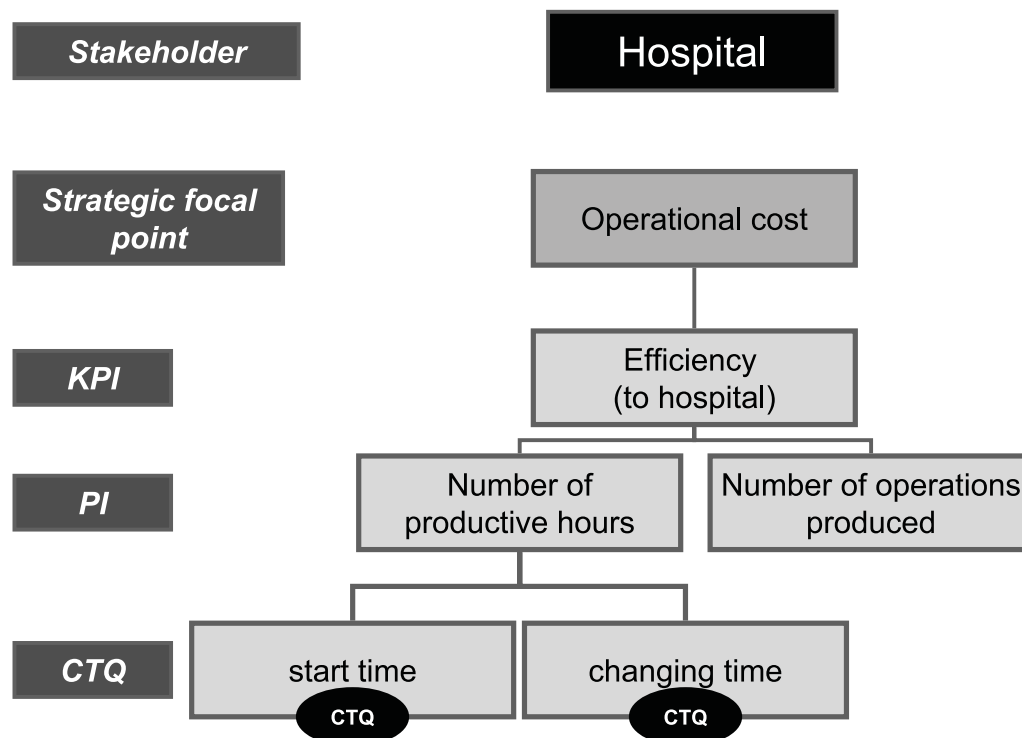


FIGURE 2. CTQ Flow Down.

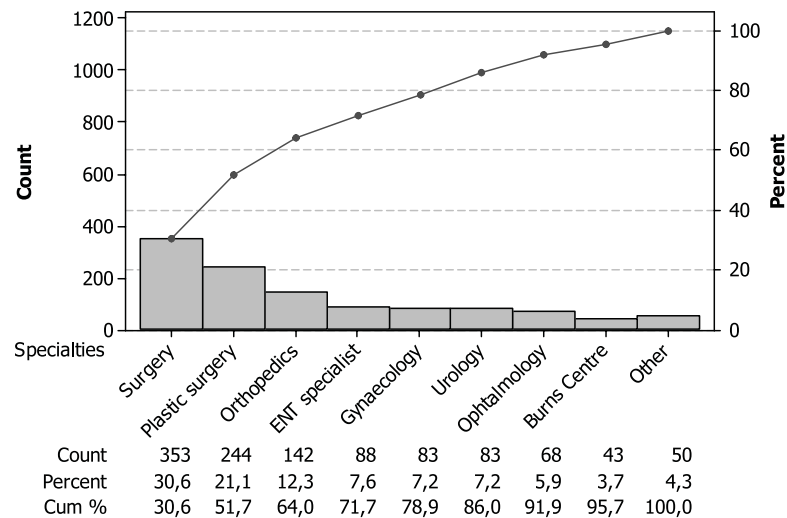


FIGURE 3. Pareto Chart of the First Operations Stratified by Specialty.

8. Anesthesia technique.

9. Specialty.

The delay in start time was defined as the start time of the incision minus the official start time. With this operational definition in place, we see that the overriding purpose of the project is to decrease this delay. The measurement unit is minutes. As we indicate below, occasionally some of the characteristics were not recorded. Such cases were in the subsequent data cleaning process labeled as “missing”.

### Analysis and Interpretation

Before we engage in the analysis of the start times, it is useful to perform a Pareto analysis of the data collected. The first surgeries can be categorized according to the methods of anesthesia used and the medical specialty performing the operation. The method of anesthesia involved 10 different types and the operations were performed by 11 different specialist departments. Figure 3 shows a Pareto chart of the specialties.

We see that more than 30% of all first operations were performed by the Surgery Department. Plastic surgery is another large category, with more than 20%, and the Orthopedic Department contributed about 12%. The remaining approximately 38% of the (first) operations came from eight other departments, each contributing a relatively low volume of patients. Thus, any effort to improve start time should initially be focused on working with the large volume departments.

A second Pareto analysis shown in Figure 4 provides a break down of the first surgeries on the type of anesthesia technique used.

From this chart, we see that the overwhelming majority (63%) of first operations used total (complete) anesthesia. Another approximately 20% used spinal anesthesia. The remaining 17% of first operations used a variety of seven other methods. Thus, again it would be useful to focus effort on improving start time on total anesthesia and spinal anesthesia. Finally, Figure 5 shows a two-way Pareto chart of anesthesia technique used by specialty.

The main observation from Figure 5 is that the two major specialties, surgery and plastic surgery, primarily use full anesthesia, whereas the orthopedic department rarely uses full anesthesia but primarily prefers to use spinal anesthesia. Also, we see that ophthalmology is, with few exceptions, the only user of bulbar.

We now turn to an analysis of the actual start time. The data collected showed that the average start times were 8:35 am and 8:55 am at the RCH and the CWH, respectively. The target start time of the incision at the RCH was 8.00 am and 8.30 am at the CWH. Figure 6 is a time series plot of the delay in start times at RCH during a period of 6 months in all nine operating rooms.

A visual screening of the data in Figure 6 reveals a nonsymmetrical distribution of the times, with a tendency to extreme outliers on the high side—a phenomenon typical of waiting times. This distributional

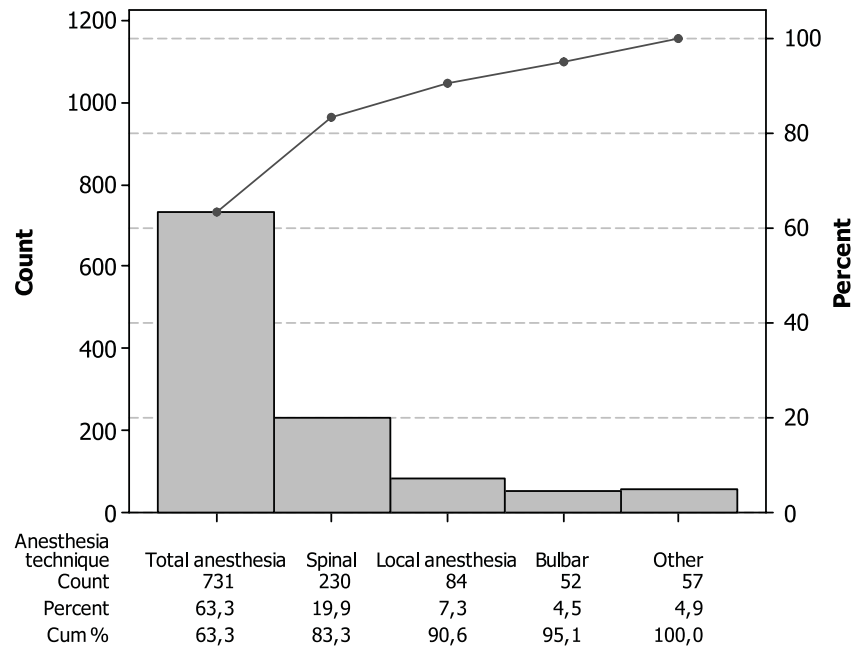


FIGURE 4. Pareto Chart of the First Operations Stratified by Anesthesia Technique.

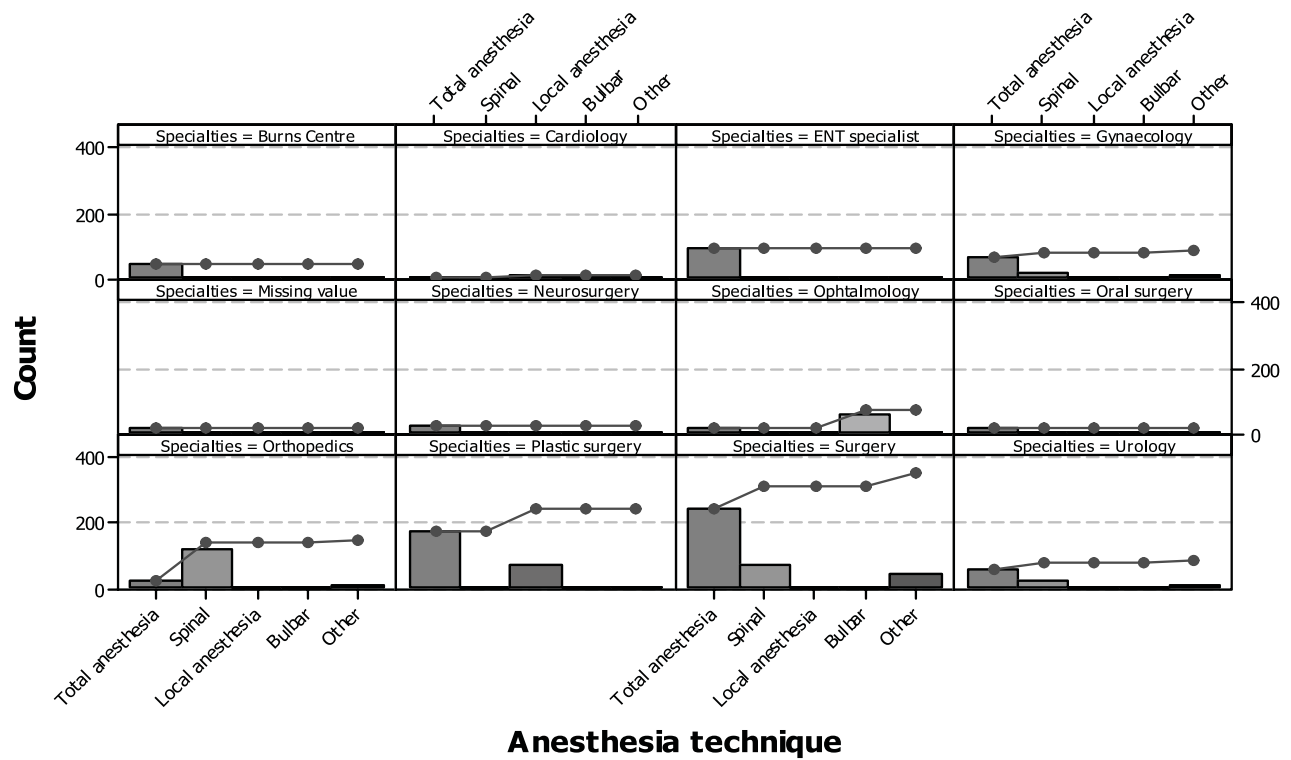


FIGURE 5. Two-Way Pareto Chart of Anesthesia Technique Used by Specialty.

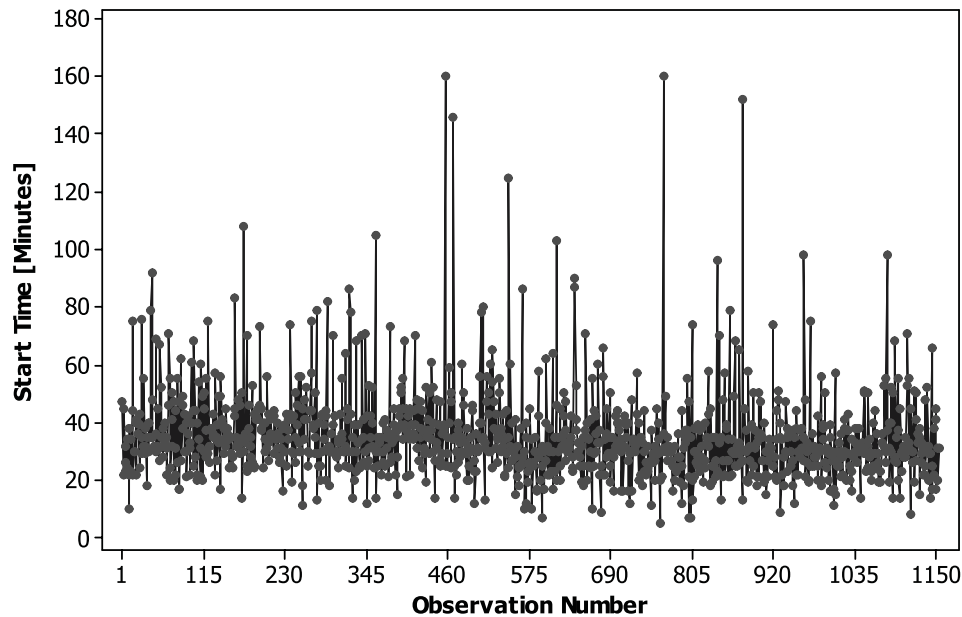


FIGURE 6. Time Series Plot of the Delay in Start Times for All Nine Operating Rooms at RCH.

skewness of the start time at the RCH is further borne out in the histogram and normal plot shown in Figures 7 and 8.

#### Data Transformations

In the analysis of data with many standard techniques of statistics, such as analysis of variance and regression analysis, it is often assumed the data are

independently normally distributed with constant variance. However, such idealized assumptions are often violated in practice. The operating room delay times are a typical example; as can be seen from the previous plots, the normality assumption is clearly violated. Such violations of the assumptions, if grave enough, can lead to misleading conclusions from a statistical analysis unless proper precautions

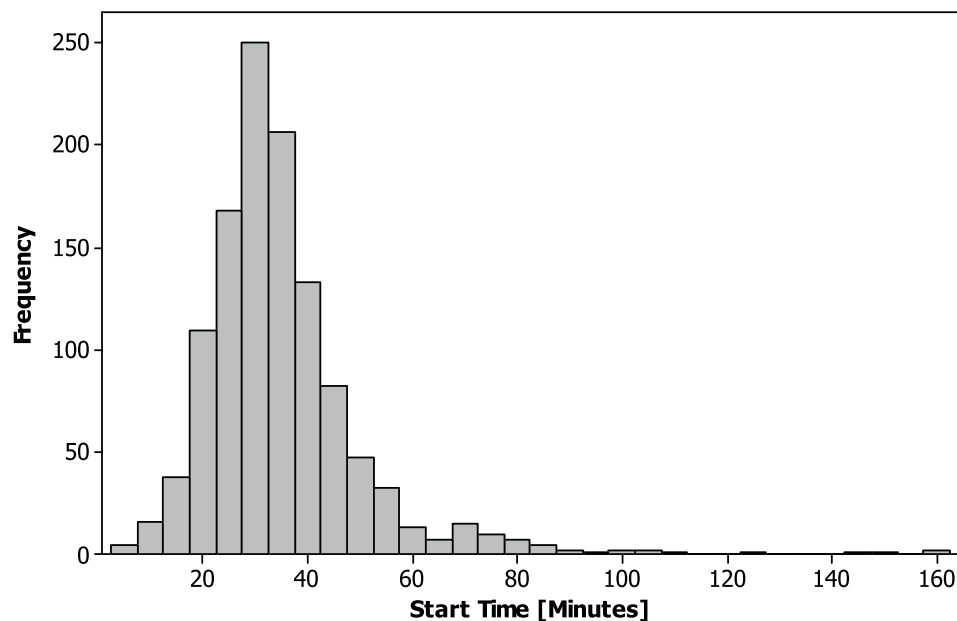


FIGURE 7. Histogram of the Delay in Start Times at the RCH.

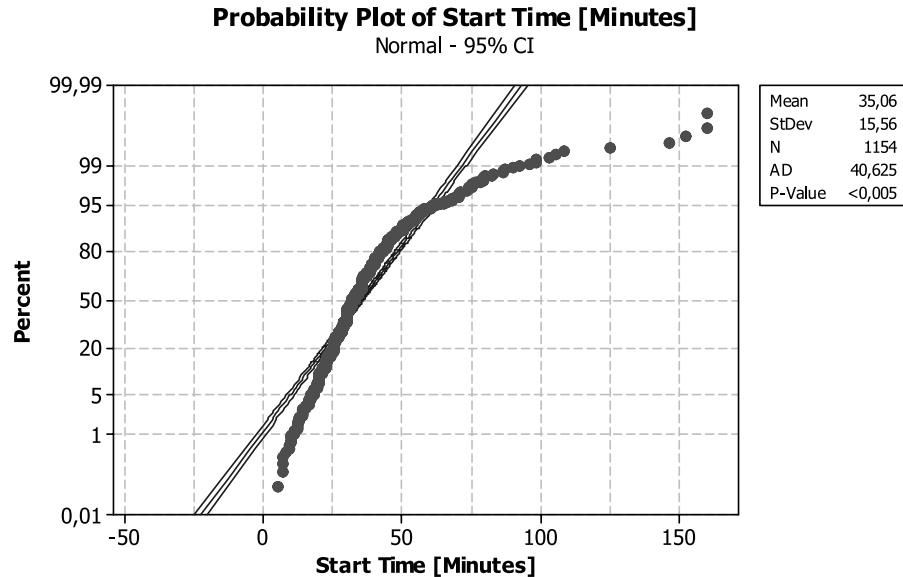


FIGURE 8. Normal Probability Plot of the Delay in Start Times at the RCH.

are taken. One such precaution, that is relatively simple and of wide utility, is to apply a suitable data transformation.

It is often the case that the scale in which the data originally were recorded is not necessarily the best for the subsequent statistical analysis. For example, which is better for measuring the efficiency of a car, miles per gallon, as in the United States, or liters per 100 kilometer, as is common in Europe? Both are proper measures of gas consumption but one is the inverse transformation of the other (as well as some linear transformations from miles to kilometers and gallons to liters that in this context are not so important).

For the operating room start time data, logical arguments and experience suggest that the data will exhibit variability that is proportional to the mean. When that is the case, experienced data analysts may immediately resort to using a log transformation; see Box et al. (2005, page 321). However, we may also proceed more formally to estimate a proper transformation from the class of Box–Cox power transformations originally proposed by Box and Cox (1964). Using this family of transformations, it is tentatively assumed that, for some  $\lambda$ , an additive model with normally distributed errors having constant variance is appropriate for  $y^{(\lambda)}$  defined by

$$y^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda} & \text{for } \lambda \neq 0 \\ \ln(y) & \text{for } \lambda = 0. \end{cases} \quad (1)$$

This family of transformations is continuous in  $\lambda$  and contains the log transformation as a special case (i.e.,  $\lambda = 0$ ). We estimate  $\lambda$  using the maximum likelihood method. The likelihood in this case is given by

$$\frac{1}{(2\pi)^{n/2}\sigma^n} \times \exp \left\{ -\frac{(\mathbf{y}^{(\lambda)} - \mathbf{E}\{\mathbf{y}^{(\lambda)}\})'(\mathbf{y}^{(\lambda)} - \mathbf{E}\{\mathbf{y}^{(\lambda)}\})}{2\sigma^2} \right\} \times J(\lambda; \mathbf{y}), \quad (2)$$

where

$$J(\lambda; \mathbf{y}) = \prod_{i=1}^n \left( \frac{dy_i^{(\lambda)}}{dy_i} \right)$$

is the Jacobian of the transformation. To find the maximum likelihood estimate, we proceed in two steps. For a given  $\lambda$ , the likelihood in Equation (2) is, except for a constant factor, the likelihood for a standard least squares problem. Thus, for a range of values of  $\lambda$ , we perform the regular least squares analysis in terms of  $y^{(\lambda)}$ . The maximum likelihood value for  $\lambda$  is then the value for which the residual sum of squares is minimized.

The formulation of the Box–Cox transformation in Equation (1) is the most commonly discussed version. However, although the transformation  $y^{(\lambda)}$  is continuous in  $\lambda$ , the variances of the transformed data are not comparable for different values of  $\lambda$  and the scale depends on  $\lambda$ . In technical terms, when we use Equation (1), we do not appropriately take into

account the Jacobian of the transformation. An alternative normalized transformation that does take into account the Jacobian recommended by Box and Cox (1964) for the practical implementation is given by

$$z^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda \dot{y}^{\lambda-1}} & \text{for } \lambda \neq 0 \\ \dot{y} \ln(y) & \text{for } \lambda = 0, \end{cases} \quad (3)$$

where  $\dot{y} = (y_1 y_2 \cdots y_n)^{1/n}$  is the geometric mean of the sample. Box and Cox (1964) then showed how, for the standardized transformation  $z^{(\lambda)}$ , the appropriate  $\lambda$  can be estimated using maximum likelihood estimation.

### Cautionary Remarks About Inappropriate Implementations of Transformations

Before we proceed to show how the Box–Cox transformation can be applied relatively simply with standard software, we first discuss a few subtle points in the calculations that must be kept in mind to do this properly. The first subtlety that we have often seen overlooked in (Six Sigma) teaching is that, to apply the Box–Cox transformation algorithm for the determination of  $\lambda$ , we need to carefully consider the expected value of the model we want to estimate; the transformation is applied to transform the error, not the response, to approximate normality. To be more specific, suppose we have control chart data that are highly skewed to the right, like the start times above. If we, for example, would like to make an individuals-moving range chart for this data and for the moment ignore that the specialties and the anesthesia techniques are factors, then, because of the skewness of the data, we clearly would violate the assumption of normality and would end up with a control chart with many false alarms. Thus, we may want to consider a transformation to make the data more approximately normal. The model assumption in this case would be that, after a proper transformation of the data  $y_i$ , the transformed data  $y_i^{(\lambda)}$  could be modeled as varying around a fixed mean and that the statistical model is  $y_i^{(\lambda)} = \mu + \varepsilon_i$ , where  $\varepsilon_i \sim N(0, \sigma^2)$ . In other words, the expected value of the transformed data is  $E\{y_i^{(\lambda)}\} = \mu$ . In that case, we seek an estimate  $\hat{\lambda}$  of the transformation parameter  $\lambda$  that will make the residuals  $\hat{\varepsilon}_i = y_i^{(\hat{\lambda})} - \hat{\mu}$  approximately normally distributed. For example, using Minitab's Stat  $\rightarrow$  Control Charts  $\rightarrow$  Box–Cox Transformation directly on  $y_i$  for this simple model is legitimate.

Now consider the situation where the expected

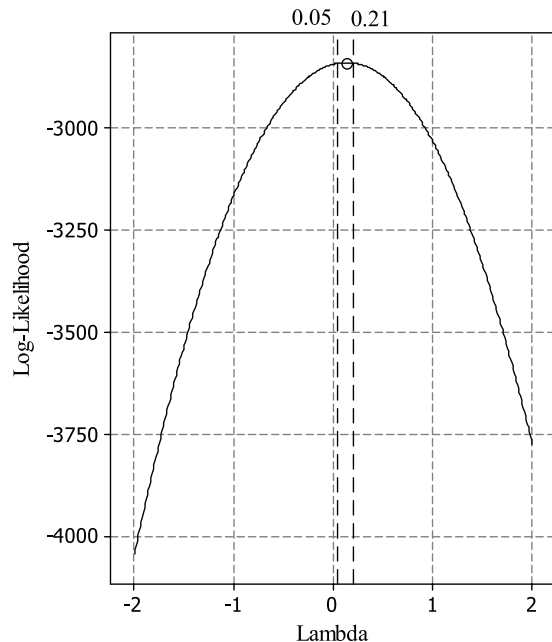
value no longer is assumed to be a fixed constant. For example, suppose the data generating process is a one-way ANOVA model (with fixed effects). The expected value of the one-way ANOVA model is  $E\{y_{ij}^{(\lambda)}\} = \mu + A_j$ , where  $A_j$ ,  $j = 1, \dots, k$  are constants. Thus, we should now seek an estimate  $\hat{\lambda}$  of the transformation parameter that will make the residuals  $\hat{\varepsilon}_{ij} = y_{ij}^{(\hat{\lambda})} - \hat{\mu} - \hat{A}_j$  approximately normally distributed. In other words, for a given  $\lambda$ , we need to estimate the expected value of the model  $E\{y_{ij}^{(\lambda)}\} = \mu + A_j$  and subtract that estimate from  $y_{ij}^{(\lambda)}$  to get  $\hat{\varepsilon}_{ij} = y_{ij}^{(\lambda)} - \hat{\mu} - \hat{A}_j$ . However, if we inadvertently use standard software that assumes a fixed mean model  $E\{y_i^{(\lambda)}\} = \mu$ , as for example Minitab's (version 15) Stat  $\rightarrow$  Control Charts  $\rightarrow$  Box–Cox Transformation, then we end up finding a  $\lambda$  that will try to make the quantity  $y_{ij}^{(\lambda)} - \bar{y}_{ij}^{(\lambda)}$  look normally distributed, where  $\bar{y}_{ij}^{(\lambda)}$  is the average of all the transformed data. However, it will likely not be very successful.

Another subtlety is that, for a data transformation like Equation (1) to make an effective impact on the analysis, it is usually recommended to check the ratio of the maximum to the minimum observation of the sample to see if  $\max(y_i)/\min(y_i) > 2$ ; see Box et al. (2005, p. 326). In the case of the operating room start times,  $\max(y_i)/\min(y_i) \approx 32$ , so this is a good candidate for a transformation. However, if  $\max(y_i)/\min(y_i) < 2$ , then the transformation over such a narrow range is approximately linear and will likely have almost no effect.

### Box–Cox Transformation Applied to the Operating Room Data

We now turn to the data at hand. A key question in the analysis of the start time data is whether the two covariates “specialty” and “anesthesia technique” had an influence on the delays. To investigate this question, we want to test the effects of each of these categorical  $X$ 's. In this case, an exploratory (i.e., informal) statistical test can be carried out separately for specialty and anesthesia technique by performing two separate one-way analyses of variances (ANOVA). Because this was an observational study and not a designed experiment, a two-way ANOVA of the simultaneous effects of specialty and anesthesia technique in this case produced a highly unbalanced two-way table of factors and was therefore deemed inappropriate. Furthermore a complication, as already mentioned, is the extreme skewness of the data and the need for a transformation.





Estimated Lambda: 0.13

Approximate 95% CI for Lambda: (0.05 , 0.21)

FIGURE 9. Box-Cox Transformation for One-Way ANOVA Anesthesia Techniques.

We therefore proceed to use two separate one-way ANOVAs one for specialty and one for anesthesia technique. The expected means for the two models are  $E\{y_{ijk}^{(\lambda)}\} = \mu + S_j$  and  $E\{y_{ijk}^{(\lambda)}\} = \mu + T_k$ , where  $S_j$  are the specialty effects and  $T_k$  are the anesthesia-technique effects. Thus, for these ANOVA models, we do not assume the mean to be a fixed constant for all observations. The Minitab pull-down menu command for estimating  $\lambda$  for control-chart data will therefore not be appropriate if used directly. However, Minitab, via its website, does provide a macro called *BCtrans* that performs a maximum likelihood estimation of  $\lambda$  for linear regression models using the Box-Cox transformation (1). Because analysis of variance is a special case of regression analysis where the  $X$ 's are indicator variables (see e.g., Draper and Smith (1998)), we can create indicator variables for the 11 specialties and the 10 anesthesia techniques. Now, because the study as indicated was unbalanced, we estimated  $\lambda$  two different ways with the *BCtrans* macro, as one-way ANOVA with specialty and as one-way ANOVA for anesthesia technique. The results are all similar, so only the ANOVA with anesthesia technique will be discussed. Figure 9 shows the log likelihood function for the anesthesia-techniques analysis.

From Figure 9, we see that the optimal lambda value is approximately zero. The pragmatic choice is therefore the log transformation. Thus, using the *BCtrans* macro with Minitab 15, we found that the best Box-Cox transformation is the natural logarithm of the start time. However, as we indicated above, the transformation (1) has the disadvantage that the scale of observations depends on  $\lambda$ , which in some cases can lead to problems; see Box and Cox (1982). Indeed, in an analysis of the Box-Cox transformation (1), Bickel and Doksum (1981) found that "... the performance ... is unstable and highly dependent on the parameters in the model in structured models with small to moderate error variance." This occurs because, using transformation (1), the estimate of  $\lambda$  and the model parameters are highly correlated. However, as Box and Cox (1982) point out, this problem can be avoided if we, instead as recommended in Box and Cox (1964), use the normalized Box-Cox transformation (3) for practical application.

The transformation (3) is currently not available as a Minitab macro. However, it is relatively simple to carry out the transformation in practice. Figure 10 provides a simple algorithm.

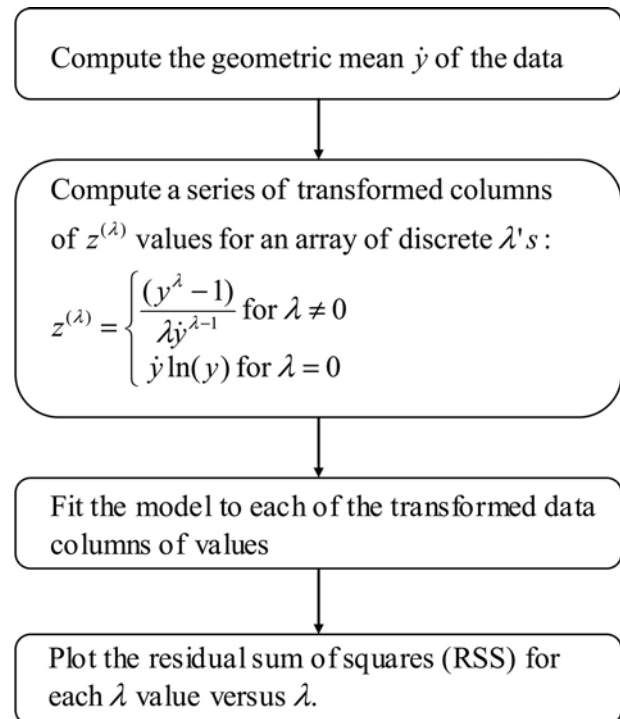


FIGURE 10. Algorithm for Manually Carrying Out a Box-Cox Transformation.

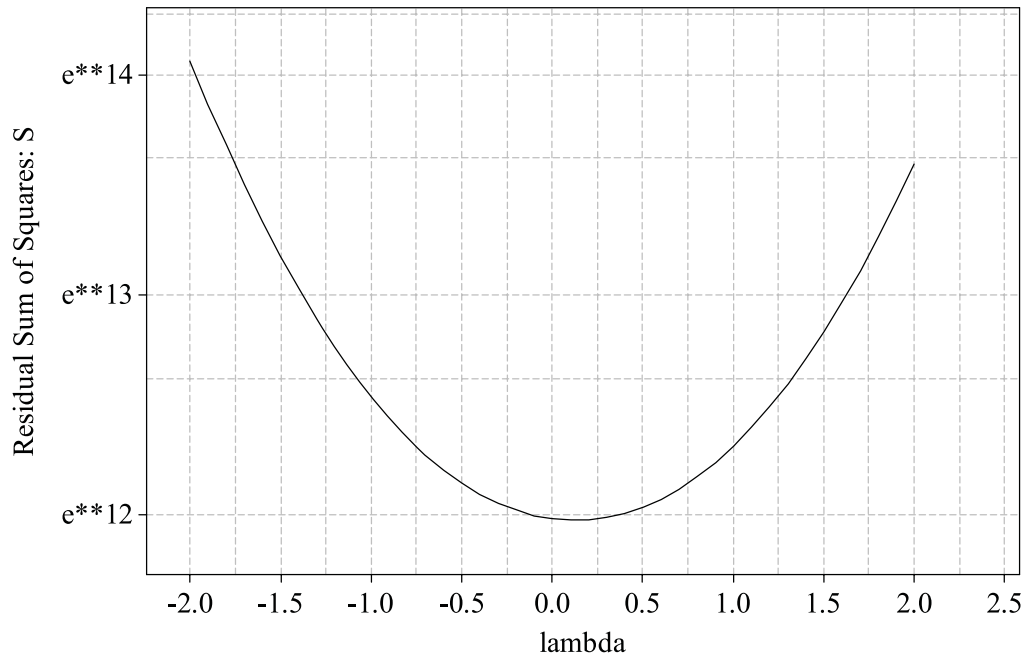


FIGURE 11. Alternative Box–Cox Transformation for One-Way ANOVA Anesthesia Techniques.

Note that a simple way to compute the geometric average  $\hat{y} = (y_1 y_2 \cdots y_n)^{1/n}$  is by using  $\hat{y} = \exp\{\ln(\hat{y})\}$ , where  $\ln(\hat{y}) = n^{-1} \sum_{i=1}^n \ln(y_i)$ . The residual sum of squares for the techniques ANOVA is plotted for a range of  $\lambda$  from  $-2$  to  $+2$  (Figure 11).

Again we see that the log transformation seems to be the appropriate transformation. Of course, this should not be a surprise, as it is common to find that waiting time distributions are approximately log normal, but it is comforting to actually have verified it as a proper transformation for the data at hand.

### Analysis of the Operating Room Data at the RCH

Figure 12 shows a residual plot of ANOVA anesthesia techniques from the RCH using the log-transformed start times.

We notice that the distribution of the residuals, despite the log transformation, still has moderately heavy tails, but not more extreme than what should be acceptable. Although it is appropriate to use a transformation to remedy for the extreme nonnormality exhibited by the original data, the ANOVA is relatively robust to such more minor differences in the distributional form we see in the transformed data; see Box et al. (2005, p. 140). Thus, we proceed to use ANOVA for the log-transformed data to look

for possible effects.

The use of formal tests for multiple comparisons is popular but, in practice, it is questionable how far we should go with such formal testing. For example, how precise does it make sense to be about something that is inherently very uncertain? Moreover, the significance levels for example 5% are somewhat arbitrarily chosen benchmarks; see Box et al. (1978, p. 206).

Figure 13 shows a graphical representation of an ANOVA per anesthesia technique. We see that the anesthesia technique clearly influences the start time. However, the explained variation is small. The specialists of the RCH argued that this was the major reason for the delay in start times. However, the anesthesiologists of the RCH argued that the specialization was the reason for the late start times. From Figure 14, we see that, although the effect of the different specialties is statistically significant, like the anesthesia technique, the practical significance on the start times is minor. Thus, both influence factors did not give a good answer to the question: “What really causes the delay in start times?”

### Benchmark Study

In 2005, the first and third authors of this article were invited to run a workshop on Six Sigma in

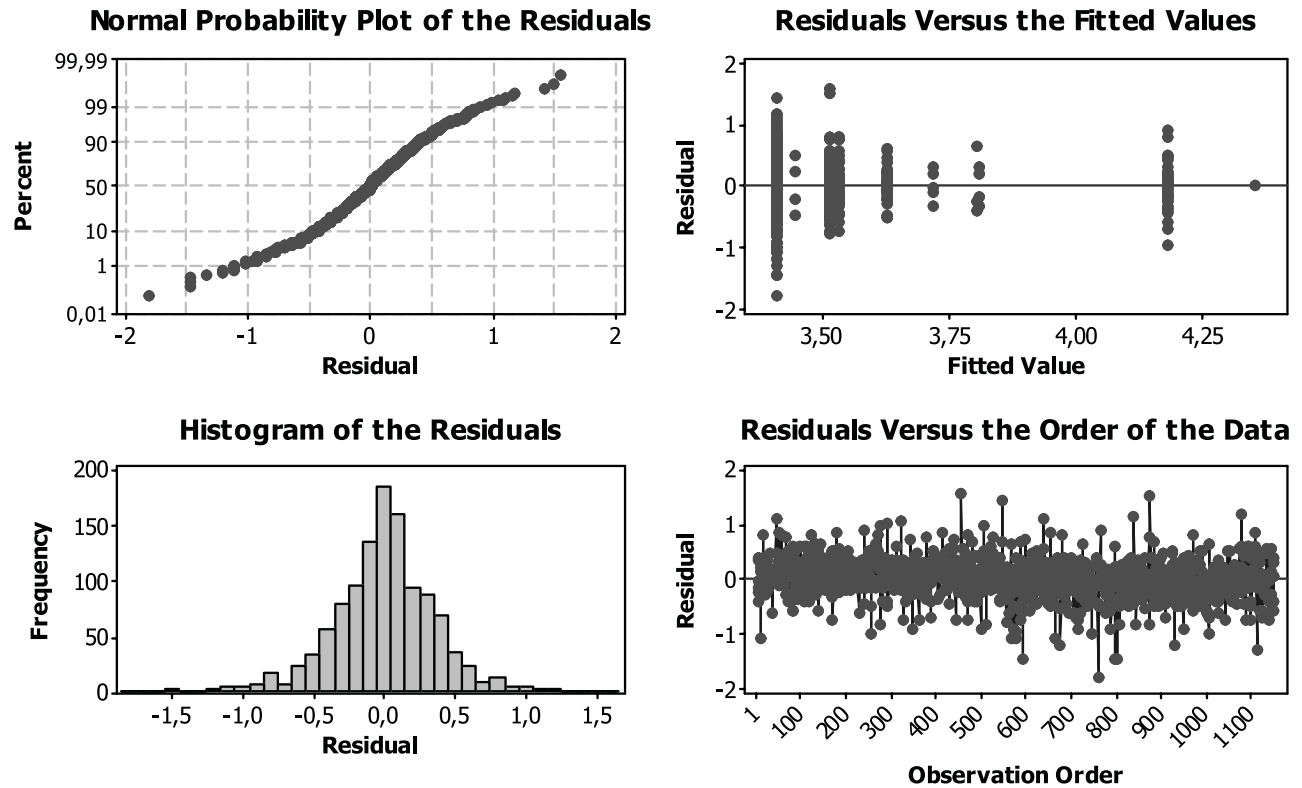


FIGURE 12. Residual Plot of ANOVA for Anesthesia Techniques.

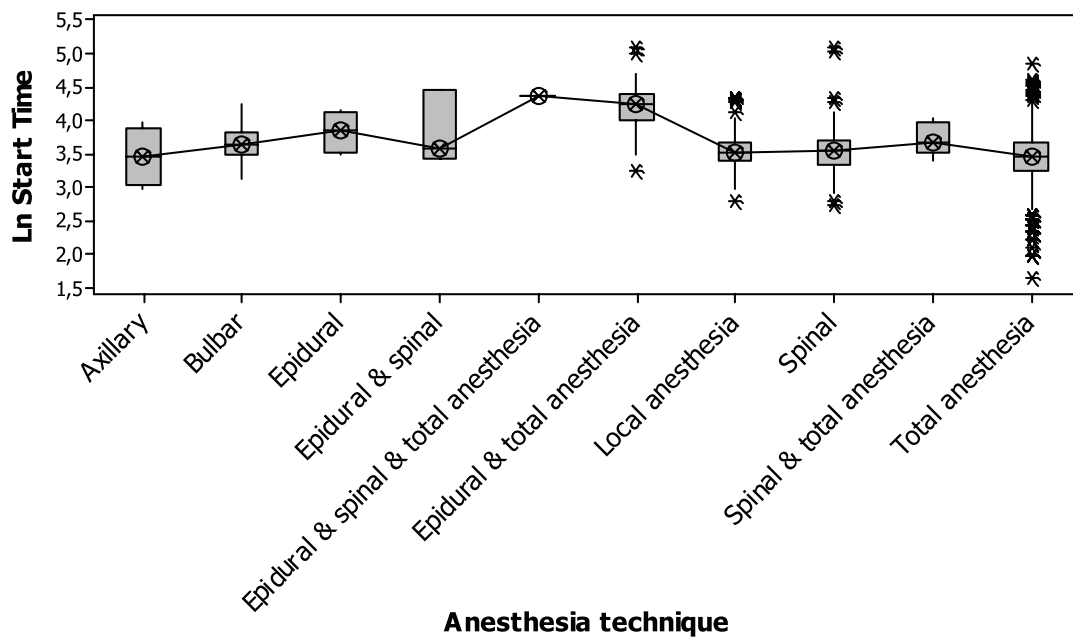


FIGURE 13. Box Plots of the Log Start Times by Anesthesia Technique in the RCH.

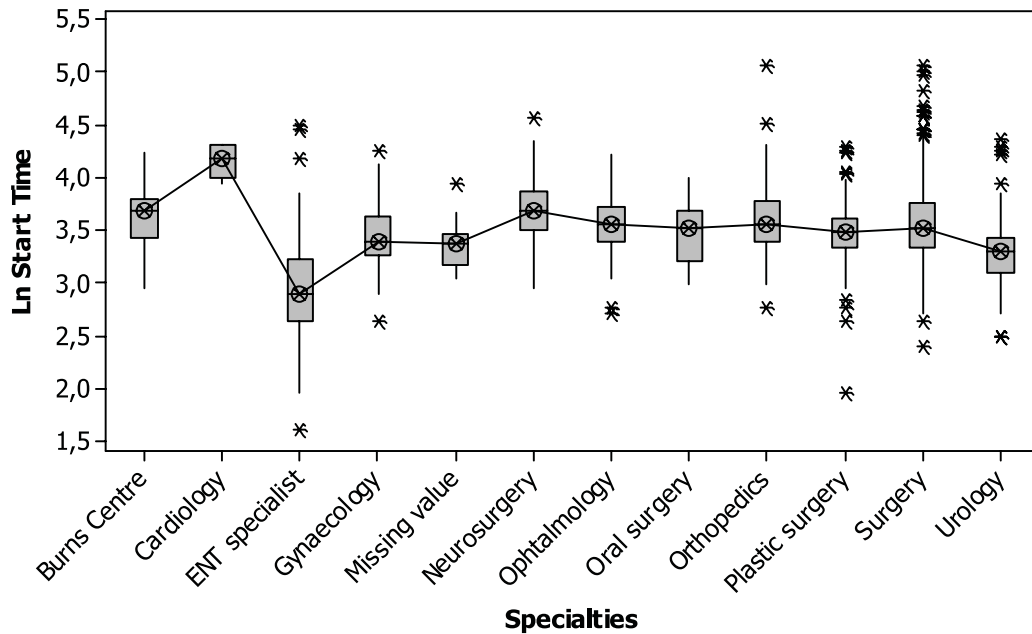


FIGURE 14. Box Plots of the Log Start Times by Specialty in the RCH.

Belgium. The purpose of the workshop was to interest health care professionals in the application of Six Sigma to hospital management. To stimulate the discussion, we asked the participants to collect data for a period of 4 weeks on start times of the operating rooms in their hospitals. Eleven hospitals pro-

vided data. Combined with the data from the RCH and CWH, we therefore have data available from 13 hospitals for a benchmark study. The average delay in start times ranges from 25 minutes to 103 minutes. Figure 15 provides an overview of the log-transformed data of the 13 hospitals presented as box

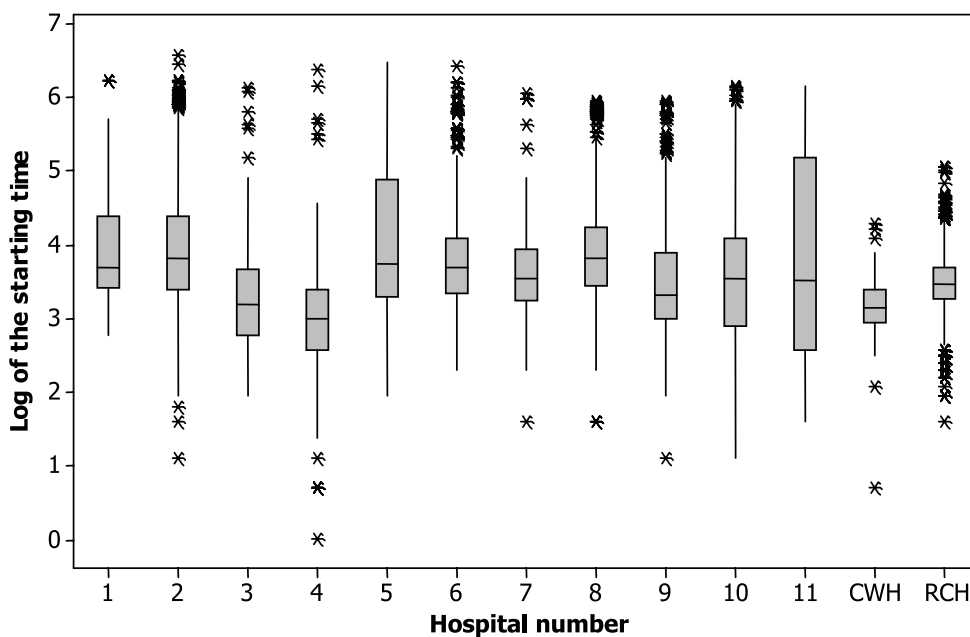


FIGURE 15. Benchmark Study of 13 Hospitals.

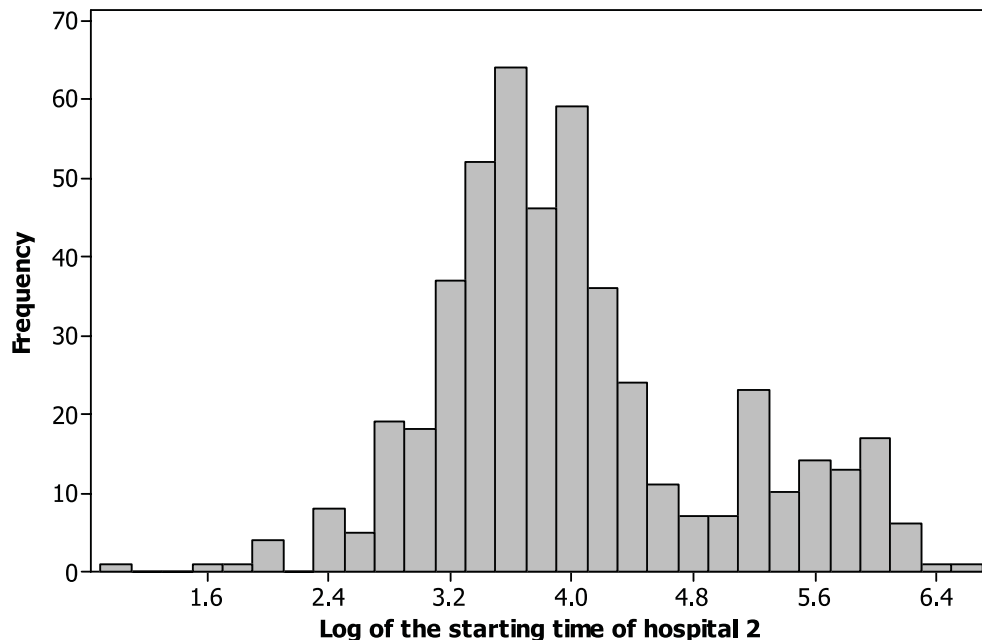


FIGURE 16. Histogram of the Transformed Start Times of Hospital 2.

plots. Note that we have excluded the 20 zeros out of 4,318 data points (3 from hospital 3, 2 from hospital 8, and 15 from hospital 10; in the data set, they are denoted by 0.01). It clearly shows that all hospitals start too late with respect to their target values.

To gain further insight about the processes in the individual hospitals, we analyzed them separately. The worst hospital in regard to start times was hospital 2. An interesting discovery for that hospital was that the distribution of the transformed start times seemed to be a mixture of two distributions; see the hump in the upper tail of the histogram in Figure 16.

Note that the histograms of hospitals 5, 6, 8, and 9 clearly show the same phenomenon. Using the idea that there could be a mixture of different distributions, we carefully studied again the original data of the RCH. With the observation from hospital 2 in mind, we see that the right-hand tail of the start times is much heavier than the tails based on a normal distribution (see Figure 7). Even after transforming the data, this still appears to be true. In the first analysis, we could not show that the delays in start time were mainly due to the anesthesia technique or the specialty. The benchmark study reveals that there could be additional but unidentified causes, so-called lurking variables.

During brainstorming sessions with the RCH team, many influence factors were suggested. Col-

lectively, however, they all provided the unmistakable symptoms of a poorly defined planning process. For example, it was not clear at what time the patient should arrive at the admissions room for the operating room, at what time to start the premedication, and at what time the anesthesiologist should be available. Furthermore, there were many adverse incidents during the week—failures of the anesthesia technique, patient not fasting, traffic jams—which delayed arrival times of the specialists, etc. Similar results were found in the CWH.

Based on the post data analysis discussions, a new planning process using a few simple rules was designed: (a) patients must be present at the operating room no later than 7:35 am in the RCH and no later than 8:00 am in the CWH, (b) measures should be taken to assure that patients have received preoperative medication before arriving at the operating room, (c) the referring department and the anesthesiologist must be informed one day in advance of the scheduled procedure. These simple rules and procedures were communicated to all employees involved. To control this new scheduling process, visual management was introduced, showing the start times of the past week. The resulting graph is reviewed weekly. As a result of these standard operating procedures (SOPs), the start time delay at RCH was reduced by more than 25%. At CWH, the reduction was more than 30%.

## Conclusions

The Six Sigma approach with the accompanying thorough data analysis has been very helpful in providing insight into the problem and has helped reduce the classical “blaming the other party” problem that often derails problem solving processes. The additional sessions with the team redirected the focus to the real issue, a poor planning and scheduling system.

After one year, both hospitals have achieved structural annual savings by reducing the delay in start times: in the RCH, more than \$350,000; in the CWH, more than \$100,000. In the CWH, additional savings of more than \$400,000 were obtained by reducing the changing times of operations and the breaks. They were able to increase the number of operations by 10% without requiring additional resources.

In this case study, quality improvement was measured in terms of reduced delays in start times and especially reduced cancellations of operations at the end of the day. The latter is particularly important with respect to patient safety. The projects clearly show that it is possible to reduce the costs while increasing quality.

## Appendix: Six Sigma in a Nutshell

Six Sigma is a company wide quality improvement approach that aims at optimizing processes while reducing defects and costs; see Snee (2004). Six Sigma uses a project based deployment approach in which a project is defined as a chronic problem scheduled to be solved. It is based on one of the principles of Juran (1989): nonstandard problems are only solved project by project. The Six Sigma method was put in an operational form as the so-called DMAIC roadmap. It employs five phases: define (D), measure (M), analyze (A), improve (I) and control (C). The roadmap guides the project leaders, individuals with training to the level of a Green Belt or Black Belt, in Six Sigma methods, through their projects, helps them ask the right questions, shows them which tools and techniques can be used, and encourages them to organize their findings in a structured form. The five phases are briefly characterized as follows:

1. Define: Select project and Black Belt/Green Belt.
2. Measure: Make the problem quantifiable and measurable.

<i>Define</i>	
<i>Measure</i>	1. Select the internal CTQ 2. Operationalize the CTQ 3. Validate the measurement system
<i>Analyze</i>	4. Establish the process capability 5. Define the objective of the project 6. Identify potential influence factors
<i>Improve</i>	7. Select the important influence factors 8. Establish relationships 9. Design improvement actions
<i>Control</i>	10. Improve the quality control system 11. Determine the new process capability 12. Close the project

FIGURE A1. DMAIC Roadmap for Improvement Projects.

3. Analyze: Analyze the current situation and make a diagnosis.
4. Improve: Develop and implement improvement actions.
5. Control: Improve the quality control system and discontinue the project.

These phases are discussed in, e.g., Harry (1997) or Snee and Hoerl (2005). Each of the DMAIC phases is broken down into three steps (see Figure A.1).

Note that the abbreviation CTQ in Figure A.1 means “critical to quality,” i.e., a specific and measurable characteristic to quantify the problem. For each step, a list of end goals is defined as well as a set of techniques that are typically used to achieve them; see, e.g., De Mast et al. (2006). Black Belts and Green Belts report progress with their projects following these steps, which makes it easy for program management and champions to track progress.

Six Sigma has been developed and widely used in industry; see Breyfogle (2003). Recently, the application of Six Sigma has also been suggested in health care; see Barry et al. (2002). A number of health-care institutions have implemented Six Sigma; see Thomerson (2001), Sehwal and De Yong (2003), Van den Heuvel et al. (2005), Christianson et al. (2005), and Van den Heuvel et al. (2006).

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