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Statistical Process Control for Improving Healthcare Processes. A Case Study in an Italian Teaching Hospital

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Abstract

This study aims to investigate the utility and potentialities of statistical process control for monitoring performances of healthcare organizations. We retrospectively applied the statistical process control for monitoring perioperative system performance, represented in this study by the operating room turnaround time. The results showed that the control charts are able to identify the steady-state behavior of the process and to detect improvements or deteriorations in process performance over time.

Keywords: Operating room turnaround time, Organizational Indicator, Shewhart control charts; EWMA control charts;

1. Introduction

There is growing attention in the use of Statistical Process Control (SPC) in healthcare, [1-5], to aid in process performance monitoring, to obtain ideas for improvement, to test changes to see whether they are improvements, and to see whether improvements are maintained.

However, SPC is relative new to clinicians and healthcare managers and cultural and conceptual barriers slow down the spread of SPC within the healthcare framework.

The Ferrara University Hospital "Sant'Anna" employs 2,628 members of staff, houses 626 beds for inpatients and 85 for those receiving day-hospital care. In 2013, there were 22,647 admissions and 9,048 day-hospital patients.

Since 2001, the hospital developed a web-based performance measurement system, comprising a total of 768 internal and 67 external measures, with a view to improving service provision, accountability and quality of care, [6].

Within this framework, in order to improve understanding of processes and increase the quality of performance, hospital management decided to monitor several clinical, organizational and economic indicators through a suitable methodology.

An important organizational indicator is the Operating Room (OR) Turnaround Time (TaT). OR TaT is defined as the time between the "incision close" of patient n to the "incision open" of patient $n+1$. It is a key process indicator for hospital business management: delays in OR turnaround time lead to a reduced number of surgical interventions per day with a consequent increase in costs and decrease in efficiency.

This study aims to investigate the utility and potentialities of statistical process control for monitoring the OR TaT, assessing the steady-state behaviour of the process and identifying changes that indicate either improvement or deterioration in quality. With this purpose, we applied SPC retrospectively to the data conveniently extracted from the hospital information system.

The results showed that Shewhart and EWMA control charts are able to identify the steady-state behaviour of the process and to detect positive or negative changes in process performance.

2. The Data

The Hospital Quality Department decided to focus attention on the five operating room suites located in Block 24. For these ORs, we examined the data from January 2013 to

February 2014 considering only the elective surgeries performed on weekdays: in total there were 2,469 surgical operations. In particular, we considered the OR 1 in detail, which was the most used with 680 (28%) surgical operations.

Table 1 contains several descriptive statistics and Figure 1 shows the histogram of the TaT of operating room 1.

First Quartile	34.75
Median	50.00
Third Quartile	70.00
Mean	57.44
Standard Deviation	40.68

Table 1: descriptive statistics for OR1 TaT

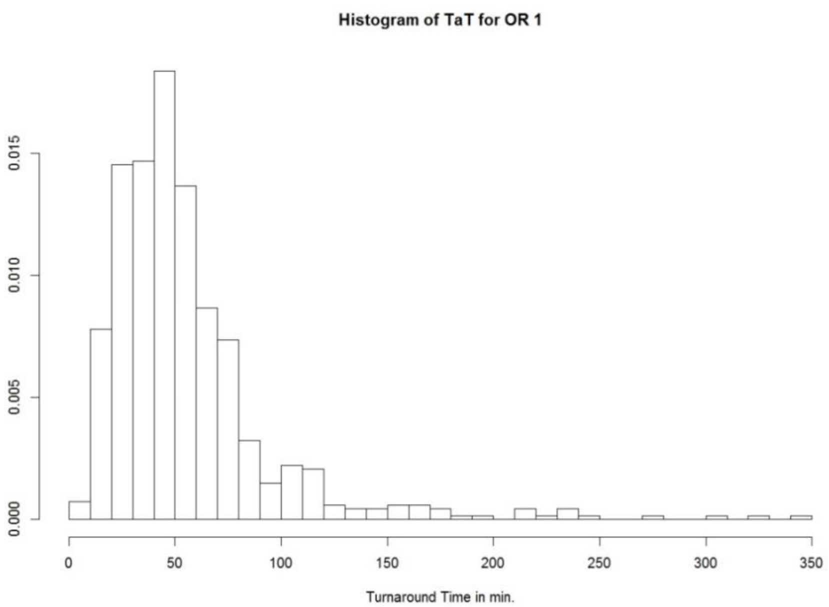

Figure 1: Histogram of the original data for OR 1 TaT

The data were highly positively skewed as evidenced by the histogram and by the estimated moment coefficient of skewness: $\hat{\gamma}_1 = 2.93$.

We performed a preliminary application of the SPC on the original data and, as expected, we found an unreasonable number of false alarms likely due to the high skewness.

In order to reduce the asymmetry, we performed a Box–Cox power transformation [7] using the R package "car" [8]. The optimal lambda value has been determined using a profile log-likelihood approach (Figure 2) and resulted: $\lambda = -0.0084$.

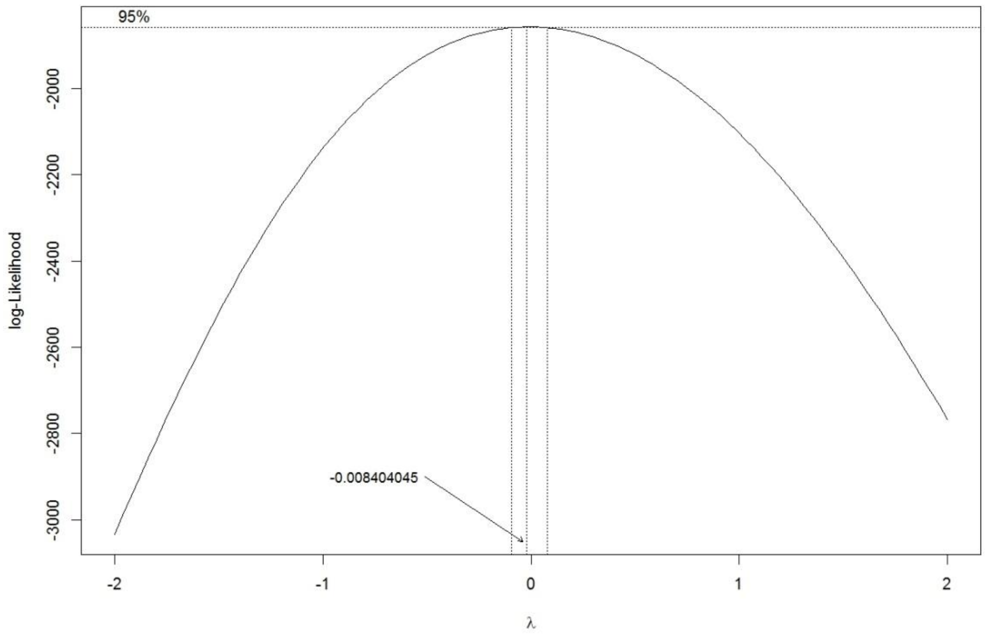

Figure 2: Profile Log-likelihood for Box-Cox transformations

Although not normally distributed (Shapiro-Wilk normality test: p<0.01), the transformed data (Figure 3) exhibited only a slight departure from symmetry: $\hat{\gamma}_1 = -0.0019$.

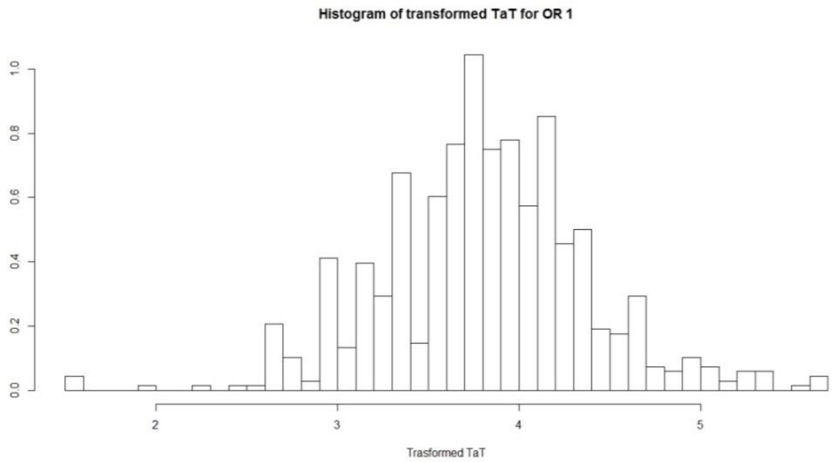

Figure 3: Histogram of transformed data for OR 1 TaT

Therefore, in the rest of the work we used the transformed data for process performance monitoring.

3. Control Charts

We were interested in monitoring the average ($\bar{X}$ -chart) and the standard deviation (*S*-chart) of the transformed operating room TaT per week. In the time interval of interest, the number of surgical operations per week was variable. On average there were 12.15 surgical interventions per week (minimum=3, median=12, maximum=26 and mode=7).

We considered the week as a suitable "small window of time" representative of a stable process subject only to natural variation. Furthermore, due to the non-elevated number of surgical interventions per week and to the consideration that in healthcare settings there is much less emphasis on sampling only a portion of the output of a process at periodic intervals than in the industrial SPC [3], we decided to consider all the surgical interventions performed in each week. In such a way, we used control charts with variable sample size [9].

To estimate process parameters on which to base the control limits, we performed "Phase I" using the first *m*=30 weeks (January 2013-August 2013).

The $\bar{X}$ and *S*-Shewhart control charts (3-sigma limits) are given by:

$$LCL = \bar{\bar{X}} - 3\hat{\sigma}\Big/\sqrt{n_i}$$

$$CL = \bar{\bar{X}}$$

$$UCL = \bar{\bar{X}} + 3\hat{\sigma}\Big/\sqrt{n_i} \ ,$$

and

$$CL = \bar{S}$$

$$UCL = \bar{S}B_4(n_i) \ ,$$

$$LCL = \bar{S}B_3(n_i)$$

respectively.

With $\bar{\bar{X}} = \sum_{i=1}^{m} n_i \bar{x}_i \Big/ \sum_{i=1}^{m} n_i$, $\hat{\sigma} = \dfrac{s_1/c_4(n_1) + ... + s_m/c_4(n_m)}{m}$ and $\bar{S} = \left[\sum_{i=1}^{m} (n_i - 1) s_i^2 \Big/ \left(\sum_{i=1}^{m} n_i - m \right) \right]^{1/2}$, where n_i is the sample size, $\bar{x}_i$ is the sample mean, s_i

is the sample standard deviation of the *i*-th subgroup (week), *m* is the number of subgroups and $B_3(n_i)$, $B_4(n_i)$, $c_4(n_i)$ are the values of the factors B_3, B_4 and c_4 for samples of size n_i [9-10].

The control charts, obtained using the R package [11], for the *m*=30 preliminary samples, are shown in the left side (Calibration) of Figures 4 and 5.

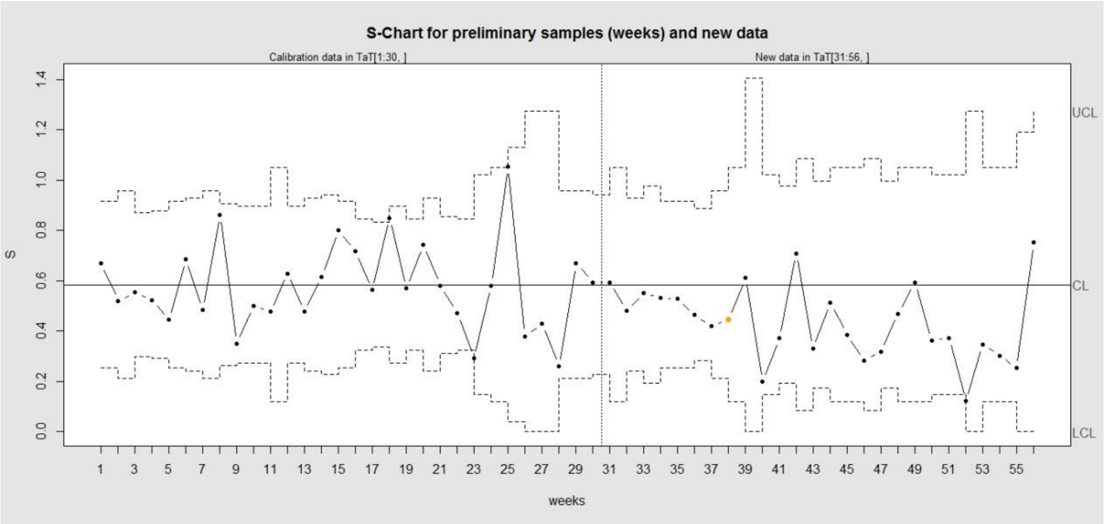

Figure 4: S-chart for the preliminary samples (Calibration 1÷30) and new observations (31÷56).

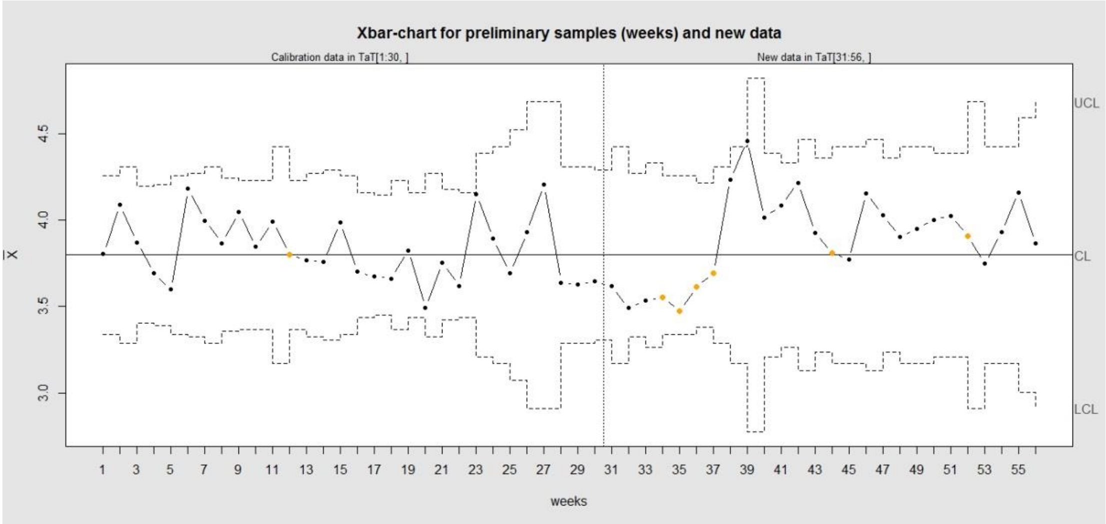

Figure 5: $\bar{X}$ chart for the preliminary samples (Calibration 1÷30) and new observations (31÷56).

Process parameters estimates should be based on a process that is in control. Therefore, we investigated the run above *CL* (weeks: 6÷12) in the calibration data of the $\bar{X}$-chart (Figure 5) seeking common features that might indicate a non-random cause for their occurrence. No consistent assignable cause was found for these data points and considering that a few "out-of control" points (in our case none, since we observed only a sequence of statistics above *CL* but below *UCL*) will not distort the control limits significantly [9], we chose to retain these data and keep the parameter estimates unchanged.

Based on these preliminary samples, we obtained: $\bar{\bar{X}} = 3.798$, $\bar{S} = 0.584$ and $\hat{\sigma} = 0.591$. These estimates were calculated on the transformed data. However, since it was of interest for the Hospital Quality Department to know the "in control" process mean and variability of the original data, we also computed the corresponding estimates on the untransformed data: the average OR TaT was 55.65 minutes and the standard deviation was 41.20 minutes.

Therefore, once we assessed the stability of the process in the preliminary samples, we retrospectively monitored the remaining data (26 weeks).

On studying the control charts from week 31 it can be noted that: the *S*-chart showed a sequence of points (weeks 32÷38) below the central line (Figure 4); the $\bar{X}$ -chart showed a similar sequence of statistics (weeks 31÷37) below the central line (Figure 5).

Then, as of week 39, the *S*-chart did not show any systematic behaviour or out-of control points, while very different results were observed in the $\bar{X}$ -chart.

Two sequences above the central line were present: the first run involving weeks 38÷44; the second sequence from week 46 to 52 (Figure 5). Applying the Western Electric run rules [9, 11-12] the presence of such a non-random behaviour is a strong indication that in this period the process was affected by assignable causes.

With the benefit of hindsight in such a retrospective study, we naturally know where to look for any anomalies in the control charts. However, it is incontrovertible that as of week 39 the performance monitored by $\bar{X}$ -chart degraded slightly: the systematic pattern above the central line indicates an increase in the average of the OR TaT.

On October 1, 2013 (week 39) an important change occurred in the OR organizational system. Patient transportation from and to the operating room, carried out until then by internal hospital staff, was committed to an external private company.

Summarising, monitoring the process from August 2013 through February 2014, an increment in average OR TaT appeared during the first week of October 2013, coinciding with the change in patient transfer service. The increase is significant, from a former average of 55.65 minutes of non-operative time between operations (for the preliminary samples) to 66.13 minutes (for the period October 2013, February 2014).

In the $\overline{X}$ -chart, to detect the shift in the process outcomes, we used one of the Western Electric rules (seven, or eight, consecutive points on one side of the centre line). Runs rules can increase the ability of the chart to detect small process shifts (<1.5σ) but can also increase the number of false alarms. To avoid this problem the combined use of Shewhart and exponentially weighted moving average (EWMA) charts is suggested and strongly encouraged also in healthcare applications [3,13]. In such a way, the relatively poor performance in detecting small process shifts of the Shewhart chart is balanced by the ability of EWMA which on the other end may be less sensitive to detect large process shifts. Therefore we complete our study using also an EWMA chart for the process mean.

Each point on the chart indicates the value of the exponentially weighted moving average for that subgroup.

The EWMA statistic for the *i*-th subgroup Z_i is defined recursively as [9]

$$Z_i = \lambda \overline{x}_i + \left(1-\lambda\right) Z_{i-1}$$

where $\overline{x}_i$ is the mean of the sample *i* of size n_i, λ is a weight parameter ($0 < \lambda \leq 1$).

When the process mean is known $Z_0 = \mu$ otherwise $Z_0 = \overline{\overline{X}}$ where $\overline{\overline{X}} = \sum_{i=1}^{m} n_i \overline{x}_i \Big/ \sum_{i=1}^{m} n_i$ and *m* is the number of preliminary samples.

In the case of variable sample size, the EWMA control limits are [9,10]

$$UCL = \overline{\overline{X}} + L\hat{\sigma}\sqrt{\lambda^2 \sum_{j=0}^{i-1} \left(1-\lambda\right)^{2j} \Big/ n_{i-j}}$$

and

$$LCL = \overline{\overline{X}} - L\hat{\sigma}\sqrt{\lambda^2 \sum_{j=0}^{i-1} \left(1-\lambda\right)^{2j} \Big/ n_{i-j}} \; ,$$

where *L* is the constant for the control limits and as before

$$\hat{\sigma} = \frac{s_1/c_4\left(n_1\right) + \ldots + s_m/c_4\left(n_m\right)}{m}$$

In our case, in order to use an EWMA chart with the same “in-control” performance of the $\bar{X}$ -chart, we chose $\lambda = 0.05$ and $L = 2.492$: in such a way the EWMA control chart has an ARL_0=370.4 [9].

The EWMA control chart for the process mean, obtained using the R package [11], is shown in Figure 6.

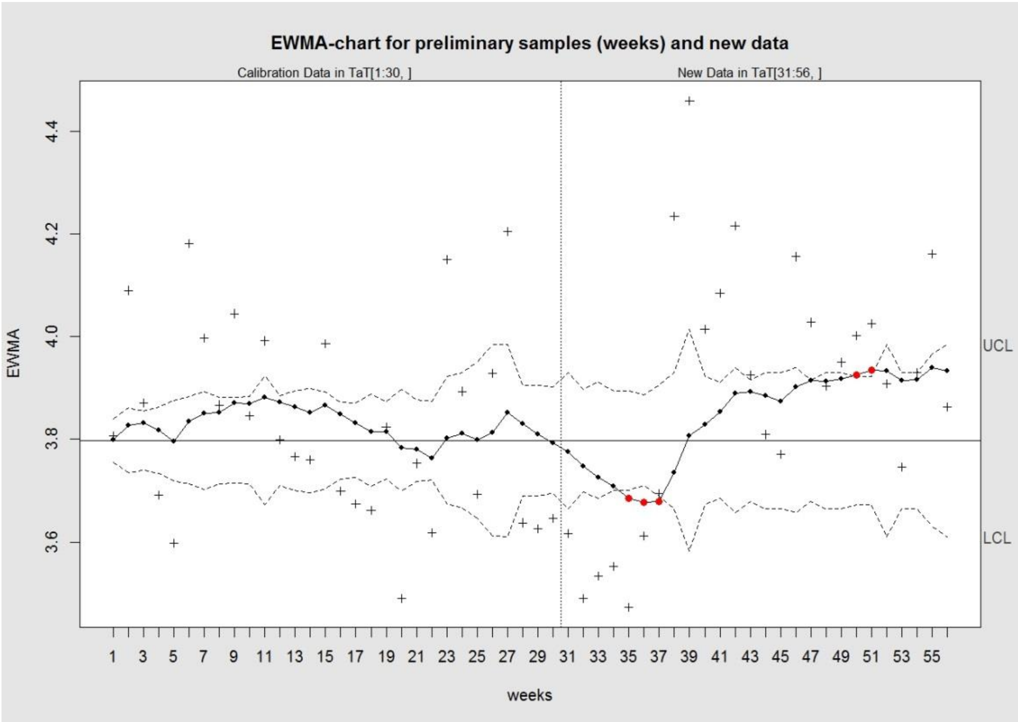

Figure 6: EWMA chart for the process mean: preliminary samples (Calibration 1÷30); new observations (31÷56).

There are several features of Figure 6 that are worthy of discussion.

First, as for the $\bar{X}$ -chart, the preliminary samples were in statistical control.

Second, in weeks 35÷37, the EWMA statistic is below the LCL. These out-of-control signals confirm the pattern observed in the $\bar{X}$ -chart where we noted a sequence of points (weeks 31÷37) below the central line (Figure 5). A very tentative explanation might be that the awareness of future changes in the OR working conditions might have affected the internal hospital staff with consequently improved performances.

Third, the performance deterioration in OR TaT since October 2013 (*i.e.* coinciding with the change in the OR patient transfer staff) is also confirmed by the EWMA chart:

since week 39, the EWMA statistic Z_i is constantly rising with two out-of-control points on weeks 50 and 51.

4. Concluding remarks

In the European Union the cost of each OR wasted minute can easily be greater than €30, [14]. Therefore, OR TaT can be extremely expensive and this measure is also a good indicator of efficiency.

Managers of health care organizations need to evaluate and monitor efficiency indicators and they also need to find benchmarks to reduce costs and increase efficiency. The challenge is thus to select a useful statistical tool for accurately monitoring and providing benchmarks for such indicators.

Statistical process control provides both a method for assessing the undisturbed, or steady-state, process behaviour and a method for detecting positive or negative changes in performance quickly.

We have retrospectively used Shewhart and EWMA control charts for monitoring the operating room turnaround time.

Our results showed that control charts are able to detect quality improvements or quality deterioration. We have not been able to test SPC as a monitoring tool applied continuously in a prospective mode: this will be the next step of our work.

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