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Monitoring the performance of university technology transfer offices in deprived areas: the bias control.

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Abstract

Education is the main activity for universities but the innovations resulting from their research become more and more a prominent and very lucrative business for them. University research and its transfer to industry has been a topic of interest in the management of technology literature over decades and several researchers focused the performances of university TTOs and many metrics have been proposed during last years. The primary role of a TTO is to manage and perform technology transfer activities (AUTM 2004), but how to control and monitoring the performance of university TTOs? In literature there are many studies regarding this theme, but many of these focused on the analysis of the driving forces of TTO performances that may help policy makers and university managers to improve technology transfer process (Hulsbeck et al., 2013), while in this paper, the approach to this theme regards the use of operative tools to control and monitoring the performance of university TTOs. TT managers oriented to use statistical tools, as a control chart, here proposed, to do this, face with an operative problem related the small samples of TT available data that can generate bias of the process only owned to this condition and not as a consequence of a bias really occurred. The described scenario of small samples regarding the TT activities is more frequent when the technology transfer actions insist on a geographical deprived area. In this paper, to overcome this problem, opportune graphs and tables, can be used by TT managers, are proposed to determine a reasonable number of subgroups of available TT data, for constructing suitable control limits. Hulsbeck et al., (2013) used the number of invention disclosures as a performance measure, to analyze how variance in performance can be explained by different organizational structures and variables of TTO. In this paper we refer to the same performance measure to be monitored. This proposed model and solution may be appealing to managers and technology transfer agents since the graphs and tables proposed could be reproduced in a number of standard optimization software.

Keyword: University technology transfer Offices; University/industry technology transfer; Organization; Performance; Deprived Areas; Control Process.

INTRODUCTION

A typical technology transfer control chart, to be used to control technology transfer process (TTP), assuming as performance measure the number of invention disclosures, already used by Hulsbeck and other authors (Hulsbeck et al., 2013) to analyze how variance in performance can be explained by different organizational structures and variables of TTO, is reported in figure 1.

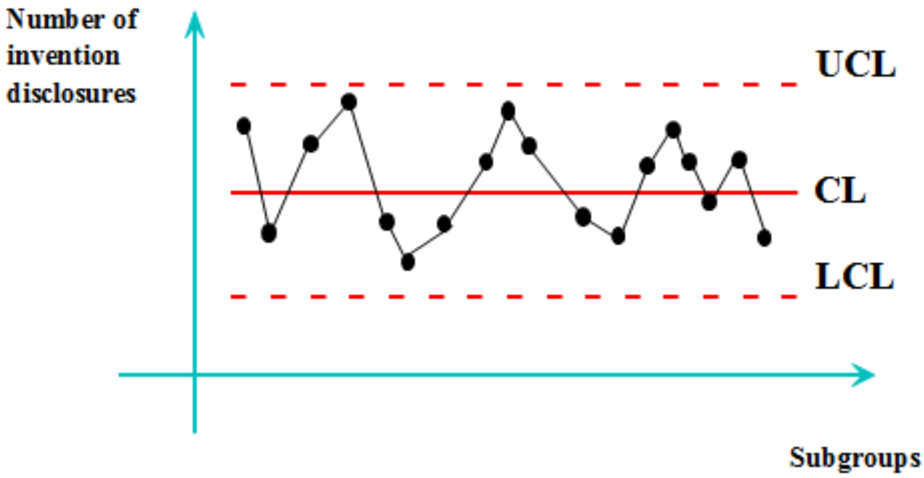


Fig. 1 TT control chart.

TT managers, oriented to use this TT control chart, face with an operative problem related to the small samples of TT available data that can generate bias of the process, only owned to this condition and not as a consequence of a bias really occurred.

The described scenario of small samples regarding the TT activities is more frequent when the technology transfer actions insist on a geographical deprived area.

The majority of the global population today is urban (Duque et al., 2015). The percentage of urban dwellers increased from 43% in 1990 to 52% in 2011, and it is expected to grow to 67% by 2050. All population growth from 2015 to 2050 is expected to be absorbed by urban areas, and most of this growth will occur in cities of less developed regions (United Nations, 2012). In developing countries, rapid urban growth normally exceeds the capacity for local governments to deliver services and infrastructure, which increases urban poverty and intra-urban inequalities (Duque, Royuela, & Norena, 2013). The monitoring of poverty is a key issue for policy makers because it can help prevent poverty traps and crime nests and allocate public investments where they are needed most (Duque et al., 2013). Urban poverty is a multidimensional phenomenon; as such, there are many ways to measure it. These measures usually include information from at least one of the following dimensions: income/consumption, health/education, and housing (Carr-Hill & Chalmers-Dixon, 2005; Moser, 1998). They are computed from survey or census data, which are quite expensive, time consuming, less frequently produced, and often statistically significant for spatial units that are too large to capture the intra-urban variability of phenomena. This last feature creates inference problems such as the ecological fallacy (Baud, Kuffer, Pfeffer, Sliuzas, & Karuppannan, 2010; Robinson, 1950) or aggregation bias (Fotheringham & Wong, 1991; Paelinck & Klaassen, 1979).

We consider as bias a condition in which the technology transfer instance relative to a certain invention disclosure proposal doesn't generate a contact link of interest with the potential users.

Since TTP parameters are seldom, if ever, known with certainty, the statistical properties of control charts, used to monitor the number of invention disclosures that generate contact links of interest with the potential users, that are based on estimates of process parameters should be of particular interest to TT managers to overcome this problem.

Typically the true process distribution related to the performance measure selected, can be assumed to be normal, but the process mean μ and variance σ^2 are estimated from some number m of initial subgroups of size n each. The upper and lower control limits UCL and LCL are then a function of these estimates, for example ± t / ($c_4\sqrt{n}$) , where is the average of the m subgroup averages , i=1,…, m, is the average of the m subgroup standard deviations S_i , i=1,…, m, c_4 is the value such that $E[S_i /c_4] = s$ for the given subgroup size n, and t is the desired number of standard deviations to use for TTP control.

From the TT manager's viewpoint, it would be desirable to use only a small number of subgroups to estimate μ and σ^2 in order to get on with charting the run as soon as possible. However, as a number of authors have discussed, basing the chart on estimates of μ and σ^2 made from a small number of subgroups may give rise to some unexpected and undesirable effects. In particular, Hillier (1954) computes the probability that a subgroup mean will fall outside the control limits when the process is in control and shows that for small m this can be much larger than 0.0027, id est the probability of a false TTPB for a chart with 3σ limits constructed using a known mean and variance.

Thus a chart with limits estimated from only a few subgroup means will tend on average to produce a greater number of technology transfer process bias (TTPB), which will affecting the performance of a technology transfer office (TTO).

Various authors have attempted to circumvent this problem; see, for example, Hillier's computation (Hillier 1964) of an adjusted constant for the number of process standard deviations enclosed by the control limits, or the Q-charts of Quesenberry (Quesenberry 1993) which allow charting to be done from the beginning of a run. Such schemes invariably trade power for safety: the price paid for a reduction in the number of TTPB from an in-control TT process is a decrease in the number of TTPB detected when the process is truly out of control.

In the quality control literature, the statistical properties of charts with limits estimated from small samples have usually been studied from the perspective of the effects of estimation on the average (expected) run length for a chart, known as its ARL. In this paper, we examine the application of a ARL chart, according to the approach proposed by Dan Trietsch and Diane Bischak (2007) to monitor the TTP and find that it is easily misunderstood and that, even when it is unambiguously defined, it has only moderate value as a focal point for the study of control charts. We argue that the rate at which TTPBs occur in a chart is both a more intuitive concept and a more useful one for determining a reasonable number of subgroups to sample in order to construct control limits for monitoring the number of invention disclosures that don't generate a contact link of interest with the potential users. In the remainder of the paper we enlarge upon this argument, discussing the properties of the distribution of the rate of false TTPB in detail.

TECHNOLOGY TRANSFER PERFORMANCE METRICS

The performance of university TTOs has been studied by many investigators, and a wide range of metrics has been selected to assess their performance (Tseng and Raudensky, 2014).

The rapid increase in university technology transfer has attracted attention in the academic literature (Rothaermel et al. 2007; Carlsson and Fridh 2002; Jensen and Thursby 2002; Di Gregorio and Shane 2003; Baldini 2006; Anderson et al. 2007; Thursby and Thrusby 2007). This emerging literature is interdisciplinary, with contributions from scholars in many disciplines, such as economics, sociology, political science, public administration, engineering, and in several fields within management, such as strategy, entrepreneurship, human resource management, and technology and innovation management. There is also some international evidence for this phenomenon. Due to the complexity of the issues raised by the rise of technology transfer at universities, many authors have employed qualitative methods (De Falco 2012) to address key research questions (Vinig and Lips 2015).

Many studies have shown that a great deal of TTOs operate inefficiently. Some studies have been conducted to understand the underlying deficiencies. When we try to assess the ratio of each output, then we start to question the effectiveness of university technology transfer. A simple calculation of ratios of research expenditures per invention disclosure and licensing income euros may at first glance lead a sceptic to question the effectiveness of university technology transfer. Heher (2006) provides a forecast of the income through university innovations. His finding of expected exponential increase also justifies exploration of the field. This issue of efficiency has been explored by using different methods. University research and its transfer to industry has been a topic of interest in the management of technology literature over decades (Anderson et Al. 2007).

We can see the literature grouped under the following titles: Organizational structures. Regional or international comparisons/case studies. Impacts of university research. Tangible outputs of university research (patents, licenses, spin-offs). Efficiency of university research transfer. Several researchers focused on the organizational issues. Siegel et al. (2003) explored such organizational structures of the TTOs linking them to their productivity suggesting that the most critical organizational factors for productivity TTOs in research universities are faculty reward systems, TTO staffing/compensation practices, and cultural barriers between universities firms. Rasmussen et al. (2006) explored initiatives provided by the universities to promote commercialization of university knowledge and identified coordination a challenge. Mc Adam et al. (2005) provide such a coordination model for university innovation centers. They analyze licensing and business building processes. Chapple et al. (2005) indicated that there is a need to increase business skills and management capabilities to TTOs. Thursby and Kemp (2002) also explored efficiency of university technology transfer by looking at the organizational issues. Siegel and colleagues studied similar issues (Siegel et al., 2003, 2004) also studied similar issues. Their focus has been the impact of organizational characteristics and the implications for education. They make recommendations based on the barriers identified in the UTT efficiency and effectiveness processes such as culture clashes, bureaucratic inflexibility, poorly designed reward systems, and ineffective management of TTOs. Lowe (2006) proposes a theoretical model to illustrate how the inventor know-how affects whether the inventor starts a firm to develop her idea or licenses an invention to an established firm for development. This model is then used to analyze the role and impact of a university TTO on this process to understand how TTOs may both positively and negatively impact the transaction. Leitch and Harrison (2005) explored the dynamics of the spin-off phenomenon with a focus on the TTO and they propose a wider role for such offices to be more efficient. Lopez (1998) explored different ways universities can get organized to improve the research efficiency. This group of literature supports our hypothesis that there are efficiency issues while transferring technology out of the university environment. We also see studies comparing different approaches or regions Goldfarb and Henrekson (2003) and Feldman et al. (2002) studied different policies for transferring university technology. Di Gregorio and Shane (2003) explored differences among universities in commercialization of technologies. Colyvas et al. (2002) studied case studies of commercialization of university inventions. Lee and Win (2004) explored three university research centers in Singapore concluding that coordination among university center, industry and government is one of the key success factors. Owen-Smith et al. (2002) compared US and European practices in terms of university industry relations. Other studies focused on individual cases to explore similar issues. Zucker et al.

(2002) looked at the efficiency of university technology transfer through a biotechnology case study. Lopez-Martinez et al. (1994) found out that in developing countries specifically in Mexico both academia and industry have implicit cultural dissimilarities which directly affect current or potential cooperative liaisons. The industry–academic interdependencies in Germany have been well studied (Meyer-Krahmer and Schmoch, 1998; Beise and Stahl, 1999). Their research findings indicate that there are certain requirements to be met by both parties to have successful long term collaborations. Boyle (1986) focused on the technology transfer between universities and the UK offshore industry; Corsten (1987) reviewed industry–university collaborations in 225 enterprises; and Goldhor and Lund (1983) provided a detailed analysis of transfer of a text to speech reading machine. This group of literature verifies the efficiency issue further by adding another dimension of variance. We see that organizational, cultural and regional differences can make a difference. Some other studies focused on the impact of university research. Feller et al. (2002) and Cohen et al. (2002) specifically explored the impact of university research on industrial innovation. Shane and Stuart (2002) studied the resulting start ups through university research. Siegel et al. (2003) concluded that science university parks do not have significant impact on research productivity. Bennet et al. (1998) focused on university–industry collaboration for technology transfer in poorer regions of the United Kingdom. Such collaborations are reported to be successful and help local economies. Studies that focused on exploring the efficiency through studying their tangible output are found frequently in relevant literature. Trune and Goslin (1998) studied performance of the TTOs from a profit/loss analysis perspective. Their results indicate that such centers are profitable and are acting as significant economic drivers. Berman (1990) also provided evidence on the economic impact of industry funded university R&D. Several studies (Agrawal and Henderson, 2002; Mowery et al., 2002; Shane, 2002) have specifically explored patenting within the universities. Geuna and Nesta (2006) fear that the increase in university patenting exacerbates the differences across universities in terms of financial resources and research outcome. Also, because of international property regulations (IPRs) there is a tendency for universities and academics to limit disclosure of materials and information, therefore helping to foster growing commercialism and competition among universities and dampen open science and knowledge transfer (Sampat, 2006). Mazzoleni (2006) presents a model of R&D competition based on a university invention where appropriability conditions are defined by the patentability of downstream innovations and imitation opportunities. He concludes that university licensing royalties are therefore a poor gauge of social welfare gains from university patenting.

CONSTRUCTION OF THE TT CONTROL CHART

We will assume the following two-stage scenario for establishing a control chart. (We ignore the dispersion chart, but implicitly it is also created, at least for use in the calculation of control limits.) At Stage 1 we sample m subgroups of n items each, relative to the number of invention disclosures monitored during n different time periods, and create a trial control chart. Assuming that the m points used to create the chart are strictly between the control limits, we declare the control chart as ready for Stage 2, i.e., it is no longer a "trial" chart (otherwise, we take action to obtain a "good" trial chart).

At Stage 2 we start collecting data. We may then ask how long we can expect to sample data until we see the first out-of-control point, defined as a TTPB. We must now specify how consider the TTPB.

a) **Case a:** TTPB deriving from the overcoming of the upper control limit UCL from the expected number of invention disclosures. This case, that is positive, should be considered however as a bias with the aim to investigate the specific nature of the invention disclosures to strengthen the corresponding research sector considering it as a strategic sector.

b) **Case b:** TTPB deriving from the overcoming of the lower control limit LCL from the expected number of invention disclosures. This case shows to TT managers that invention disclosures concern a not strategic research sector.

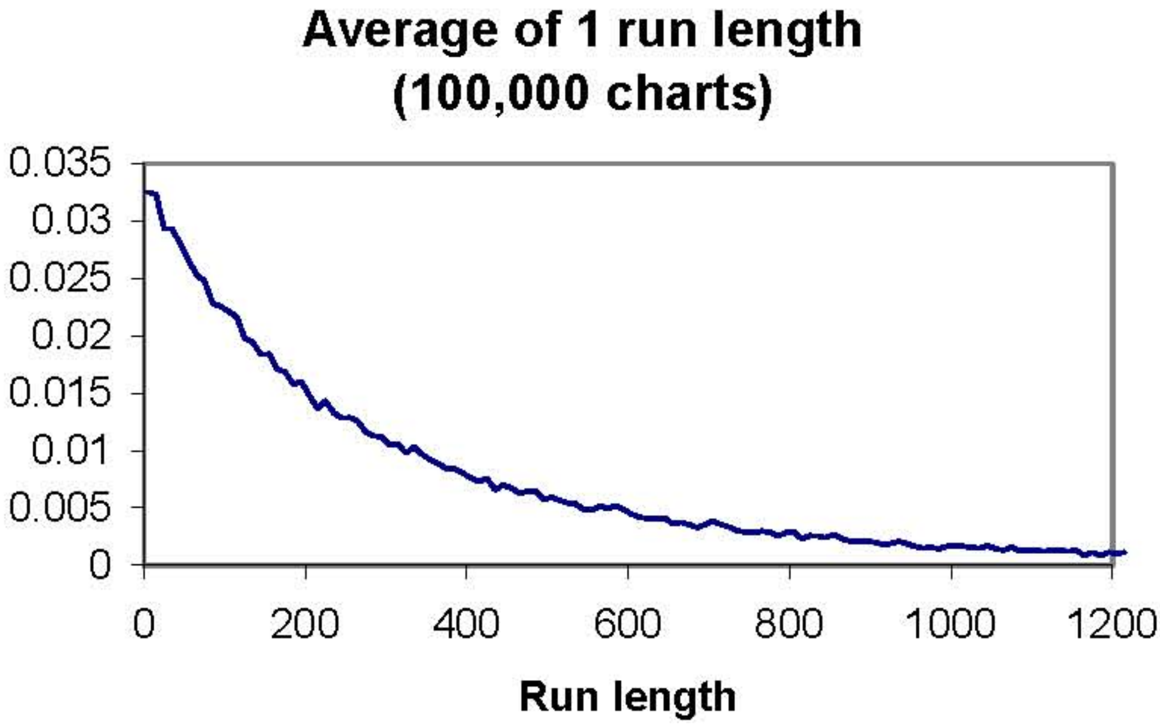
TT managers may do this under two assumptions: one that the TTP is in control, and therefore the TTPB in question is false; two that the TTP is out of control in some specific way (e.g., the adjustment is off center by a given amount). The discussion here will concentrate on the case that the first assumption is true. Under the first assumption, the quantity we are interested in is the ARL.

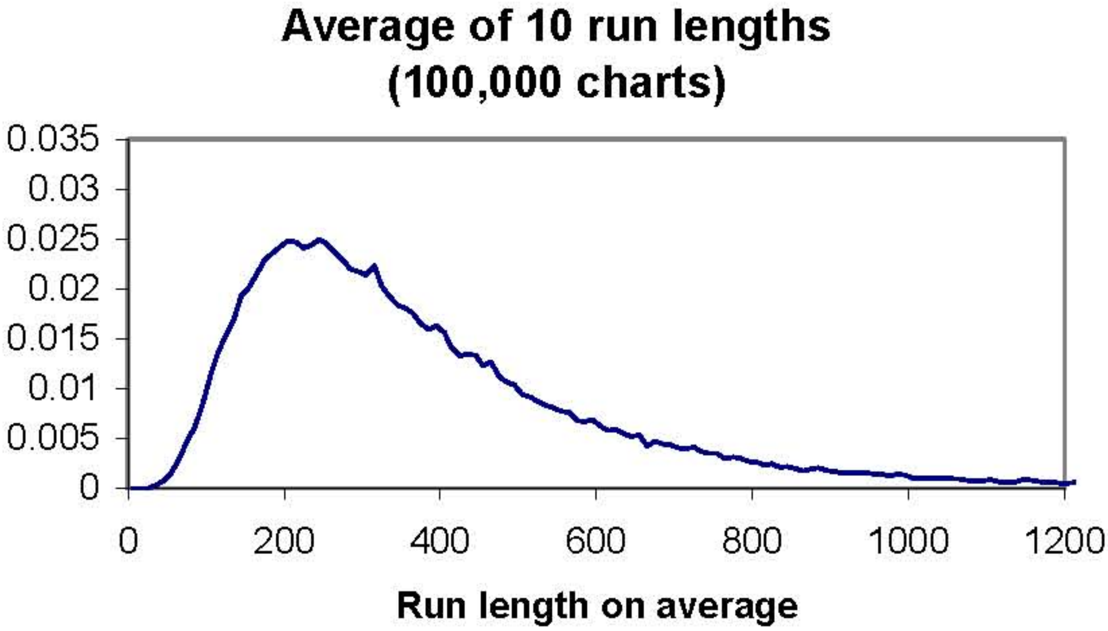
The ARL is the expected value of the random variable that represents the sample number, of number of invention disclosures, on which the first (false) out-of-control point appears for a process that is operating in control. That is, for a Stage 2 charted process {t, t=1, 2 …}, ARL = E [RL], where the run length RL = min {t: t [LCL, UCL]} (Del Castillo 1996). The ARL can then be thought of as the average across a sample of charts of the number of samples plotted on a chart until the first false TTPB occurs, where every chart in the sample for given values of m, n, and t is counted exactly once in that average. Note that for the case that the control limits are known with certainty and thus are not estimated at Stage 1, a process producing independent samples will produce a series of TTPBs that can be considered to be independent of one another, and therefore the ARL has a geometric distribution with parameter p = 0.0027 for a 3σ chart.

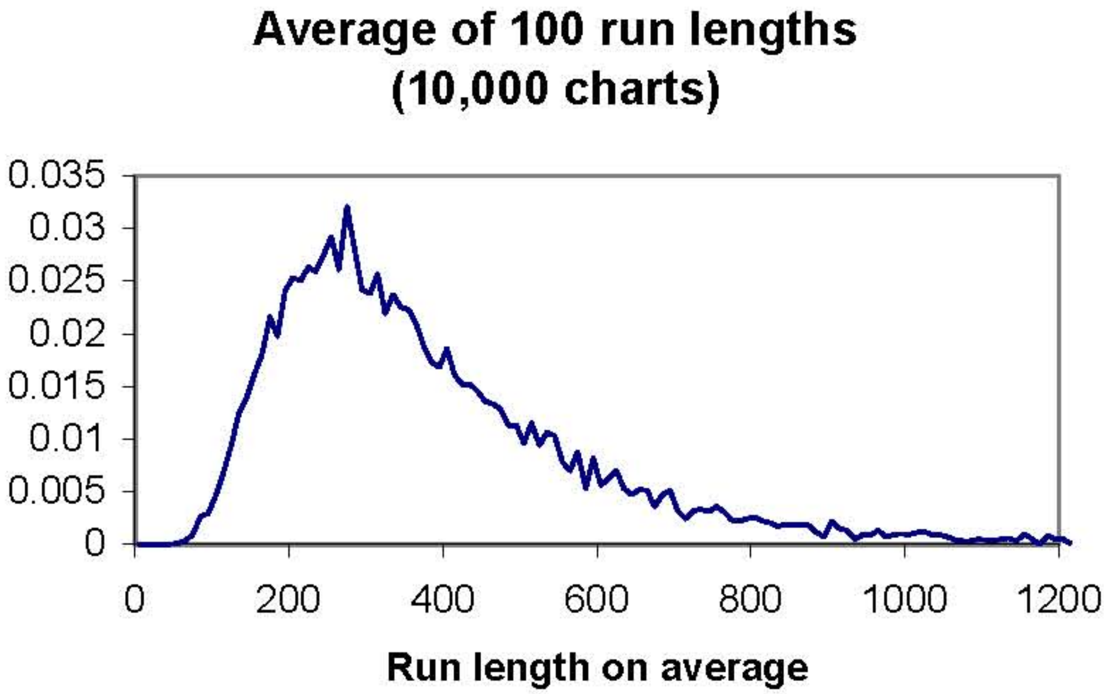
Most previous authors have measured a chart's tendency to produce false out-of-control points by its ARL. Historically, this interest in the ARL has often come about because of the usefulness of the quantity in the economic design of control chart procedures: for example, Ghosh et al. [1981] present an economic model of long-run average cost per unit time in which the ARL figures as one of the most important parameters. However useful the ARL may be to researchers, to a practitioner the ARL is a peculiar and somewhat irrelevant measure. As the definition of ARL above shows, the ARL is the average over a large number of charts of a single false TTPB per chart, the first one that the chart produces. It is defined as though each chart were to be used only until the first out-of-control point occurred, then thrown out and replaced by a new chart, even though investigation reveals that the process is still in control. Unless a chart is indeed thrown away after the first out-of-control point, which is unlikely in practice, a better measure of a chart's performance over time is not the expected run length but the expected run length on average (RLOA), which is the average of the run lengths between out-of control points on a given chart when the process is in control. This is especially true since, as Quesenberry noted (1993), there can be many very short runs between out-of control points on a chart with estimated limits. For a given chart, the RLOA has a negative binomial distribution with parameters r, equal to the number of runs averaged together, and p, equal to the probability of a point being out of control. Although the across-chart expected values and variances of the RL and the RLOA are the same, their distributions are not. Figure 1 shows the estimated distribution of RLOA for m=50 and various numbers of run lengths averaged within a given chart, based on 10,000 (or, in the top graphs, 100,000) simulated charts with n=5 and t=3. If only one run length is gathered per chart, we have the ARL distribution. (The top graphs' curves are smoother than the bottom two because of the additional charts simulated.) Averaging ten or more run lengths together on a given chart produces very similar distributions, but the distribution of a single run length is different: the probability of seeing an RLOA of less than, say, 50 is very high if only one run length is gathered per chart but very low if ten or more run lengths per chart are averaged together. These distributions are all positively skewed with a heavy tail, and the single run length distribution is similar to a heavytailed geometric distribution. The RLOA distributions are clearly not normal, which would be the approximate distribution for a chart constructed with known limits. The Central Limit Theorem does not apply here, because each plotted point is a sample from a different distribution, that is, from a given chart's distribution of average run lengths. Thus the RLOA distribution should itself be of interest to both researchers, practitioners and TT managers.

Previous authors have also used the ARL to explain why the properties of charts with control limits estimated from small m turn out to be inferior to those of charts with known limits. Ghosh et al. (1981) point out that any procedure that uses the same estimate of σ2 to judge whether each sample mean is in control, as will be true in the two-stage scenario we describe above, will result in a dependent, rather than independent, series of comparisons of subgroup means against the control limits. That is, as Quesenberry (1993) shows there will be a dependence between the events "false TTPB at subgroup i" and "false TTPB at subgroup j". This dependence, which is negligible for large m but sizeable for very small m, has implications for the run length distribution and the ARL. Ghosh et al. derive an expression for the distribution of the run length for an estimated chart and show that small m increases both the ARL and the variance of the run length distribution.

As noted above, for a chart with known limits, false TTPBs points are independent of each other, and therefore the ARL for a single run length per chart has a geometric distribution. But the dependence found by Ghosh et al. (1981) and Quesenberry (1993) implies that the run length distribution (across charts) is not geometric when the control limits are estimated. Figure 2 shows, for m=10 with n=5 and t=3, the empirical cumulative distribution function (cdf) of the run length for charts with estimated limits, a geometric distribution which forms a bound for this cdf [2], and the limiting cdf for a chart with known limits. The bounding geometric distribution has parameter p = Pr (-t ≤ T (m-1) ≤ t), where T (m-1) follows a Student's t-distribution with m-1 degrees of freedom. The limiting cdf is that of a geometric random variable with p = 0.0027 = Pr (-t ≤ Z ≤ t), where Z is a standard normal random variable. The bounding geometric is stochastically smaller than the estimated chart run length distribution, so although in this case it is a very loose bound it is a useful one, as for any given run length the probability of seeing a run length less than that length is always less for the chart with estimated limits than for the bounding distribution. The limiting cdf is of interest for comparison purposes, because it shows just how different the estimated chart's distribution is from the known limits case. As Quesenberry (1993) points out, estimated charts produced from small samples will have many more very short runs and more (although not as many) extremely long runs between false TTPBs, which leads Quesenberry to recommend using larger m to produce charts in general. Seeing more short runs in a chart means chasing a false TTPB more frequently; seeing more extremely long runs means that the power of the chart to detect a real change in the process is reduced.


Average of 1 run length
(100,000 charts)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
200
400
600
800
1000
1200
Run length


Average of 10 run lengths
(100,000 charts)
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
200
400
600
800
1000
1200
Run length on average



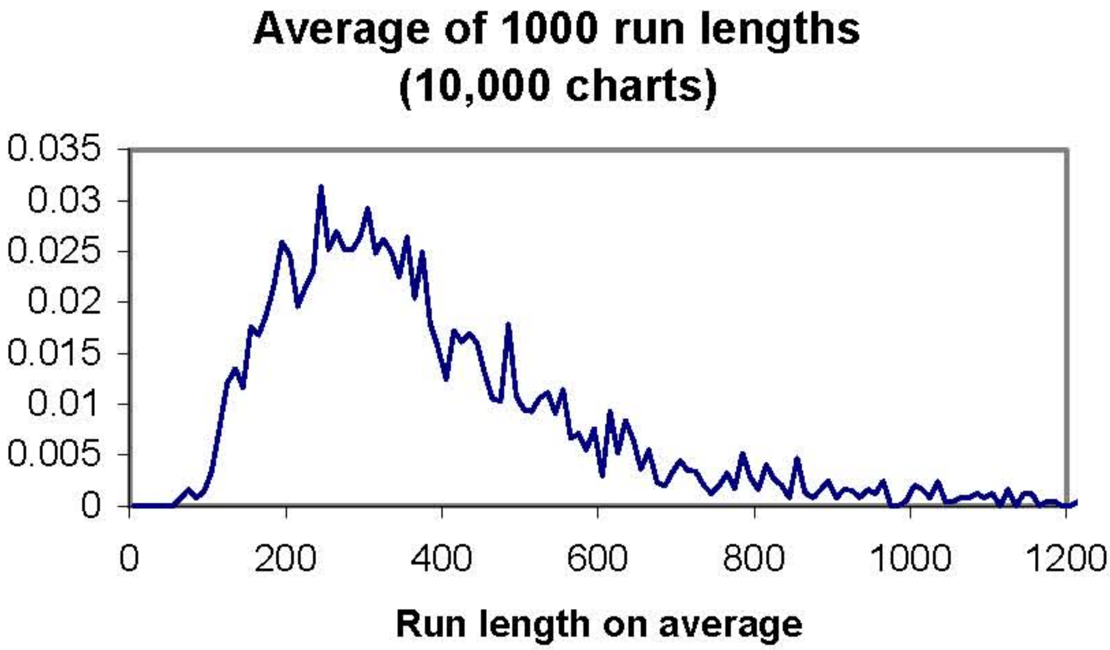


Fig. 2 Estimated distribution of run length on average, m=50, n=5, and t=3. Source: Trietsch and Bischak (2007)

THE RATE OF FALSE TTPBS

Consider now the false TTPBs that a chart with estimated limits will produce. It is true that, from a standpoint before the production of the chart, there is dependence between these false TTPBs, so that an unusually low mean estimate, for example, will push the whole chart down relative to the data and will tend to result in a larger number of false TTPBs. However, after a particular chart is actually produced from estimates of and σ2, it will have independent runs between false TTPBs and a geometric run length distribution, because the limits are fixed values. This claim is true even if the control limits are determined by, say, reading random tables: once control limits are obtained, one way or another, the rate of false TTPBs, p, is a constant, but it is a different constant for each control chart.

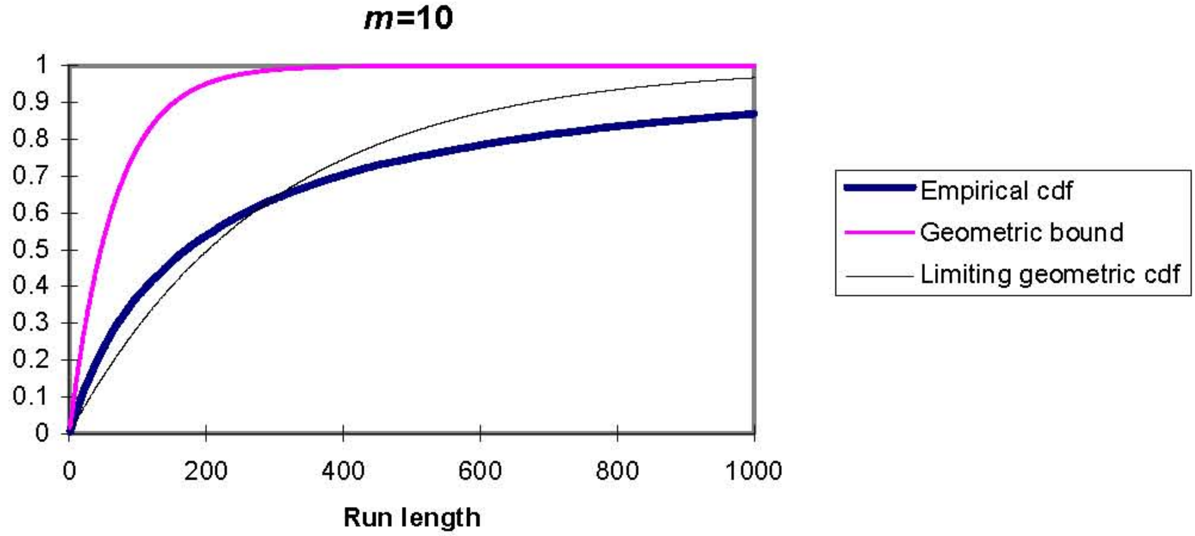


Fig. 3 Empirical, bounding geometric, and limiting geometric cdf's of the run length for n=5 and t=3. Source: Trietsch and Bischak (2007)

Unfortunately, the TT managers, as users of a given chart with estimated limits, do not know their chart's p: all they know is that they sampled m subgroups in Stage 1 and subsequently the first, say, k subgroups of Stage 2 were not out of control. For these users the best estimate of the probability of a false TTPB on subgroup k+1 is the average rate of false TTPBs of all charts based on m subgroups with no TTPB on the first k subgroups. This rate is highly unlikely to be exactly equal to p, the true rate of false TTPBs that their own chart possesses. However, as users gain experience with a particular chart and obtain many points on it that cannot be explained by investigating the TTP, they may have a much better idea of their chart's true rate of false TTPBs. Thus treating the chart as if nothing is known about it, as though it is a random draw from the universe of possible charts, is invalid in the long run.

We refer to the rate of false TTPBs across all possible charts as the RFB. Assuming
That the underlying process is normal, the rate of false TTPBs for a chart with fixed
Limits UCL = u and LCL = l is a constant equal to

$$1 - \Phi\left(\frac{u-\mu}{\sigma/\sqrt{n}}\right) + \Phi\left(\frac{1-\mu}{\sigma/\sqrt{n}}\right)$$

Where μ and σ are the mean and standard deviation of the process and F(x) is the cumulative normal distribution at x. (This expression evaluates to 0.0027 for 3σ limits.) However, for estimated charts RFB is not a constant but is instead a random variable: it is the (random) probability that a subgroup mean will fall outside the (random) control limits UCL and LCL, given that the process is in control. The random variable RFS has the expected value

$$E[RFS] = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}[1-\phi\left(\frac{u-\mu}{\sigma/\sqrt{n}}\right)+\phi\left(\frac{l-\mu}{\sigma/\sqrt{n}}\right)]fucl,lcl(u,l)dudl$$

Where fUCL, LCL (u, l) is the joint distribution of UCL and LCL. The probability that is given in Table 1 (Hillier 1964) is the expected value of RFB for a 3σ chart with limits estimated from m subgroups of n=5 each, for various values of m; these probabilities approach 0.0027 as m becomes large.

To understand more clearly the difference between the ARL and the RFS as measures of chart performance, consider the following scenario. Suppose that a group of charts are all constructed by estimating limits by the same procedure in Stage 1, and suppose further that all the charts will be used for the same length of time. Then some charts will generate more false TTPBs than others. A chart that has small ARL will tend to contribute many false TTPBs to the pool of false TTPBs during this time period, and a chart that has large ARL will tend to contribute fewer of them. An estimate of the RFB for this charting procedure based on these charts would average the charts by placing equal weight on each chart's contributions of run lengths (out-of-control points) that occur in the given period of time. An estimate of the ARL, on the other hand, would average only the run lengths until the first out-of-control point on each chart, thus counting each chart exactly once. Note that for estimated charts the average overall rate of false TTPBs across all charts (as computed by Hillier 1964) is not simply the reciprocal of the average run length until the first TTPB (as studied by, for example, Quesenberry 1993). If each constructed chart will be used over a period of time, it is likely to generate more than one TTPB. The rate of false TTPBs is then a natural measure of the chart's performance.

QUANTILES OF THE RATE OF FALSE TTPBS

Because charts' limits will vary, it is useful to look not just at the expected rate of false TTPBs but also at the probability distribution of that rate across charts. This will show, for example, just how likely it is to get a bad chart if a small number of subgroups is used. Figure 3 shows the probability density function of RFB for a 3σ chart using various values of m. These graphs were created from smoothed histograms of data from simulations, hence the graphs do not begin at the origin. The graphs are similar to Weibull density functions for various parameter values. At small values of m the density functions display an extremely large spread, indicating the wide range of possible false TTPB rates achievable across charts. As m increases the density gradually tightens up; if m were to go to infinity, which would in effect mean that the limits are not estimated but are known with certainty, the density function would become a single spike at 0.0027.

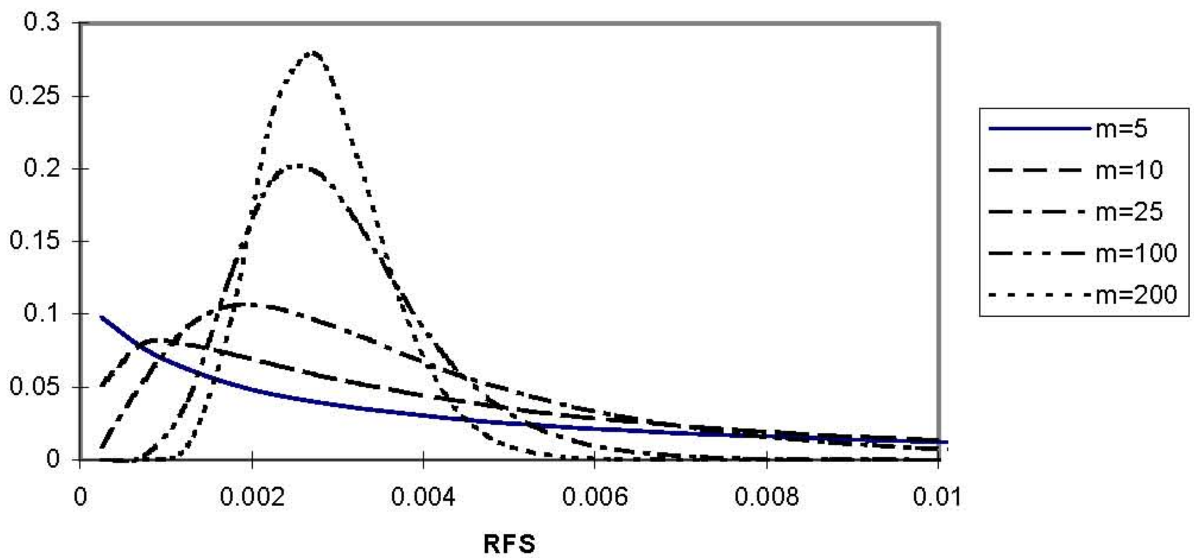


Fig.4 Probability density function of RFB for various values of m. Source: Trietsch and Bischak (2007)

Figure 4 shows various quantiles of the rate of false TTPBs as a function of m,
Based on simulation results. The values plotted in Figure 4 are (m, QP), where pr (RFB ≤qp) = p, p = 0.01, 0.05, 0.10, and 0.25. For example, 1% of charts created from 25 subgroups, a number recommended by many authors, have an RFS which is less than 0.0005, and 10% have an RFS less than 0.0012. Even at m=100, recommended by Quesenberry (1993), 10% of charts will have an RFS of 0.0018 or less, that is, at most two-thirds of the "planned" 0.0027 value.

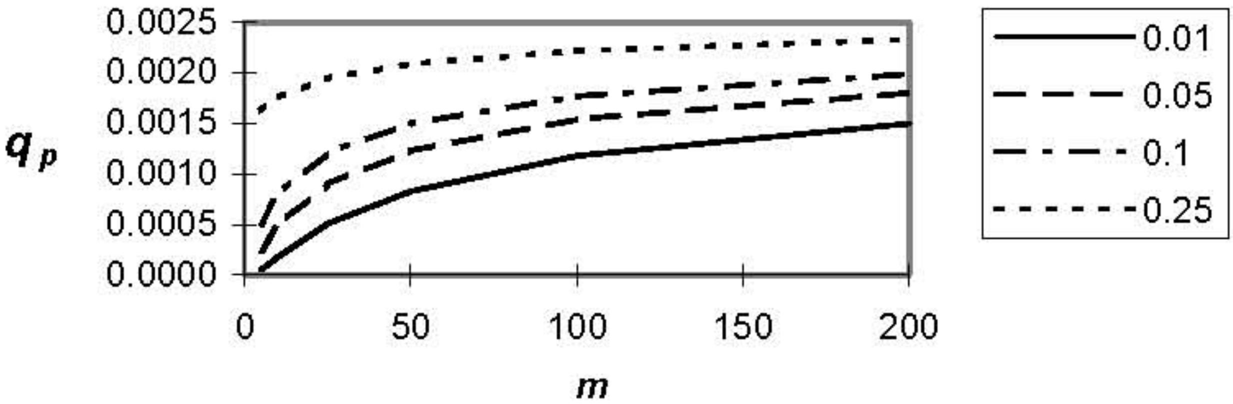


Fig. 5 Quantiles of RFB as a function of m. Source: Trietsch and Bischak (2007)

We can look at these quantiles QP as functions of t, the number of standard Deviations the chart is based upon; z, where λ (z) = p; and m. Call these values λ (t, z,m). Tabled values of λ (t, z, m) are given in Table 1, calculated using the Mathematica software package. For large m the estimate of the true standard deviation, whether based on S or R, will be approximately normally distributed. We can use this fact and approximations based on the normal distribution to interpolate in Table 1 to obtain quantiles for any p and m>25. Interpolation between tabled values for m>25 can beeffectively performed with a two-step procedure, details of which are given in Trietsch and Bischak (2007).

Table 1 λ (t, z, m) for R-based charts with n=5. Source: Trietsch and Bischak (2007)

	z	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5
	p	0.5	0.69146	0.84134	0.93319	0.97725	0.99379	0.99865	0.99977
t	m								
1	25	0.32680	0.34509	0.36402	0.38359	0.40378	0.42460	0.44604	0.46808
	100	0.31972	0.32879	0.33802	0.34743	0.35699	0.36672	0.37661	0.38667
	400	0.31792	0.32243	0.32699	0.33158	0.33622	0.34091	0.34563	0.35039
	1600	0.31746	0.31971	0.32198	0.32425	0.32653	0.32883	0.33113	0.33345
	∞	0.31731	0.31731	0.31731	0.31731	0.31731	0.31731	0.31731	0.31731
2	25	0.04986	0.05898	0.06945	0.08140	0.09497	0.11028	0.12749	0.14672
	100	0.04658	0.05081	0.05535	0.06022	0.06544	0.07103	0.07701	0.08339
	400	0.04577	0.04782	0.04995	0.05215	0.05444	0.05681	0.05927	0.06181
	1600	0.04557	0.04658	0.04761	0.04866	0.04973	0.05082	0.05193	0.05307
	∞	0.04550	0.04550	0.04550	0.04550	0.04550	0.04550	0.04550	0.04550
2.5	25	0.01423	0.01826	0.02325	0.02939	0.03687	0.04592	0.05677	0.46808
	100	0.01286	0.01463	0.01661	0.01882	0.02129	0.02403	0.02708	0.38667
	400	0.01253	0.01337	0.01427	0.01521	0.01621	0.01727	0.01839	0.35039
	1600	0.01245	0.01286	0.01329	0.01372	0.01417	0.01464	0.01512	0.33345
	∞	0.01242	0.01242	0.01242	0.01242	0.01242	0.01242	0.01242	0.01242
3	25	0.00326	0.00462	0.00647	0.00895	0.01226	0.01660	0.02225	0.02949
	100	0.00283	0.00339	0.00405	0.00482	0.00572	0.00677	0.00799	0.00940
	400	0.00273	0.00299	0.00328	0.00358	0.00391	0.00427	0.00466	0.00509
	1600	0.00271	0.00283	0.00297	0.00310	0.00325	0.00340	0.00355	0.00371
	∞	0.00270	0.00270	0.00270	0.00270	0.00270	0.00270	0.00270	0.00270

CONCLUSIONS AND FUTURE WORK

In this paper we have pointed out the importance, for TT managers, to use operative tools to control and monitor the performance of TTOs and for this aim a TT control chart, based, as performance measure, on the number of invention disclosures by TTO, is been proposed. This proposed model and solution may be appealing to managers and technology transfer agents since the graphs and tables proposed could be reproduced in a number of standard optimization software.

To overcome the problems, affecting the particular process of technology transfer, related to thes mall samples of TT available data that can generate bias of the process only owned to this condition and not as a consequence of a bias really occurred, opportune graphs and tables, can be used by TT managers, studied by Trietsch and Bischak (2007), are proposed to determine a reasonable number of subgroups of available TT data, for constructing suitable control limits.

The distribution of the rate of false technology transfer bias directly provides information to the TT managers concerning the probability that a chart will have control limits which either have an excessive rate of false technology transfer bias or a rate of false technology transfer bias that is too low which consequently provides little power to determine that a technology transfer process change has actually occurred.

Such authors (Anderson et al. 2007) studied the efficiency of university technology transfer and they reported some propositions, between some of them, the following:

Proposition 6. There are no differences in university technology transfer efficiency between private and public institutes.

Proposition 7. There are differences in university technology transfer efficiency between universities with medical schools and those without.

Further research will provide to evaluate and compare the rate of false technology transfer bias to verify the transposition of the previous propositions in term of the following:

Proposition 1. There are no differences in rate of false technology transfer bias of university technology transfer activities between private and public institutes.

Proposition 7. There are differences in rate of false technology transfer bias of university technology transfer activities between universities with medical schools and those without.

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