Improving the quality of Higher Education teaching through the exploitation of student evaluations and the use of control charts

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Improving the quality of Higher Education teaching through the exploitation of student evaluations and the use of control charts

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Abstract

Student evaluations of faculty members' teaching effectiveness are considered quite important in Higher Education (HE). In this paper, we elaborate on the framework of Nikolaidis and Dimitriadis (2014), based mainly on Statistical Process Control techniques and tools, which enables a deeper analysis and broader exploitation of student evaluation data. More specifically, we thoroughly examine and evaluate through simulation, several popular types of control charts (CCs), identifying the most suitable among them, using as comparison criteria various statistical properties of CCs. The ultimate goal of our research is to provide decision makers in HE institutions with an easy-to-use reliable tool for not only monitoring the teaching process, but also identifying the effective and ineffective faculty members' teaching performance to promote the quality of their Institution.

KEYWORDS

Higher Education; SPC; Control chart; ARL; Simulation.

1. Introduction

"Measurement is the first step that leads to control and, eventually, to improvement. If you cannot measure something, you cannot understand it. If you cannot understand it, you cannot control it and if you cannot control it, you cannot improve it."

The quote of James Harrington clearly states what should constitute the foundation stone of any effort in operations management. Any index such as performance, efficiency and, why not, quality, can be significant in the cycle of "measure-understand-control-improve".

Traditionally, various "quantitative" tools of quality (e.g. control chart) have been implemented mainly in industry and manufactured products. However, since the late 1980s, quality has gradually been introduced in the service sector as well. Over the years, quality of services has been linked to increased profitability and it is considered to provide an important competitive advantage to service companies by generating repeated sales and higher market shares, ensuring customer retention and positive word-of-mouth (Abdullah et al., 2011). Thus, service providers should always be persistent in measuring quality in order to be capable to establish methods for improving it.

Undoubtedly, there are several points of differentiation between quality of products and quality of services. As per the latter, several researchers highlight that the difficulty in defining and measuring it, should generally be attributed to the unique characteristics of services, namely intangibility, inseparability, heterogeneity, perishability, variability and lack of ownership, unlike product quality which is far more objective. Despite these difficulties, there are, nowadays, quite a few service companies worldwide which manage to measure and, subsequently, improve the quality of services they provide.

Among the various existing types of services, we focus on Education and, more specifically, on Higher Education (HE). The role of HE as a major driver of economic growth is well documented in literature. This happens not only in particular areas of the world, e.g. Massachusetts, New York, London, Glasgow, where numerous Universities are located, but even in whole countries, such as the USA, the United Kingdom, the Netherlands etc. Economic significance of HE becomes clear when the following numerals are considered:

- Indicative annual tuition and fees per student of US colleges are the following: Amherst College-\$71,240, Connecticut College-\$70,138, Colby College-\$69,451 and Union College-\$69,273[1].
- Tuition revenue per student at public universities in the U.S. has risen dramatically (namely more than 150%) during the period of 1987-2013.
- In 2015-16, there were 162 HE institutions in the UK, 1.75 million undergraduate students, 532,970 postgraduate students, 127,440 and 310,575 students from the EU and non-EU countries respectively[2].

HE institutions have been persuaded that tertiary education should be regarded as a potentially profitable service industry and they have begun to focus more on meeting or even exceeding the needs of their students (Gruber et al., 2010). To this end HE quality is crucial and, consequently, it should be continuously monitored to ensure that it always remains at the highest possible level.

The necessary first step for HE institutions to take before measuring their quality is to determine it as accurately as possible. HE quality is a multifaceted concept for which we lack an appropriate definition. The concept of quality should best be connected with the values and priorities of HE in order to be clear. For example, according to Dew (2009), there are five perspectives to frame HE quality, namely quality i) as conformance to requirements, ii) as continuous improvement, iii) as added value, iv) as endurance and v) as luxury and prestige.

All in all, to fulfill their goals and achieve the highest quality, a crucial -if not the most significant- activity of HE institutions is teaching. Considering among other things the numerous teaching styles worldwide and the great number of teaching hours in every HE Institution, one can easily argue for the importance and value not only of the teaching process, but also of its evaluation. The fact that HE institutions aim to produce graduates who meet the human resource needs of companies basically through their teaching process has been an additional motive for us so as to focus on the teaching process and its evaluation.

In this paper the statistical model initially introduced by Nikolaidis and Dimitriadis (2014) is further evolved. The integrated model we propose is based mainly on Statistical Process Control (SPC) techniques and tools, such as the control charts (CCs), which are quite simple to apply in practice and can be supported, if necessary, by the appropriate commercial software. The integration of the framework of Nikolaidis and Dimitriadis (2014) is related to the determination of the best CCs to be used during the exploitation of student evaluations' data. More

[1] http://phillips-scholarship.org/new-applicants/cost-of-college-list/
[2] http://www.universitiesuk.ac.uk/facts-and-stats/Pages/higher-education-data.aspx

specifically, we compare and assess through simulation several types of CCs, and identify the best of them using various statistical properties as comparison criteria. By offering the appropriate statistical tool to HE institution decision makers (e.g. Rectors, Deans, Chairmen of Departments etc.), we intend to enable them

- to monitor the teaching process of their Institutions,
- to further exploit student evaluations of courses and faculty members' teaching performance,
- to identify the effective and ineffective faculty members' teaching performance,
- to overcome potential reactions of those negatively evaluated faculty members, through the statistical reliability of the developed framework, and through all these
- to assess their Institution's overall quality.

In Section 2 the student evaluation process is briefly presented, while in Section 3 we refer to the basic rules of SPC. Then (Section 4) we develop our quantitative framework, namely we present the properties of the examined CCs, the differences in their application in monitoring HE teaching processes, the measures of CC performance and the simulation model. Finally, the numerical investigation is conducted (Section 5) and the main findings are concluded (Section 6).

2. Student evaluation process

The evaluation of the teaching process effectiveness has always been a major issue in HE, due to the need for standardizing and improving, if possible, HE quality and the students' learning process. There are various evaluation mechanisms that are used, including (sometimes online) questionnaires, interviews with instructors, peer reviews, administrative evaluations (McGee, 1995) or, even, analysis of student drop-out rates (Slade and McConville, 2006). A very common mechanism employed in many HE institutions worldwide, is student evaluation of the quality of university courses and the teaching ability and performance of faculty members (Utt et al., 2017). This type of evaluation usually exploits multi-item questionnaires/forms with Likert-scale questions (Dommeyer et al., 2002, Kuzmanovic et al., 2013) regarding various teaching and learning aspects, such as:

- faculty member characteristics and effectiveness, for example, communication skills, organization skills and knowledge of the taught subject,
- various course aspects, for example content and difficulty,
- students' participation, for example, the overall experience of the course, comments on ways of teaching improvement, self-evaluation (in achieving the learning outcomes),
- university facilities, for example, the number, capacity, and quality of labs or classrooms.

In Greece, the legislation provides for the establishment of an organizational structure at every HE institution, namely the Quality Assurance Unit (MODIP). These Units apply in all Greek Universities evaluation processes, which are coordinated and supported by the Hellenic Quality Assurance and Accreditation Agency (ADIP). ADIP has designed a standard questionnaire (Figure 1) which has been adopted and used by the majority of Greek HE institutions. Through this general, university-wide questionnaire, faculty members have their teaching performance evaluated by their students. Then, every HE institution can benchmark courses and faculty members, not only within its Departments and Schools, but also at a national level, considering the respective metrics of other Institutions. The analysis we present below is only slightly affected if the questionnaire is not standard; HE institutions could benchmark courses and faculty members only in regard to the common questions of the various questionnaires.

Figure 1 about here

The evaluation of every course and faculty member (to whom the former has been assigned) is carried out in Greek HE institutions during any lecture taking place in the last weeks of each semester. Questionnaires are completed anonymously by students who are present in the classroom the day the questionnaires are distributed, either online or in a paper form. Students respond on a 5-point Likert scale where 5 stands for Very Good/Strongly agree and 1 for Very Poor/Strongly disagree. Again, the analysis presented subsequently would be similar, regardless of the number of points of the Likert scale that a University uses for the evaluation of its courses and faculty members.

In Greece, there is currently no institutionalized process of exploiting the results of faculty members' student evaluation for teaching quality improvement. This has definitely been a motive for our research. However, MODIP processes the information collected by the completed questionnaires and analyzes the results by determining basic descriptive statistical measures, per course/faculty member. The results of the statistical analysis are forwarded to faculty members. Accordingly, they can make corrective interventions into the organization and teaching method of their course(s), if and to the extent they wish to do so.

3. Statistical Process Control basics

SPC and, more specifically, CCs have been widely used as industrial tools for solving various quality problems, as they are very useful in the achievement of production stability through the reduction of unwanted volatility. In any process (e.g. a production process), regardless of how well it is designed or how carefully it is maintained, a certain amount of inherent variability always exists (Montgomery, 2012). This variability is the cumulative effect of many small, essentially unavoidable causes which are often called *common causes* (of variability). A process that presents only this type of variation is considered to be *in control*.

Regarding HE teaching process which constitutes the main research interest of this paper, several unavoidable common causes can be identified. For example, faculty members are unique in terms of personality and values, with different educational backgrounds and working experiences. They work with students, who have their own unique personalities, backgrounds, and abilities. Their work involves the use of different kinds of equipment and a variety of resources (Maguad, 2007). Obviously, all these contribute to the inherent variability of any HE teaching process.

In contrast, *special* or *assignable causes* can be attributed to external sources that are not inherent in a process, produce an unnatural variation of the latter and, most importantly, cannot be eliminated by themselves. Consequently, these causes have to be identified as soon as possible and then removed, in order to reduce the increased process variability. When special causes appear, the process is said to be *out of control*. Focusing again on the teaching process, indicative examples of special causes are hiring unqualified or untrained faculty members, use of malfunctioning equipment, inadequately equipped labs or libraries and a faculty member long-term illness. In general, these special causes have an unpredictable effect on the outcome of the teaching and learning process (Maguad, 2007).

The major objective of SPC is to detect the occurrence of special causes in a timely manner, so that investigation of the process and corrective action(s) may be undertaken. The most significant statistical tool for this purpose is the CC (Figure 2). As long as the points are plotted within its control limits, the process is assumed to be in control and no action is necessary. However, any point that is plotted out of control limits is considered as evidence of an out of control process, which requires investigation to find and eliminate the assignable cause(s) responsible for this behavior (Montgomery and Runger, 2006). Focusing on HE teaching issues, CCs can be used for monitoring separate faculty members' performance over time. The simultaneous comparison of several faculty members' performance at a particular moment (e.g. semester) is certainly doable, but beyond the scope of this paper.

Figure 2 about here

Even if SPC and CCs are primarily applied in industry, the literature includes several papers which describe applications elsewhere, such as in service sector and, particularly, in Education and HE. The papers of Grygoryev and Karapetrovic (2005), Ding et al. (2006), Green et al. (2012) are some of them.

4. Quantitative framework

4.1 Basic characteristics of the examined CCs

In our research we focus on various types of $\overline{X}$ CCs, such as $\overline{X}$, EWMA, CUSUM $\overline{X}$, and Moving Average (MA), which are considered to be the most popular and widely applied CCs in SPC applications. The use of a CC of this type enables us to identify as soon as possible any process mean shift attributed to a particular assignable cause. We consider that the sample mean $\overline{X}_i$ of sample *i* is distributed according to $N(\mu_0, \frac{\sigma^2}{n})$, where μ_0 is the nominal process mean and *σ* is the process standard deviation. The magnitude of a process mean shift in multiples of standard deviations is denoted as *δ*; thus $\mu_1 = \mu_0 + \delta\sigma$, where μ_1 is the out of control process mean. The process is considered to be in control when *δ*=0 and out of control when *δ*≠0. The basic characteristics of the CCs that we examine in this paper are presented briefly in Table 1.

Table 1 about here

4.2 SPC vs teaching process monitoring: differences in the implementation of CCs

In what follows we point out the main differences between the use of CCs in a production process (Case 1) and in the proposed application area of HE student evaluations (Case 2):

1. In Case 2 the values of the monitored *X* variable are student responds/ratings on a 5-point Likert scale; thus, *X* is a discrete variable. On the contrary, the majority of monitored statistics in Case 1 is continuous or, if discrete, the number of permitted *X* values is much larger than in Case 2.
2. A significant characteristic of any assignable cause that we try to eliminate in Case 1 is that since it appears, it

remains and affects negatively the production process until the moment it is identified (by the CC) and removed (by the Quality Control staff). On the contrary, in Case 2 there might be assignable causes affecting the teaching process that are self-eliminated (e.g. low performance of a faculty member due to temporary health problems), which makes the monitoring process unusual and, perhaps, less effective.

3. In addition, the elimination of an assignable cause in Case 1 is often quite simple, especially when it affects the central tendency of the process, and it usually requires just a mechanical adjustment. In Case 2, the restoration of the teaching process may be much more demanding and even if an assignable cause is detected, the human factor involved in this process makes the problem hard to eliminate.
4. The values of the magnitude of the process mean shift, δ, in Case 2 are much smaller than the ones in Case 1. This can be attributed to the nature of the X variable.
5. In Case 1, researchers often assume that they study assignable causes that affect only the process mean. In Case 2 and considering remark #1, an assignable cause affects most of the times both the mean and the variability. However, in order to keep our study simple, we have determined and studied numerical examples where the assignable cause affects only the process mean.
6. As per the CC design parameters in Case 2: sample size n cannot be a decision variable as it represents the number of students who are present at the lecture the day the evaluation takes place. Moreover, despite the fact that sampling interval h could be a decision variable, a well-established value arising from the student evaluation process is 1, namely one semester. Any other, particularly smaller value, even if theoretically is possible, it would affect in a negative way the evaluation process; for instance, it would discourage students to take part in repeated evaluations of courses and faculty members.
7. In Case 2 there are some types of CCs that cannot actually be used, such as
   - individual measurements CC or adaptive sample size CC, due to the particularity of the sample size n mentioned previously (remark #6),
   - adaptive sampling interval CC, due to the particularity of the sampling interval h that we have mentioned (remark #6),
   - R CC, because especially in classes with large audiences the R values would be most probably equal to 4, (i.e. 5-1), due to the permitted X values.
8. Finally, in Case 1 popular ARL_0[3] choices are 370, 400 or 500, while in Case 2 much smaller ARL_0 values should be considered, because in teaching processes the time unit is a semester, thus extremely large ARL_0 values are unnatural in practice.

4.3 Measures of any CC performance

In literature, any CC performance is typically assessed according to its statistical properties and, most of the times, according to certain measures associated with its run length (RL) distribution (Figure 3). The RL is a random variable representing the number of samples taken from a process before a point falls beyond the control limits.

[3] ARL_0 is defined in subsection 4.3

The traditional measure of a CC performance is the average run length (ARL). In fact, to assess the performance of a CC, two types of ARL are used:

- the in control ARL of a CC (ARL_0), which is determined when there is not any assignable cause affecting the monitored process and
- the out of control ARL of a CC (ARL_1), which is used when the monitored quality characteristic has shifted due to an assignable cause.

For any well-designed CC, ARL_0 should be as large as possible, while ARL_1 should be as small as possible.

Figure 3 about here

To compare the performance of different CCs, a common practice is to examine their ARL_1 values for particular $\delta>0$ values, ensuring that the ARL_0 values of the compared CCs are identical (Wu et al., 2009).

In view of the fact that the RL relative frequency distributions is highly right-skewed especially for low δ values (Figure 3), several researchers such as Chakraborti (2007) and Teoh et al. (2014) have recommended more representative statistical measures for the assessment of a CC performance: e.g. particular percentiles of the RL distribution[4]. Bear in mind that in any right-skewed distribution, the mean which is always larger than the median is somehow misleading regarding the central tendency of the monitored statistic. In this sense, the median run length (MRL), i.e. the 50th percentile of the RL distribution, seems to be a more accurate indicator of any CC performance than the respective ARL. In our numerical investigation we also compare the performance of the examined CCs ensuring that the MRL_0 values of the compared CCs are kept identical.

Usually, along with the ARL or MRL, the standard deviation of the run length (SDRL) is computed and is taken into consideration too. When the monitored process is out of control, it is desirable to use CCs with small values of both ARL_1 (or MRL_1) and $SDRL_1$.

4.4 The simulation mechanism

It can be found in literature, that ARL, MRL and SDRL values of CCs can be determined using various analytical and numerical methods including Monte Carlo simulation, Markov chains, numerical integral equations and, in some cases, analytic determination (Peerajit et al., 2018). Particularly Monte Carlo simulation is an important OR research method used in a variety of disciplines. Indicatively, in SPC, Ali and Haq (2017) explore the RL profiles of the GWMA–CUSUM CC through simulation, while a few years earlier, Abbas et al. (2014) develop a code in R language to assess the ARL values of a bivariate EWMA CC.

In order to assess the performance of CCs that are studied in our research, using the statistical measures mentioned previously, we simulated the student evaluation process presented in Section 2. Initially, the use of simulation aimed at debugging the modeling and formulations that were developed in Microsoft Excel 2016 spreadsheets. Note that all necessary simulations were conducted using the Add-in feature MCSim.

More specifically, due to

- the reduced number of semesters for which real student evaluation data was accessible to us and

[4] … or the differences between the 3rd and the 1st quartiles or the 95th and the 5th percentiles.

- the small number (i.e. sample size) of students who usually evaluate courses per semester (in several cases less than 30 students),

we chose Monte Carlo simulation for "creating" the datasets that were necessary for spreadsheet modeling and formulations. To do this, we considered the real data distribution of student evaluations/ratings arising from several courses in regard to a particular question of the questionnaire (Figure 4): the question that we focus on evaluates the overall performance of the assessed faculty member (namely question 1 in Figure 1). Apparently, the same simulation process would be applied for any other question of the questionnaire or (and this is an interesting direction of future research) for a group of questions, where student evaluations could be used to determine a more complex statistic (e.g. the sum of student ratings in the group of chosen questions) to be monitored with CCs.

Figure 4 about here

We observe that the distribution of ratings presents a clear negative skew. Thorough examination of various questions and courses reveals that the distribution of student evaluations would be similar to the one represented in Figure 4, regardless of the chosen question of the questionnaire.

According to the discrete distribution of Figure 4, we simulated the ratings of 100,000 imaginary classes of n=150 students (i.e. the sample size was fixed, without loss of generality) and then computed the average (rating) per class[5], as well as the monitored statistic of each type of examined CC (Table 1, 2[nd] column). Despite the fact that classes with such large audiences are rarely met in practice, the aforementioned large sample size was chosen deliberately: since we study various $\overline{X}$ CCs, the large sample size allows us to apply the Central Limit Theorem and consider that the average rating per class is distributed according to $N\left(\mu_j, \frac{\sigma}{\sqrt{n}}\right)$, when the teaching process is in (j=0) or out (j=1) of control. Moreover, the large sample size leads to 5^{150} permutations with repetitions of n=150 ratings and, consequently, to average ratings per class. This means that the average rating per class $\overline{X}$ can be safely assumed to be a continuous variable.

By simulating the student evaluation process repeatedly (namely for 100,000 imaginary semesters) and taking into consideration

- the control limits and
- the signaling mechanism

of every examined CC, we finally obtain numerous RL values for all selected CCs, both for in and out of control teaching processes. The RL values can be depicted in (relative) frequency distributions such as the ones in Figure 3 and allow us to determine ARL_j, MRL_j and $SDRL_j$, which can be used for the assessment of the examined CCs.

4.5 Determining our numerical examples

To assess the performance of the selected CCs, we set and examine a variety of values for several parameters

[5] For reasons of consistency and objectivity in the comparisons of CCs, we choose to use the same dataset for every δ value in order to compare the selected CCs. This way, any differences in ARL, MRL and SDRL values cannot be attributed to the randomness of datasets, but only to the performance of CCs.

related to the operation and implementation of these CCs, trying to reflect several real life HE situations. In what follows we present them in detail:

- Bearing in mind that in HE student evaluation process (Case 2) the units of ARL_0 values are semesters, we choose to examine four alternative values of ARL_0, namely, 30, 50, 100 and 370.
- The aforementioned choices of ARL_0 values and an extensive numerical experimentation have led to the determination of i) the control limit parameter L values (in all examined but CUSUM $\overline{X}$ CCs) and ii) the respective H values (in CUSUM $\overline{X}$ CCs), which are presented in Tables 2 to 9. These values have allowed us to set ARL_0 (or MRL_0) to the desired values mentioned in the previous remark.
- As per the EWMA CC, we examine four values of the smoothing parameter λ: 0.1, 0.25, 0.5 and 0.75.
- As per the CUSUM $\overline{X}$ CC, we examine two reference values K: 0.4 and 0.5.
- As per the MA CC, we examine four values of the span w: 2, 3, 4 and 5.
- As per the magnitude δ, we examine the following (1+8) values: 0, -0.0201, -0.0705, -0.1208, -0.151, -0.2416, -0.2719, -0.3121 and -0.3524. Note that by examining negative δ values we deliberately emphasize on cases where $\mu_1 < \mu_0$, namely on cases where the teaching process mean shift corresponds to a deterioration of the faculty members' teaching performance. However, for reasons of simplicity, we will refer subsequently to their positive counterparts.

The aforementioned choices have lead to several parameter combinations and have allowed us to examine multiple numerical examples, the results of which are depicted in Tables 2 to 9.

Tables 2 to 9 about here

5. Numerical investigation

5.1 The results of simulation

The ultimate goal of our research is to compare 11 variations of the $\overline{X}$, EWMA, CUSUM $\overline{X}$ and MA CCs, considering that they are used for monitoring the average student rating for a particular question of the questionnaire. The performance of these CCs is assessed and compared in terms of their ARL_j, MRL_j and $SDRL_j$ values, for j=0 or 1. The main findings are summarized below.

- Focusing on the in control teaching processes, i.e. when $\boldsymbol{\delta}$**=0**, in case $\mathbf{ARL_0}$ is kept **identical** for all compared CCs (Tables 2 to 5):
    - We notice that it is always ARL_0>MRL_0. This is normal as the RL relative frequency distribution is right-skewed (Figure 3) and in distributions of this type the average is always larger than the median.
    - In terms of $SDRL_0$, the optimal CC differs depending on the fixed ARL_0: EWMA CC with λ=0.1 has the best performance when fixed ARL_0 is equal to 30 (Figure 5, for δ=0) or 50, CUSUM CC with K=0.5 when ARL_0=100, and EWMA CC with λ=0.5 when ARL_0=370.

Figure 5 about here

-
    - We notice that keeping ARL_0 values identical for all examined CCs, does not ensure identical MRL_0 values: the differences among the latter are sometimes significant, especially for larger fixed ARL_0 values. This

means that there are differences in the shape of the RL distributions of the examined CCs.

- Focusing on the out of control teaching processes, i.e. when **$\delta \neq 0$**, in case **ARL_0** values are kept **identical** for all examined CCs (again Tables 2 to 5):
  - Not surprisingly, we see that it is always $ARL_1 > MRL_1$. Moreover, the increase of δ results in the decrease of both ARL_1 and MRL_1 values, for any studied CC. Additionally, the difference ARL_1-MRL_1 decreases as δ increases, which means that progressively ARL_1 and MRL_1 values converge, independently of the examined CC. This is another indication that the skew of the RL relative frequency distribution is reduced with the magnitude of the process mean shift δ (Figure 3).
  - Concentrating on the MA CC, we find out that the increase of *w* improves its performance, without any exceptions: mainly the ARL_1 and MRL_1, and most of the times the $SDRL_1$ values decrease when *w* increases.
  - In Tables 2 to 5 we do not present teaching processes with $\delta > 0.3524$, because in our experimentation we have noticed that for such δ values ARL_1 tends to 1. Therefore, there is no performance differentiation among the examined CCs: for large shifts, all CCs can identify the assignable cause almost immediately.
  - Not only a similar but an even more intensive tendency is ascertained as per the MRL_1 values: for even lower δ values, MRL_1 of all examined CCs become equal to 1, which means that all CCs can identify most of the times the assignable cause at the first sample (i.e. at the first semester that student evaluation takes place) after the appearance of the assignable cause.
  - The comparison of the 11 types of CCs of our study reveals the following:

    i) We notice that for all δ values but 0.0201, the MA CC with w=5 has the best ARL_1 performance no matter which the fixed ARL_0 value is.

    ii) EWMA CC with λ=0.1 outperforms the other examined CCs regarding ARL_1, only for δ=0.0201 and all fixed ARL_0 values but 30.

    iii) For the larger shifts that we study (i.e. $0.151 \leq \delta \leq 0.3524$), again the MA CC with w=5 has the lowest $SDRL_1$ value, no matter which the fixed ARL_0 value is (we identify only one exception: for δ=0.151 and ARL_0=370 the minimum $SDRL_1$ is noticed for EWMA CC with λ=0.1).

    iv) For low δ values (i.e. $0.0201 \leq \delta \leq 0.1208$), EWMA CC with λ=0.1 presents the lowest $SDRL_1$ value (e.g. Figure 5).
  - As per the MRL_1 values, the advantage of the MA CC with w=5 is verified for all δ and fixed ARL_0 values (we identify only one exception: for ARL_0=370 and δ=0.0201 the minimum MRL_1 is noticed for EWMA CC with λ=0.1).
  - The fact that we examine low δ values results in small power (i.e. 1-β) of the $\overline{X}$ CC (and to some extent for the rest of the examined CCs). Considering also

    i) that the RL is geometrically distributed and

    ii) the formulas determining the average and the standard deviation of the geometric distribution, then it is not surprising that our analysis reveals no significant difference between the ARL and their corresponding SDRL values, for the $\overline{X}$ CC (and to some extent for the rest of the examined CCs), for any δ value. This observation verifies the relevant analysis and remark of Quesenberry (1992).

- Focusing on the in control cases (i.e. $\boldsymbol{\delta}$**=0**), when we keep **MRL$_0$** values **identical** for all compared CCs (Tables 6 to 9):
  - We see once again that it is always $ARL_0>MRL_0$.
  - As per the best (i.e. minimum) $SDRL_0$ values of the examined CCs, we come to different conclusions in this case: CUSUM CC with K=0.4 performs better, when fixed MRL_0 is 30, EWMA CC with λ=0.25 when fixed MRL_0 is 50, $\overline{X}$ and EWMA CC with λ=0.5 when fixed MRL_0 is 100 and EWMA CC with λ=0.75 when fixed MRL_0 is 370. Evidently, no single conclusion can be drawn regarding $SDRL_0$.
  - Similarly to what happens when we keep ARL_0 values identical for all examined CCs, we notice that fixing MRL_0 values for all compared CCs does not ensure identical ARL_0 ones. This becomes obvious in several cases; for example when fixed MRL_0=100, the maximum ARL_0 value is 170.056 and the minimum 140.787 (Figure 6, for δ=0). The different shape of the RL distributions of the examined CCs is verified again.

Figure 6 about here

- Focusing on the out of control teaching processes (i.e. $\boldsymbol{\delta\neq 0}$), in case **MRL$_0$** values are kept **identical** for all examined CCs (Tables 6 to 9 again):
  - We verify that the increase of δ
    i) results in the decrease of both ARL_1 (Figure 6) and MRL_1 values, for any studied CC and
    ii) make ARL_1 and MRL_1 values to converge (progressively at 1).
  - Focusing on the MA CC, we observe again that for δ>0.0201, the higher the value of w the better the performance of the particular CC. This means that the ARL_1, MRL_1 and $SDRL_1$ values decrease as w increases.
  - In this group of Tables (i.e. 6 to 9) too, we do not present teaching processes with δ>0.3524, because we have found out that for such δ values ARL_1 becomes almost equal to 1. Therefore, all examined CCs become equivalently efficient in identifying shifts of large magnitude.
  - Similarly, an even more intensive tendency is recognized for the MRL_1 values too: for even lower δ values than 0.3524, MRL_1 becomes equal to 1, which means that in practice all examined CCs identify most of the times the assignable cause at the first sample (i.e student evaluation) after its appearance.
  - Comparing the performance of the 11 CCs of our study we notice that
    i) for shifts with δ=0.0201 and any fixed MRL_0 value (see Figure 6 for MRL_0=100), as well as for δ=0.0705 and fixed MRL_0=370, EWMA CC with λ=0.1 has the minimum ARL_1 value,
    ii) for $\delta \geq 0.0705$, the MA CC with w=5 has the best ARL_1 performance (Figure 6).
  - Another conclusion arising from Tables 6 to 9 is that for low δ values, the EWMA $SDRL_1$ values for λ=0.1 are the smallest among all studied CCs, for all fixed MRL_0 values.

- As per the MRL_1 values, the advantage of the MA CC with w=5 is verified for all δ and fixed MRL_0 values, apart from the case of δ=0.0201 and fixed MRL_0=100 or 370. In these cases EWMA CC with λ=0.1 outperforms the rest CCs.
- Even when we keep the MRL_0 values identical (instead of the ARL_0 ones) in order to compare our CCs, we verify that there is no significant difference between the ARL and the corresponding SDRL values, for the $\overline{X}$ CC (and to some extent for the rest of the examined CCs).

5.2 A real-life example

In what follows we present a real-life case illustrating the model and the methodology suggested in this paper. After conducting an extensive Phase I analysis of a large amount of student evaluation data, arising from numerous classes and courses during a recent 5-year period of time, we managed to determine the nominal in control μ_0 and σ values corresponding to all Departments of an indicative Greek HE institution. To do this we had to remove all data corresponding to classes where courses and faculty members were evaluated either extremely positively or, on the contrary, extremely negatively, as we considered them non-representative of the average teaching performance at this Institution. We reached the following results: μ_0 = 3.98 and σ = 0.5, which we use below as the Phase II CC design parameters.

In our example we monitor through the $\overline{X}$, EWMA, CUSUM $\overline{X}$ and MA CCs the evaluations of 12 semesters and classes of n=50 students, for a particular question. To ensure the (arbitrarily chosen) value of ARL_0 = 30 semesters in our example, we use i) the control limit parameter L values (in all examined but CUSUM $\overline{X}$ CCs) and ii) the respective H values (in CUSUM $\overline{X}$ CCs), which are presented in the first row of Table 2. In our experimentation

- as per the EWMA CC, we examine all four values of the smoothing parameter λ, namely 0.1, 0.25, 0.5 and 0.75,
- as per the CUSUM $\overline{X}$ CC, we examine both reference values K, namely 0.4 and 0.5 and
- as per the MA CC, we examine only one span value w, namely 5.

The monitored statistics for all examined CCs are represented in the second column of Table 2, while in Table 10 we show first the particular values (in fact the average ratings per class and per semester) that have been exploited in our real-life example (second column), then the values of the monitored statistics (first column-s in each subarea) and finally the control limits of every CC. The arising CCs are depicted in Figures 7a to 7h. As per the 12 average ratings, an elementary statistical analysis can reveal that they are divided in two groups. The first one consists of seven classes/courses where the teaching process seems to be in control with μ_0 = 3.983 and σ = 0.494. The second group comprises five classes/courses where μ_0 has shifted to an out of control mean value, i.e. μ_1 = 3.919, while σ remains unaffected. Thus, we are dealing with a magnitude of the process mean shift of δ = - 0.13 standard deviations approximately.

Table 10 and Figures 7a to 7h about here

What we can clearly see from Figures 7a to 7h is that the MA CC is the only chart that identifies the shift of the process mean: it gives an out of control signal at the 12th sample/semester, despite the small δ value. All the rest

CCs fail to detect the mean shift. This finding is in line with our simulation findings and underlines the superiority of the MA CC performance.

6. Discussion-Conclusions

In this paper we elaborate on a statistical framework which is based on SPC techniques and tools, such as the widely used in several applications CC. The ultimate goal of our work is to assist decision makers in HE institutions (e.g. Rectors, Deans, Chairmen of Departments etc.) to analyze and exploit student evaluations to a greater extent than they actually do nowadays. The information included in the completed questionnaires each semester is valuable, and if all collected data is properly analyzed there will be plenty of useful quality management insights to consider. Moreover, through the scientific determination of the limits of the proposed CCs, decision makers are able to not only identify the ineffective faculty members, but also reduce any negative reactions caused by the identified members. Thus, they are equipped with a powerful tool that can definitely facilitate their administrative work.

For HE institutions worldwide where student evaluation through questionnaires is not conducted, we offer an integrated framework which can easily be applied in practice to improve the monitoring and, consequently, the quality of university courses, as well as the teaching ability and performance of faculty members.

Our extensive numerical investigation has revealed several significant partial findings. Considering the right-skewed shape of the RL distribution of every CC and, consequently, the fact that MRL_1 is most probably the best statistical property in the comparison and assessment of CCs, we find out that

- MA CCs outperform the other examined CCs if we use this particular statistical measure (i.e. MRL_1) as a criterion of assessment,
- the higher the value of w, the better the MA CC performance,
- there are only few cases where EWMA CC with λ=0.1 presents the best performance.

Considering ARL_1 as the statistical criterion to assess the 11 types of examined CCs, we notice once more the advantage of MA CC with w=5 in the majority of cases. Then, we see again that EWMA CC with λ=0.1 is proven to be the best choice for low δ values. Overall, every decision maker should choose any of these two CCs in order to monitor efficiently the average rating per class and identify reliably and timely any undesirable shift in faculty members' performance.

Another interesting conclusion that can be raised from our numerical analysis is that the $\overline{X}$ CC that is so broadly used in SPC, is in most cases of our research application one of the worst performing CCs. Thus, its use should be avoided.

Obviously, the numerical analysis that we have presented can be easily enriched in the future, as several other types of CCs could also be examined and compared. For example, CCs monitoring the median rating instead of the average or FIR EWMA and CUSUM $\overline{X}$ could also be studied. Moreover, the operation of CCs could incorporate run rules to become more effective in recognizing assignable causes, especially those causing shifts of small magnitude.

Although this statistical framework is related mainly to HE, it can easily be applied -modified accordingly, if necessary- into any education level. The need to make the most of the student evaluation process is clear throughout all levels of any educational system. Additionally, the existence of an exploitation mechanism, such as the proposed, could encourage the establishment of a student evaluation process in cases it does not exist today, for example in the case of high schools.

Finally, the aforementioned comparison and assessment of various CCs can be interesting per se as to the best of our knowledge such a comparison of so many types of CCs does not currently exist in the SPC literature.

References

Abbas, N., Riaz, M., & Does, R.J.M.M., (2014). An EWMA-Type Control Chart for Monitoring the Process Mean using Auxiliary Information. *Communications in Statistics - Theory and Methods*, 43(16), 3485–3498.

Abdullah, F., Suhaimi, R., Saban, G., & Hamali, J., (2011), Bank Service Quality (BSQ) Index, an Indicator of Service Performance. *International Journal of Quality & Reliability Management*, 28(5), 542–555

Ali, R., & Haq, A., (2017). A Mixed GWMA–CUSUM Control Chart for Monitoring the Process Mean. *Communications in Statistics - Theory and Methods*, 47(15), 3779–3801.

Chakraborti, S., (2007). Run Length Distribution and Percentiles: The Shewhart $\overline{X}$ chart with unknown parameters. *Quality Engineering,* 19 (2), 119–127.

Dew, J.R., (2009). Quality Issues in Higher Education. *Journal for Quality and Participation,* 32(1), 4-9.

Ding, X., Wardell, D., & Verma, R., (2006). An Assessment of Statistical Process Control-based Approaches for Charting Student Evaluation Scores, *Decision Sciences Journal of Innovative Education*, 4(2), 259-272.

Dommeyer, C.J., Baum, P., Chapman, K.S., & Hanna, R.W. (2002). Attitudes of Business Faculty towards two Methods of Collecting Teaching Evaluations: Paper vs. Online. *Assessment and Evaluation in Higher Education*, 27, 455-462.

Green, K.W., Toms, L., & Stinson, T., (2012), Statistical Process Control Applied within an Education Services Environment, *Academy of Educational Leadership Journal*, 16(2), 33-46.

Gruber, T., Fuß, S., Voss, R., & Gläser-Zikuda, M., (2010). Examining Student Satisfaction with Higher Education Services. *International Journal of Public Sector Management*, 23(2), 105-123.

Grygoryev, K., & Karapetrovic, S., (2005), Tracking Classroom Teaching and Learning: An SPC Application, *Quality Engineering*, 17, 405-418.

Kuzmanovic, M., Savic, G., Popovic, M., & Martic. M., (2013). A New Approach to Evaluation of University Teaching Considering Heterogeneity of Students' Preferences. *Higher Education,* 66(2), 153-171.

Maguad, B.A., (2007). Using Process Variation Analysis to Monitor Teacher's Performance. *The Journal of Adventist Education*, 69(4), 26-32.

McGee, R., (1995). Faculty Evaluation Procedures in 11 Western Community Colleges, *Community College Journal of Research and Practice*, 19(4), 341-348.

Montgomery, D.C., (2012). *Introduction to statistical quality control.* 7th Ed., John Wiley & Sons Inc.

Montgomery, D.C., & Runger, G.C., (2006). *Applied Statistics and Probability for Engineers*. 4th Ed. John Wiley &

Sons, Inc.

Nikolaidis, Y., & Dimitriadis, S., (2014). On the Student Evaluation of University Courses and Faculty Members' Teaching Performance. *European Journal of Operational Research,* 238 (1), 199-207.

Peerajit, W., Areepong, Y., & Sukparungsee, S., (2018). Numerical Integral Equation Method of ARL of CUSUM Chart for Long Memory Process with Non-Seasonal and Seasonal ARFIMA Model, *Thailand Statistician,* 16(1), 26-37.

Quesenberry, C.P., (1992). *On the Sample Size Problem for* $\overline{X}$ *and X Shewhart Control Charts for a Mean and Implications for Designing Q-Charts.* North Carolina State University. Dept. of Statistics.

Slade, P., & McConville, C., (2006). Student Evaluation of Teaching. *International Journal for Educational Integrity*, 2(2), 43-59.

Teoh, W.L., Khoo, M.B.C., Castagliola, P. & Chakraborti, S., (2014). Optimal Design of the Double Sampling $\overline{X}$ Chart with Estimated Parameters based on Median Run Length. *Computers & Industrial Engineering*, 67(1), 104-115.

Utt, B., White, C.A., & Gonzalez, D.W., (2017). Meta-analysis of Faculty's Teaching Effectiveness: Student Evaluation of Teaching Ratings and Student Learning are not Related. *Studies in Educational Evaluation*, 54, 22-42

Wu, Z., Jiao, J. X., Yang, M., Liu, Y., & Wang, Z.J., (2009). An Enhanced Adaptive CUSUM Control Chart. *IIE Transactions*, 41(7), 642-653.

Table 1. Basic characteristics of the examined CCs

Type of CC	Monitored statistic	Center line	Control Limit(s)	Notes
$\overline{X}$	$\overline{X}_i$	μ_0	$\mu_0 \pm L \cdot \frac{\sigma}{\sqrt{n}}$	-
Moving average (of averages - MA)	$M_i = \begin{cases} \frac{\overline{x}_1 + \ldots + \overline{x}_i}{i} & \text{when } i < w \\ \frac{\overline{x}_{i-w+1} + \ldots + \overline{x}_{i-1} + \overline{x}_i}{w} & \text{when } i \geq w \end{cases}$	μ_0	$M_i = \begin{cases} \mu_0 \pm L \cdot \frac{\sigma}{\sqrt{n \cdot i}} & \text{when } i < w \\ \mu_0 \pm L \cdot \frac{\sigma}{\sqrt{n \cdot w}} & \text{when } i \geq w \end{cases}$	• *i* is the sample number • *w* is the span of the moving average of averages • after every indication out of the CC limits the monitored statistic (but not the control limits) is reset, namely we set *i*=1
EWMA	$Z_i = \lambda \cdot \overline{X}_i + (1-\lambda) \cdot Z_{i-1}$	μ_0	$\mu_0 \pm L\sigma\sqrt{\frac{\lambda[1-(1-\lambda)^{2i}]}{2-\lambda}}$	• *i* is the sample number • $0 < \lambda \leq 1$ is the smoothing parameter • Z_0 is usually set equal to μ_0 • $1-(1-\lambda)^{2i} \cong 1$ as *i* increases • after every indication out of the CC limits the monitored statistic (but not the control limits) is reset, namely we set $Z_{i-1} = \mu_0$
CUSUM $\overline{X}$	$C_i^+ = \max[0, \overline{X}_i - \mu_0 - K + C_{i-1}^+]$ $C_i^- = \max[0, \mu_0 - K - \overline{X}_i + C_{i-1}^-]$	0	H	• *i* is the sample number • $C_0^+ = C_0^- = 0$ • *K* is the reference value and is usually set equal to $\delta\sigma / 2$, where $\delta\sigma = \lvert\mu_1 - \mu_0\rvert$ • after every indication out of the CC limits the monitored statistic (but not the control limits) is reset, namely we set $C_{i-1}^+ = 0$ or $C_{i+1}^+ = 0$

Table 2. ARL, SDRL and MRL values of $\overline{X}$, EWMA, CUSUM $\overline{X}$ and MA charts, for various δ values when $ARL_0 = 30$

δ		$\overline{X}$	EWMA				CUSUM $\overline{X}$		Moving Average (MA)			
		$L = 2.128$	$L = 1.559$, $\lambda = 0.1$	$L = 1.891$, $\lambda = 0.25$	$L = 2.052$, $\lambda = 0.50$	$L = 2.109$, $\lambda = 0.75$	$H = 2.798$, $K = 0.4$	$H = 2.402$, $K = 0.5$	$L = 2.117$, $w = 2$	$L = 2.100$, $w = 3$	$L = 2.094$, $w = 4$	$L = 2.099$, $w = 5$
0	**MRL_0**	21	22	21	21	21	22	22	20	17	15	11
	ARL_0	30.108	30.012	30.011	29.993	29.991	30.002	30.002	29.851	30.028	29.992	30.002
	$SDRL_0$	30.202	26.279	27.835	28.675	29.821	26.859	27.365	32.603	36.017	39.427	43.268
0.0201	**MRL_1**	17	15	16	16	17	16	16	16	13	10	7
	ARL_1	25.287	20.231	21.246	22.708	23.925	22.018	22.539	23.878	22.086	20.675	19.830
	$SDRL_1$	24.985	16.935	19.033	21.922	23.245	18.944	20.050	25.249	26.670	27.055	27.997
0.0705	**MRL_1**	7	5	5	5	6	5	5	4	3	2	1
	ARL_1	9.515	5.905	5.822	6.350	7.539	6.304	6.322	6.457	5.162	4.389	3.905
	$SDRL_1$	8.978	3.240	3.825	5.020	6.690	3.9178	4.288	6.578	5.650	5.150	4.788
0.1208	**MRL_1**	3	3	3	3	3	3	3	2	1	1	1
	ARL_1	3.875	3.366	3.057	2.976	3.232	3.337	3.206	2.561	2.087	1.833	1.669
	$SDRL_1$	3.340	1.358	1.495	1.835	2.404	1.533	1.611	2.243	1.854	1.628	1.449
0.1510	**MRL_1**	2	3	2	2	2	2	2	1	1	1	1
	ARL_1	2.566	2.709	2.394	2.207	2.265	2.615	2.479	1.776	1.502	1.368	1.291
	$SDRL_1$	1.998	0.957	1.025	1.191	1.477	1.045	1.082	1.326	1.062	0.895	0.778
0.2416	**MRL_1**	1	2	1	1	1	2	1	1	1	1	1
	ARL_1	1.252	1.795	1.487	1.300	1.246	1.642	1.510	1.084	1.044	1.030	1.022
	$SDRL_1$	0.563	0.543	0.558	0.507	0.501	0.578	0.570	0.327	0.230	0.185	0.158
0.2719	**MRL_1**	1	2	1	1	1	1	1	1	1	1	1
	ARL_1	1.129	1.619	1.328	1.173	1.131	1.463	1.346	1.037	1.018	1.012	1.009
	$SDRL_1$	0.381	0.526	0.488	0.394	0.361	0.528	0.498	0.205	0.140	0.113	0.096
0.3121	**MRL_1**	1	1	1	1	1	1	1	1	1	1	1
	ARL_1	1.047	1.403	1.168	1.074	1.051	1.266	1.179	1.010	1.005	1.003	1.002
	$SDRL_1$	0.223	0.496	0.376	0.264	0.224	0.446	0.386	0.103	0.068	0.052	0.043
0.3524	**MRL_1**	1	1	1	1	1	1	1	1	1	1	1
	ARL_1	1.015	1.231	1.073	1.027	1.017	1.132	1.079	1.003	1.001	1.001	1.000
	$SDRL_1$	0.124	0.422	0.260	0.162	0.129	0.339	0.270	0.051	0.034	0.026	0.021

Table 3. ARL, SDRL and MRL values of $\bar{X}$, EWMA, CUSUM $\bar{X}$ and MA charts, for various δ values when ARL_0 = 50

δ		$\bar{X}$	EWMA				CUSUM $\bar{X}$		Moving Average (MA)			
		L = 2.326	L = 1.820, λ = 0.1	L = 2.124, λ = 0.25	L = 2.266, λ = 0.50	L = 2.303, λ = 0.75	H = 3.347, K = 0.4	H = 2.857, K = 0.5	L = 2.311, w = 2	L = 2.302, w = 3	L = 2.301, w = 4	L = 2.289, w = 5
0	**MRL_0**	34	37	36	35	35	36	35	34	32	28	24
	ARL_0	49.980	49.997	50.022	49.997	49.955	50.021	49.971	49.903	50.021	49.972	50.023
	$SDRL_0$	50.833	45.349	47.139	48.903	49.635	46.500	46.654	52.935	56.749	65.130	68.427
0.0201	**MRL_1**	28	21	23	25	26	23	24	25	23	18	13
	ARL_1	40.727	27.982	31.343	34.789	37.155	31.343	32.557	37.070	35.119	33.372	29.998
	$SDRL_1$	40.607	23.515	28.073	32.520	36.292	27.616	29.478	38.892	40.121	42.549	41.135
0.0705	**MRL_1**	10	6	6	6	7	6	6	6	4	2	2
	ARL_1	13.710	7.036	6.977	8.096	10.123	7.484	7.485	8.575	6.692	5.552	4.747
	$SDRL_1$	13.018	3.699	4.632	6.563	9.169	4.493	4.928	8.892	7.416	6.594	5.911
0.1208	**MRL_1**	4	4	3	3	3	4	3	2	1	1	1
	ARL_1	5.070	3.897	3.478	3.462	3.894	3.850	3.677	3.055	2.395	2.060	1.837
	$SDRL_1$	4.516	1.513	1.678	2.189	3.005	1.670	1.746	2.799	2.246	1.952	1.714
0.1510	**MRL_1**	3	3	2	2	2	3	3	1	1	1	1
	ARL_1	3.173	3.094	2.683	2.507	2.625	2.999	2.816	2.008	1.643	1.465	1.356
	$SDRL_1$	2.628	1.050	1.114	1.369	1.777	1.122	1.154	1.595	1.261	1.060	0.901
0.2416	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.355	2.034	1.655	1.406	1.332	1.892	1.727	1.114	1.059	1.038	1.028
	$SDRL_1$	0.692	0.521	0.588	0.575	0.585	0.570	0.594	0.389	0.272	0.213	0.180
0.2719	**MRL_1**	1	2	1	1	1	2	2	1	1	1	1
	ARL_1	1.186	1.858	1.471	1.248	1.184	1.700	1.535	1.050	1.025	1.015	1.011
	$SDRL_1$	0.470	0.486	0.533	0.459	0.427	0.537	0.544	0.243	0.166	0.129	0.110
0.3121	**MRL_1**	1	2	1	1	1	1	1	1	1	1	1
	ARL_1	1.072	1.648	1.271	1.116	1.077	1.474	1.322	1.015	1.006	1.004	1.002
	$SDRL_1$	0.279	0.500	0.450	0.324	0.273	0.512	0.474	0.127	0.081	0.062	0.050
0.3524	**MRL_1**	1	1	1	1	1	1	1	1	1	1	1
	ARL_1	1.025	1.447	1.135	1.046	1.027	1.286	1.169	1.004	1.002	1.001	1.001
	$SDRL_1$	0.159	0.500	0.342	0.209	0.165	0.454	0.376	0.063	0.041	0.032	0.025

Table 4. ARL, SDRL and MRL values of $\overline{X}$, EWMA, CUSUM $\overline{X}$ and MA charts, for various δ values when ARL_0 = 100

δ		$\overline{X}$	EWMA				CUSUM $\overline{X}$		Moving Average (MA)			
		L = 2.576	L = 2.15, λ = 0.1	L = 2.406, λ = 0.25	L = 2.535, λ = 0.50	L = 2.582, λ = 0.75	H = 4.106, K = 0.4	H = 3.510, K = 0.5	L = 2.557, w = 2	L = 2.551, w = 3	L = 2.512, w = 4	L = 2.548, w = 5
0	**MRL_0**	71	68	69	66.5	71	67	67.5	67	64.500	58	56
	ARL_0	100.461	99.995	99.993	99.959	100.159	99.993	99.993	100.086	99.979	100.294	99.993
	$SDRL_0$	100.292	96.715	100.159	96.146	96.388	98.048	95.656	104.100	119.046	122.505	130.079
0.0201	**MRL_1**	56	31	36	45	52	35	40	46	40	34	28
	ARL_1	81.024	42.170	50.497	62.49	73.843	48.937	54.455	69.430	63.361	59.690	54.251
	$SDRL_1$	83.562	35.414	45.715	58.752	71.774	43.0634	49.514	73.110	71.660	73.427	72.242
0.0705	**MRL_1**	16	8	7	8	12	8	8	9	6	5	2
	ARL_1	22.507	8.642	8.760	11.249	16.011	9.080	9.210	12.864	9.420	7.624	6.402
	$SDRL_1$	21.293	4.466	5.888	9.553	14.827	5.177	5.829	13.518	10.595	9.081	8.119
0.1208	**MRL_1**	5	4	4	4	4	4	4	3	1	1	1
	ARL_1	7.416	4.604	4.064	4.248	5.259	4.560	4.356	3.921	2.909	2.414	2.108
	$SDRL_1$	6.831	1.714	1.957	2.767	4.264	1.847	1.932	3.775	2.884	2.426	2.129
0.1510	**MRL_1**	3	3	3	3	3	3	3	1	1	1	1
	ARL_1	4.286	3.619	3.070	2.959	3.319	3.514	3.301	2.398	1.867	1.613	1.465
	$SDRL_1$	3.755	1.175	1.255	1.641	2.384	1.235	1.261	2.047	1.564	1.293	1.100
0.2416	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.536	2.303	1.861	1.563	1.488	2.194	2.021	1.162	1.081	1.052	1.037
	$SDRL_1$	0.906	0.556	0.601	0.653	0.717	0.565	0.584	0.479	0.330	0.253	0.210
0.2719	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.290	2.100	1.662	1.371	1.287	1.992	1.819	1.075	1.035	1.022	1.015
	$SDRL_1$	0.613	0.455	0.554	0.536	0.531	0.489	0.535	0.304	0.202	0.154	0.127
0.3121	**MRL_1**	1	2	1	1	1	2	2	1	1	1	1
	ARL_1	1.119	1.907	1.430	1.188	1.130	1.778	1.585	1.023	1.010	1.006	1.004
	$SDRL_1$	0.367	0.411	0.509	0.401	0.353	0.475	0.520	0.159	0.100	0.075	0.061
0.3524	**MRL_1**	1	2	1	1	1	2	1	1	1	1	1
	ARL_1	1.043	1.741	1.251	1.083	1.051	1.582	1.383	1.006	1.002	1.001	1.001
	$SDRL_1$	0.212	0.456	0.435	0.277	0.223	0.502	0.490	0.082	0.050	0.037	0.030

Table 5. ARL, SDRL and MRL values of $\bar{X}$, EWMA, CUSUM $\bar{X}$ and MA charts, for various δ values when ARL_0 = 370

		$\bar{X}$	EWMA				CUSUM $\bar{X}$		Moving Average (MA)			
δ		L = 3.040	L = 2.720	L = 2.918	L = 3.010	L = 3.014	H = 5.651	H = 4.735	L = 2.998	L = 2.977	L = 2.972	L = 2.987
			λ = 0.1	λ = 0.25	λ = 0.5	λ = 0.75	K = 0.4	K = 0.5	w = 2	w = 3	w = 4	w = 5
0	**MRL_0**	252	230.500	260.500	256	259.500	230	241	242	251	229.500	186
	ARL_0	369.425	369.670	369.670	369.511	369.511	370.352	370.352	369.511	371.590	369.670	371.721
	$SDRL_0$	368.302	399.982	374.060	351.240	364.125	352.587	367.063	384.575	393.023	408.593	490.250
0.0201	**MRL_1**	233	71	106.500	144	190.500	80	91	154	142	111.500	103
	ARL_1	334.378	93.438	141.613	216.874	261.725	106.587	122.674	237.480	211.372	177.899	168.034
	$SDRL_1$	317.465	79.424	130.164	226.908	247.599	93.773	110.143	241.971	216.289	199.356	211.158
0.0705	**MRL_1**	48	11	11	16	27	11	11	21	12	8	6
	ARL_1	66.150	12.085	13.775	22.271	37.074	12.434	12.496	30.088	18.966	14.114	11.595
	$SDRL_1$	63.847	6.146	9.854	19.805	35.085	6.449	7.472	30.386	20.905	17.060	14.867
0.1208	**MRL_1**	12	6	5	5	7	6	5	5	2	1	1
	ARL_1	17.086	5.967	5.366	6.414	9.358	6.002	5.609	6.746	4.353	3.338	2.817
	$SDRL_1$	16.761	2.109	2.638	4.547	8.129	2.153	2.249	6.832	4.619	3.638	3.124
0.1510	**MRL_1**	6	4	4	3	4	4	4	3	1	1	1
	ARL_1	8.555	4.593	3.882	4.034	5.123	4.586	4.208	3.583	2.465	1.984	1.736
	$SDRL_1$	8.067	1.394	1.594	2.379	4.075	1.421	1.459	3.406	2.317	1.832	1.544
0.2416	**MRL_1**	2	3	2	2	2	3	2	1	1	1	1
	ARL_1	2.135	2.809	2.228	1.908	1.842	2.769	2.500	1.304	1.140	1.084	1.060
	$SDRL_1$	1.570	0.672	0.635	0.776	0.985	0.677	0.644	0.706	0.457	0.341	0.276
0.2719	**MRL_1**	1	2	2	2	1	2	2	1	1	1	1
	ARL_1	1.631	2.514	1.996	1.641	1.525	2.477	2.243	1.145	1.062	1.036	1.025
	$SDRL_1$	1.010	0.579	0.538	0.644	0.722	0.576	0.521	0.449	0.279	0.206	0.168
0.3121	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.274	2.218	1.755	1.379	1.261	2.190	2.011	1.050	1.019	1.010	1.007
	$SDRL_1$	0.594	0.442	0.504	0.521	0.498	0.433	0.416	0.242	0.142	0.102	0.082
0.3524	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.112	2.047	1.545	1.203	1.118	2.020	1.843	1.015	1.005	1.003	1.002
	$SDRL_1$	0.351	0.315	0.510	0.410	0.335	0.323	0.417	0.128	0.071	0.051	0.041

Table 6. ARL, SDRL and MRL values of $\bar{X}$, EWMA, CUSUM $\bar{X}$ and MA charts, for various δ values when MRL_0 = 30

δ		$\bar{X}$	EWMA				CUSUM $\bar{X}$		Moving Average (MA)			
		L = 2.277	L = 1.729	L = 2.056	L = 2.205	L = 2.250	H = 3.150	H = 2.700	L = 2.265	L = 2.281	L = 2.334	L = 2.364
			λ = 0.1	λ = 0.25	λ = 0.50	λ = 0.75	K = 0.4	K = 0.5	w = 2	w = 3	w = 4	w = 5
0	**MRL_0**	30	30	30	30	30	30	30	30	30	30	30
	ARL_0	43.861	41.525	43.138	43.044	43.123	41.356	42.283	44.067	47.457	54.881	60.164
	$SDRL_0$	44.405	37.521	40.220	41.997	43.279	37.183	39.201	46.770	54.855	70.336	81.383
0.0201	**MRL_1**	25	19	21	22	23	21	21	22	21	19	16
	ARL_1	36.187	25.076	28.188	30.936	32.825	27.827	28.830	33.216	33.173	35.811	35.443
	$SDRL_1$	35.445	21.331	25.511	29.531	32.024	24.535	26.172	35.281	37.936	45.842	47.189
0.0705	**MRL_1**	9	6	5	6	7	6	6	5	4	3	2
	ARL_1	12.546	6.642	6.605	7.538	9.290	7.060	7.111	8.018	6.519	5.800	5.165
	$SDRL_1$	11.885	3.527	4.356	6.084	8.342	4.300	4.723	8.303	7.223	6.921	6.476
0.1208	**MRL_1**	3	3	3	3	3	3	3	2	1	1	1
	ARL_1	4.720	3.706	3.357	3.322	3.696	3.673	3.517	2.927	2.358	2.101	1.907
	$SDRL_1$	4.184	1.461	1.626	2.087	2.820	1.626	1.700	2.656	2.205	2.008	1.824
0.1510	**MRL_1**	2	3	2	2	2	3	2	1	1	1	1
	ARL_1	3.009	2.962	2.596	2.420	2.516	2.858	2.695	1.949	1.626	1.481	1.384
	$SDRL_1$	2.455	1.015	1.083	1.318	1.689	1.094	1.130	1.528	1.236	1.088	0.954
0.2416	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.327	1.954	1.604	1.372	1.306	1.805	1.651	1.106	1.057	1.040	1.031
	$SDRL_1$	0.658	0.527	0.582	0.555	0.561	0.575	0.591	0.374	0.267	0.218	0.188
0.2719	**MRL_1**	1	2	1	1	1	2	1	1	1	1	1
	ARL_1	1.170	1.778	1.428	1.224	1.168	1.615	1.467	1.047	1.024	1.016	1.012
	$SDRL_1$	0.446	0.505	0.523	0.440	0.408	0.541	0.534	0.234	0.163	0.132	0.115
0.3121	**MRL_1**	1	2	1	1	1	1	1	1	1	1	1
	ARL_1	1.065	1.562	1.237	1.102	1.069	1.394	1.267	1.014	1.006	1.004	1.003
	$SDRL_1$	0.264	0.510	0.430	0.307	0.260	0.497	0.448	0.121	0.080	0.064	0.053
0.3524	**MRL_1**	1	1	1	1	1	1	1	1	1	1	1
	ARL_1	1.022	1.366	1.113	1.039	1.024	1.222	1.132	1.004	1.002	1.001	1.001
	$SDRL_1$	0.149	0.484	0.318	0.195	0.155	0.417	0.340	0.061	0.040	0.032	0.027

Table 7. ARL, SDRL and MRL values of $\overline{X}$, EWMA, CUSUM $\overline{X}$ and MA charts, for various δ values when $MRL_0 = 50$

δ		$\overline{X}$	EWMA				CUSUM $\overline{X}$		Moving Average (MA)			
		$L = 2.473$	$L = 1.999$, $\lambda = 0.1$	$L = 2.255$, $\lambda = 0.25$	$L = 2.412$, $\lambda = 0.50$	$L = 2.458$, $\lambda = 0.75$	$H = 3.726$, $K = 0.4$	$H = 3.162$, $K = 0.5$	$L = 2.455$, $w = 2$	$L = 2.471$, $w = 3$	$L = 2.510$, $w = 4$	$L = 2.504$, $w = 5$
0	**MRL_0**	50	50	50	50	50	50	50	50	50	50	50
	ARL_0	73.230	71.169	68.866	72.871	71.861	70.817	70.567	74.933	78.609	89.922	87.560
	$SDRL_0$	74.412	67.585	64.883	72.014	69.232	65.586	65.218	78.589	88.735	111.452	110.819
0.0201	**MRL_1**	42	27	29	35	38	29	31	36	32	31	25
	ARL_1	60.304	35.068	39.163	47.096	53.525	39.486	41.416	53.926	52.430	54.754	49.326
	$SDRL_1$	59.974	29.291	34.941	43.357	52.717	34.168	36.970	57.597	59.571	68.278	66.374
0.0705	**MRL_1**	13	7	6	7	9	7	7	7	5	4	2
	ARL_1	18.286	7.871	7.758	9.636	12.974	8.285	8.288	10.841	8.447	7.230	6.065
	$SDRL_1$	17.282	4.100	5.169	8.027	11.797	4.841	5.355	11.278	9.468	8.614	7.645
0.1208	**MRL_1**	5	4	3	3	3	4	4	3	1	1	1
	ARL_1	6.318	4.275	3.734	3.867	4.575	4.213	3.995	3.520	2.724	2.345	2.052
	$SDRL_1$	5.720	1.629	1.792	2.486	3.649	1.758	1.843	3.325	2.652	2.341	2.042
0.1510	**MRL_1**	3	3	3	2	2	3	3	1	1	1	1
	ARL_1	3.765	3.368	2.859	2.740	2.981	3.254	3.045	2.222	1.785	1.587	1.445
	$SDRL_1$	3.248	1.119	1.177	1.503	2.076	1.183	1.203	1.846	1.455	1.252	1.064
0.2416	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.455	2.182	1.753	1.486	1.412	2.049	1.869	1.140	1.073	1.049	1.035
	$SDRL_1$	0.813	0.533	0.596	0.617	0.656	0.560	0.591	0.439	0.309	0.246	0.204
0.2719	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.242	1.996	1.558	1.311	1.236	1.855	1.670	1.064	1.031	1.020	1.014
	$SDRL_1$	0.548	0.459	0.547	0.501	0.482	0.513	0.549	0.278	0.189	0.150	0.124
0.3121	**MRL_1**	1	2	1	1	1	2	1	1	1	1	1
	ARL_1	1.098	1.798	1.342	1.152	1.103	1.631	1.440	1.019	1.008	1.005	1.003
	$SDRL_1$	0.328	0.456	0.482	0.366	0.316	0.511	0.509	0.145	0.094	0.073	0.059
0.3524	**MRL_1**	1	2	1	1	1	1	1	1	1	1	1
	ARL_1	1.035	1.612	1.183	1.064	1.039	1.427	1.258	1.005	1.002	1.001	1.001
	$SDRL_1$	0.189	0.495	0.387	0.245	0.196	0.499	0.440	0.073	0.047	0.036	0.030

Table 8. ARL, SDRL and MRL values of $\bar{X}$, EWMA, CUSUM $\bar{X}$ and MA charts, for various δ values when MRL_0 = 100

δ		$\bar{X}$	**EWMA**				**CUSUM** $\bar{X}$		**Moving Average (MA)**			
		L = 2.694	L = 2.323 λ = 0.1	L = 2.576 λ = 0.25	L = 2.674 λ = 0.50	L = 2.709 λ = 0.75	H = 4.583 K = 0.4	H = 3.836 K = 0.5	L = 2.693 w = 2	L = 2.685 w = 3	L = 2.715 w = 4	L = 2.744 w = 5
0	**MRL_0**	100	100	100	100	100	100	100	100	100	101	102
	ARL_0	140.787	147.928	148.358	146.353	148.749	144.708	143.668	145.422	148.193	161.507	170.056
	$SDRL_0$	140.915	150.143	148.774	141.001	142.795	143.239	143.932	151.137	171.238	188.911	213.547
0.0201	**MRL_1**	77.500	40	48	66	76	46	49	65.5	56	54	53
	ARL_1	111.589	53.410	69.720	88.875	106.707	63.479	68.338	98.405	89.347	91.473	90.644
	$SDRL_1$	113.801	46.024	65.439	82.363	102.428	55.333	61.735	105.139	100.751	112.994	113.276
0.0705	**MRL_1**	21	8	8	10	14	9	8	11	7	6	3
	ARL_1	29.047	9.583	10.072	13.496	20.042	10.109	10.088	16.282	11.522	9.578	8.238
	$SDRL_1$	27.788	4.897	6.852	11.586	18.687	5.618	6.272	16.853	13.013	11.537	10.397
0.1208	**MRL_1**	6	5	4	4	5	5	4	3	2	1	1
	ARL_1	8.970	5.003	4.457	4.747	6.161	5.001	4.680	4.575	3.270	2.723	2.378
	$SDRL_1$	8.438	1.827	2.150	3.165	5.111	1.949	2.017	4.481	3.312	2.832	2.511
0.1510	**MRL_1**	4	4	3	3	3	4	3	2	1	1	1
	ARL_1	5.018	3.899	3.319	3.228	3.751	3.839	3.539	2.685	2.022	1.738	1.569
	$SDRL_1$	4.539	1.236	1.361	1.825	2.771	1.286	1.316	2.379	1.767	1.479	1.278
0.2416	**MRL_1**	1	2	2	2	1	2	2	1	1	1	1
	ARL_1	1.651	2.448	1.984	1.655	1.575	2.364	2.155	1.197	1.097	1.063	1.046
	$SDRL_1$	1.038	0.598	0.606	0.689	0.785	0.594	0.585	0.540	0.367	0.284	0.236
0.2719	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.354	2.216	1.776	1.441	1.347	2.141	1.947	1.092	1.042	1.027	1.019
	$SDRL_1$	0.692	0.485	0.552	0.569	0.584	0.487	0.514	0.343	0.222	0.173	0.144
0.3121	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.149	2.011	1.538	1.235	1.161	1.929	1.719	1.029	1.012	1.004	1.005
	$SDRL_1$	0.415	0.379	0.523	0.438	0.393	0.419	0.499	0.182	0.113	0.085	0.070
0.3524	**MRL_1**	1	2	1	1	1	2	2	1	1	1	1
	ARL_1	1.056	1.863	1.341	1.110	1.066	1.759	1.512	1.009	1.003	1.002	1.001
	$SDRL_1$	0.241	0.390	0.478	0.315	0.254	0.453	0.508	0.095	0.056	0.043	0.035

Table 9. ARL, SDRL and MRL values of $\bar{X}$, EWMA, CUSUM $\bar{X}$ and MA charts, for various δ values when MRL_0 = 370

		$\bar{X}$	EWMA				CUSUM $\bar{X}$		Moving Average (MA)			
δ		L = 3.135	L = 2.876 λ = 0.1	L = 3.092 λ = 0.25	L = 3.083 λ = 0.5	L = 3.105 λ = 0.75	H = 6.289 K = 0.4	H = 5.221 K = 0.5	L = 3.105 w = 2	L = 3.080 w = 3	L = 3.102 w = 4	L = 3.164 w = 5
0	**MRL_0**	370	372	368	368	370	368	372	370	368	368	365
	ARL_0	553.106	567.108	587.124	500.146	497.633	641.019	598.772	562.229	532.545	562.676	697.387
	$SDRL_0$	557.045	608.297	603.07	455.787	450.426	674.173	633.972	558.260	530.813	619.633	853.614
0.0201	**MRL_1**	307.500	89	156.500	188	246	97	117	217.5	185.5	168	161.5
	ARL_1	450.356	121.334	218.295	280.84	362.243	135.29	163.098	326.729	285.654	260.362	268.763
	$SDRL_1$	453.058	106.459	209.754	277.49	358.339	120.369	145.438	328.573	297.659	275.085	316.798
0.0705	**MRL_1**	64	12	13	19	33	12	12	26	15	10	8
	ARL_1	86.990	13.278	16.345	26.022	45.309	13.790	13.869	37.825	22.935	17.432	15.167
	$SDRL_1$	83.877	6.732	12.164	23.398	42.689	6.933	8.027	38.249	24.785	20.882	19.399
0.1208	**MRL_1**	14	6	5	6	8	6	6	5	3	2	1
	ARL_1	20.634	6.380	5.917	6.963	10.726	6.595	6.108	7.823	4.853	3.742	3.219
	$SDRL_1$	20.260	2.226	2.945	5.028	9.407	2.274	2.365	8.033	5.245	4.165	3.666
0.1510	**MRL_1**	7	5	4	4	4	5	4	3	1	1	1
	ARL_1	10.021	4.871	4.187	4.295	5.693	5.015	4.570	4.019	2.660	2.142	1.888
	$SDRL_1$	9.508	1.449	1.725	2.595	4.593	1.495	1.512	3.898	2.568	2.045	1.786
0.2416	**MRL_1**	2	3	2	2	2	3	3	1	1	1	1
	ARL_1	2.319	2.959	2.355	1.980	1.937	3.027	2.694	1.354	1.158	1.098	1.071
	$SDRL_1$	1.767	0.689	0.665	0.803	1.051	0.701	0.683	0.775	0.493	0.372	0.307
0.2719	**MRL_1**	1	3	2	2	1	3	2	1	1	1	1
	ARL_1	1.735	2.645	2.103	1.698	1.587	2.695	2.400	1.170	1.071	1.042	1.030
	$SDRL_1$	1.127	0.603	0.546	0.660	0.767	0.612	0.565	0.494	0.304	0.223	0.186
0.3121	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.324	2.313	1.854	1.422	1.299	2.354	2.131	1.059	1.021	1.012	1.008
	$SDRL_1$	0.658	0.487	0.485	0.538	0.531	0.505	0.422	0.266	0.153	0.113	0.092
0.3524	**MRL_1**	1	2	2	1	1	2	2	1	1	1	1
	ARL_1	1.134	2.109	1.654	1.235	1.139	2.133	1.965	1.018	1.006	1.003	1.002
	$SDRL_1$	0.390	0.346	0.499	0.433	0.361	0.365	0.353	0.141	0.078	0.056	0.047

Table 10. Monitored statistics and CC design parameters for all examined CCs in a real-life example

i	values	$\overline{X}$				EWMA (λ=0.1)				EWMA (λ=0.25)			
		xi	LCL	CL	UCL	zi	LCL	CL	UCL	zi	LCL	CL	UCL
1	3.891	3.891	3.830	3.980	4.130	3.971	3.969	3.980	3.991	3.958	3.947	3.980	4.013
2	3.996	3.996	>>	>>	>>	3.974	3.965	>>	3.995	3.967	3.938	>>	4.022
3	4.014	4.014	>>	>>	>>	3.978	3.963	>>	3.997	3.979	3.934	>>	4.026
4	3.952	3.952	>>	>>	>>	3.975	3.961	>>	3.999	3.972	3.932	>>	4.028
5	4.089	4.089	>>	>>	>>	3.986	3.960	>>	4.000	4.001	3.931	>>	4.029
6	3.91	3.91	>>	>>	>>	3.979	3.959	>>	4.001	3.979	3.930	>>	4.030
7	4.03	4.03	>>	>>	>>	3.984	3.958	>>	4.002	3.991	>>	>>	>>
8	3.841	3.841	>>	>>	>>	3.970	3.957	>>	4.003	3.954	>>	>>	>>
9	3.979	3.979	>>	>>	>>	3.971	3.957	>>	4.003	3.960	>>	>>	>>
10	3.91	3.91	>>	>>	>>	3.965	3.956	>>	4.004	3.948	>>	>>	>>
11	4.001	4.001	>>	>>	>>	3.968	3.956	>>	4.004	3.961	>>	>>	>>
12	3.862	3.862	>>	>>	>>	3.958	3.956	>>	4.004	3.936	3.929	>>	4.031

i	EWMA (λ=0.5)				EWMA (λ=0.75)				CUSUM $\overline{X}$ (K=0.4)			CUSUM $\overline{X}$ (K=0.5)			Moving Average (MA, w=5)			
	zi	LCL	CL	UCL	zi	LCL	CL	UCL	Ci-	C_{i+}	H	Ci-	C_{i+}	H	Mi	LCL	CL	UCL
1	3.936	3.907	3.980	4.053	3.913	3.868	3.980	4.092	0.859	0.000	2.798	0.759	0.000	2.402	3.891	3.832	3.980	4.128
2	3.966	3.899	>>	4.061	3.975	3.865	>>	4.095	0.232	0.000	>>	0.032	0.000	>>	3.976	3.875	>>	4.085
3	3.990	3.897	>>	4.063	4.004	3.864	>>	4.096	0.000	0.081	>>	0.000	0.000	>>	3.973	3.894	>>	4.066
4	3.971	3.896	>>	>>	3.965	>>	>>	>>	0.000	0.000	>>	0.000	0.000	>>	3.964	3.906	>>	4.054
5	4.030	>>	>>	>>	4.058	>>	>>	>>	0.000	1.141	>>	0.000	1.041	>>	3.968	3.914	>>	4.046
6	3.970	>>	>>	>>	3.947	>>	>>	>>	0.590	0.000	>>	1.126	0.000	>>	3.940	>>	>>	>>
7	4.000	>>	>>	>>	4.009	>>	>>	>>	0.000	0.307	>>	0.000	0.207	>>	3.940	>>	>>	>>
8	3.920	>>	>>	>>	3.883	>>	>>	>>	1.566	0.000	>>	1.466	0.000	>>	3.933	>>	>>	>>
9	3.950	>>	>>	>>	3.955	>>	>>	>>	1.180	0.000	>>	0.980	0.000	>>	3.938	>>	>>	>>
10	3.930	>>	>>	>>	3.921	>>	>>	>>	1.770	0.000	>>	1.470	0.000	>>	3.924	>>	>>	>>
11	3.965	>>	>>	>>	3.981	>>	>>	>>	1.073	0.000	>>	0.673	0.000	>>	3.932	>>	>>	>>
12	3.914	>>	>>	>>	3.892	>>	>>	>>	2.342	0.000	>>	1.842	0.000	>>	3.862	>>	>>	>>

Figure 1. Part of the questionnaire distributed to students to evaluate every semester and for every course the teaching performance of the responsible faculty member.

HELLENIC REPUBLIC
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STUDENT COURSE EVALUATION QUESTIONNAIRE

This questionnaire is distributed during the lectures between the 8th and 10th week of classes and is completed anonymously by students. The completed questionnaires are collected and returned to the Graduate Secretary of the Department in the sealed envelope provided by a nominated student.
Completion of this anonymous questionnaire is very important. It collects valuable information that is used exclusively by the instructors for their future planning of courses and improvement of the delivery lessons. Special attention is paid to the comments you can provide at the end of the questionnaire.

Course Title:	**Course Code:**

Department:
Instructor:
Date:

Please answer questions 1-12 using a scale 1-5, with 1 the least favorable and 5 the most favorable. *
* 1= Very poor / Strongly disagree, 2= Poor / Disagree, 3= Acceptable / Neutral, 4= Good / Agree, 5= Very good / Strongly agree

A. GENERAL QUESTIONS

1. Overall performance of the instructor has been good. (1) (2) (3) (4) (5)
2. Quality of the course has been high. (1) (2) (3) (4) (5)

B. COURSE EVALUATION

3. Organization and presentation of the course has been effective. (1) (2) (3) (4) (5)
4. Subject of the course has been interesting and useful for your studies. (1) (2) (3) (4) (5)
5. Lecture/reading material (textbooks, notes, exercises, articles, etc.) has been sufficient. (1) (2) (3) (4) (5)

Figure 2. A typical CC

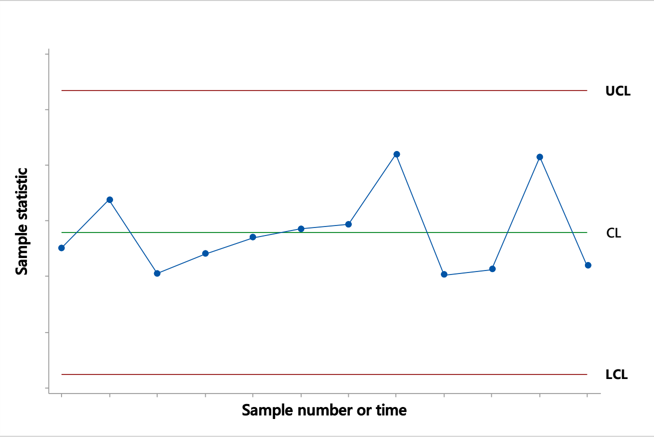


Figure 3. Run length relative frequency distributions for three indicative δ values

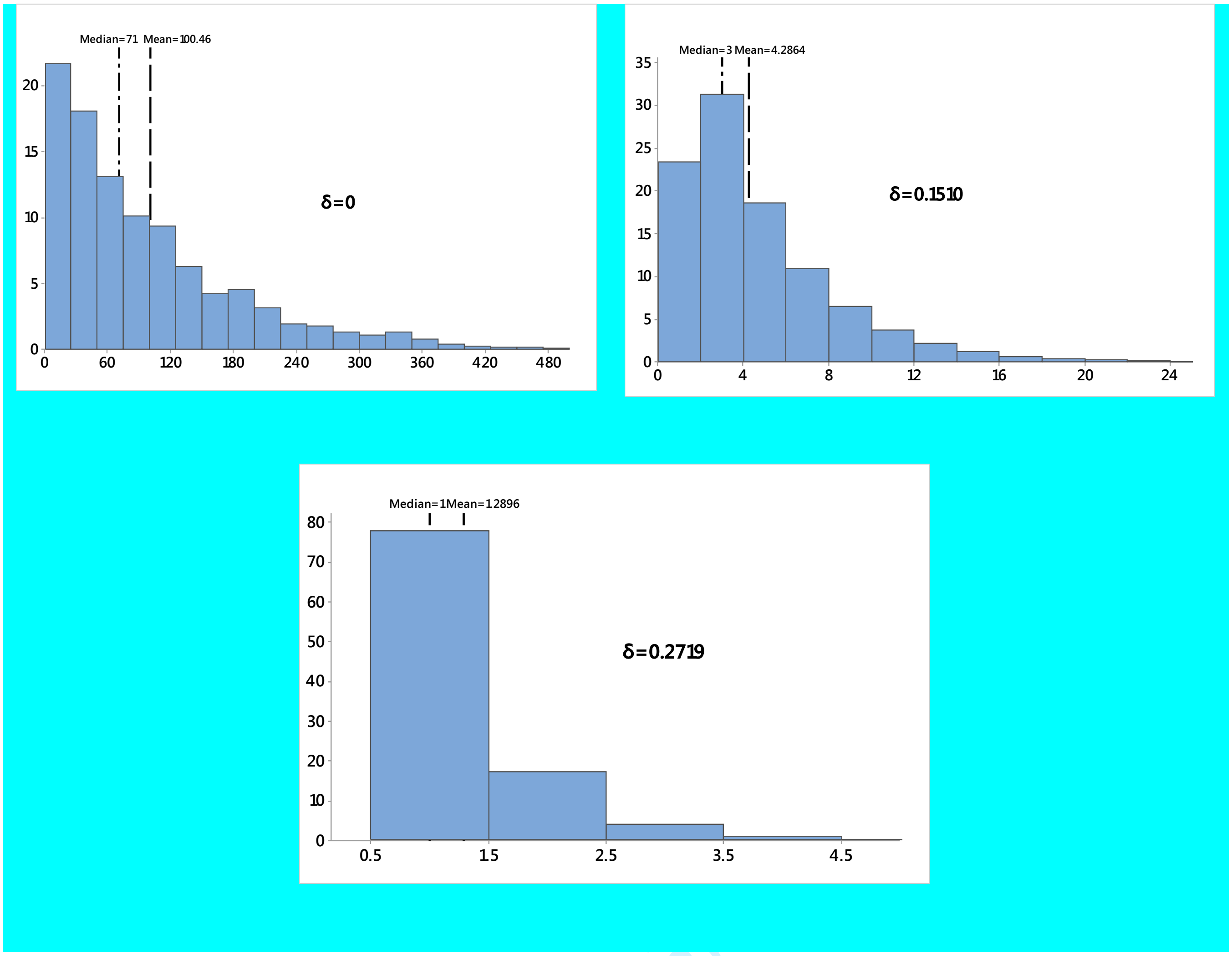


Figure 4. Distribution of student evaluations about the overall performance of a faculty member

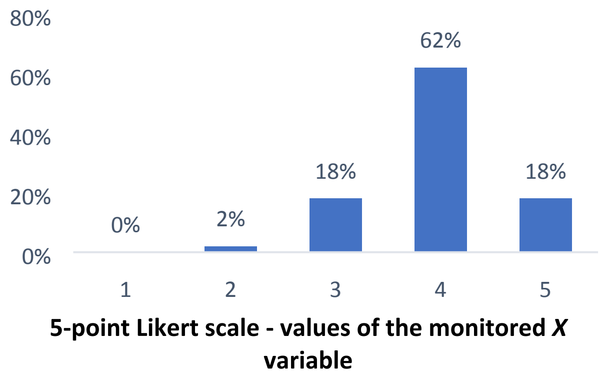


Figure 5. SDRL for various δ values in case ARL_0=30 for all compared CCs

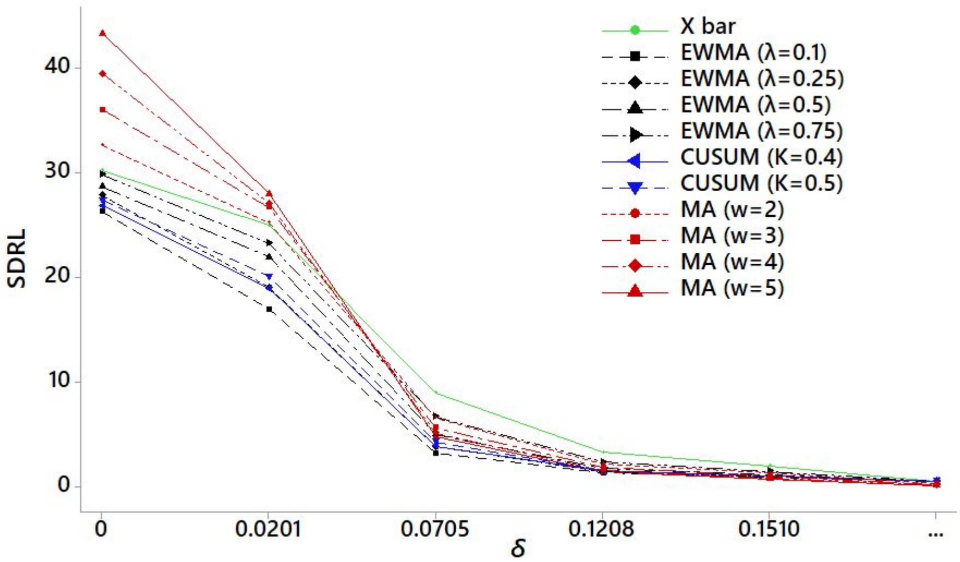
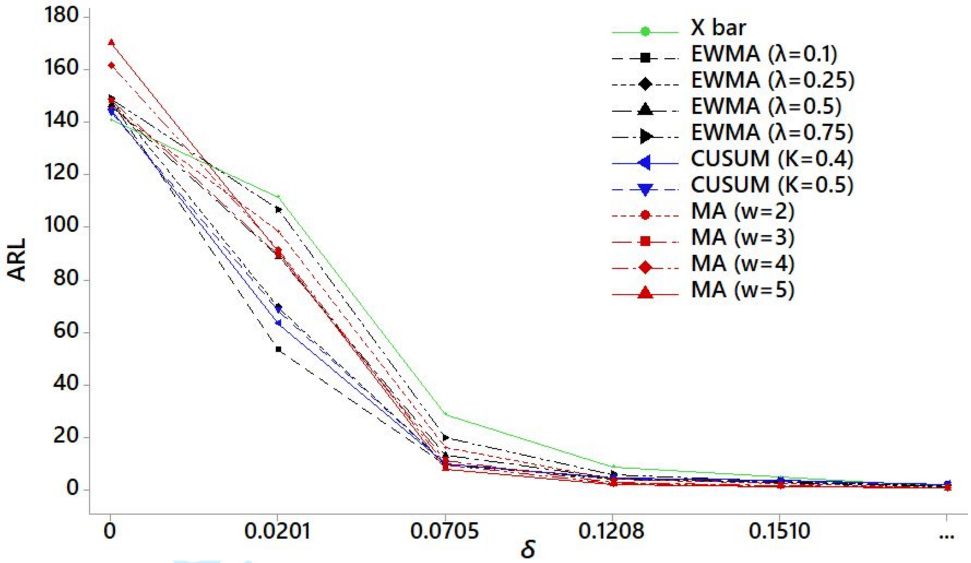


Figure 6. ARL for various δ values in case MRL_0=100 for all compared CCs



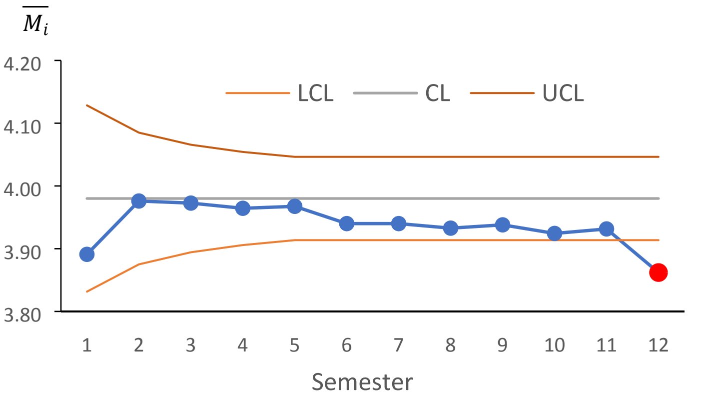


Figure 7a. The MA CC with w = 5

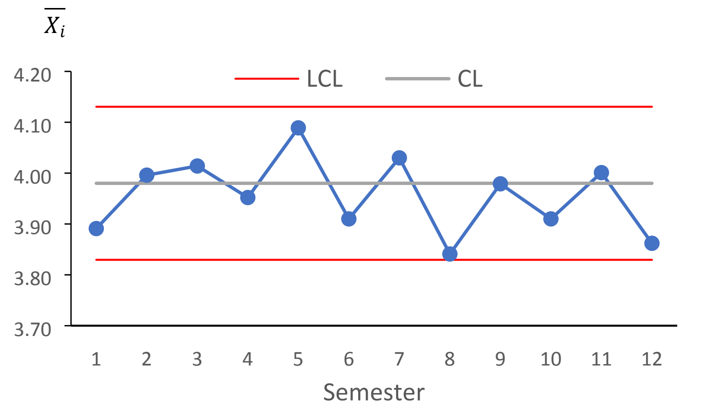


Figure 7b. The $\overline{X}$ CC

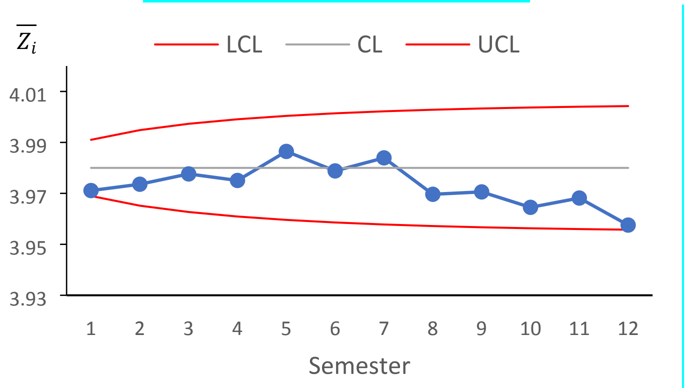


Figure 7c. The EWMA (λ=0.1) CC

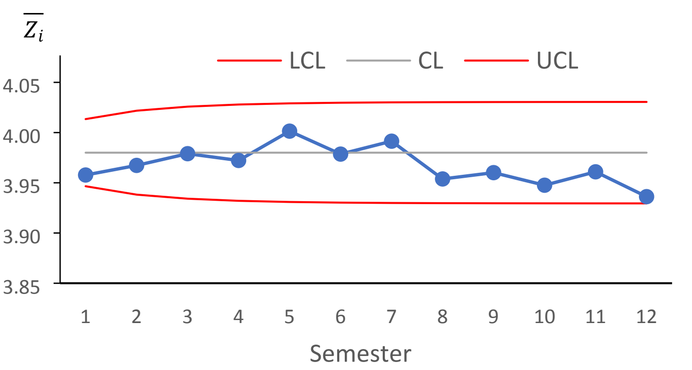


Figure 7d. The EWMA (λ=0.25) CC

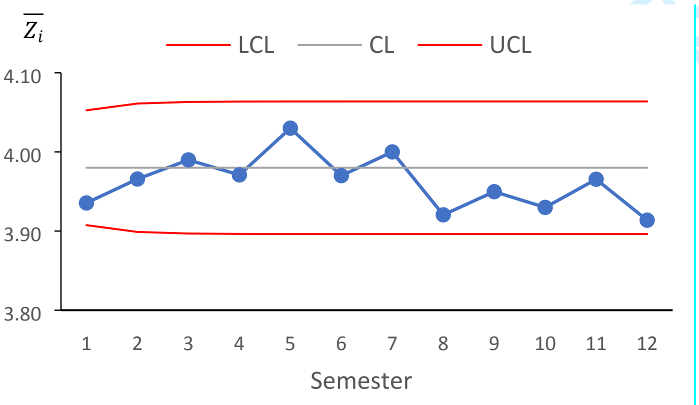


Figure 7e. The EWMA (λ=0.50) CC

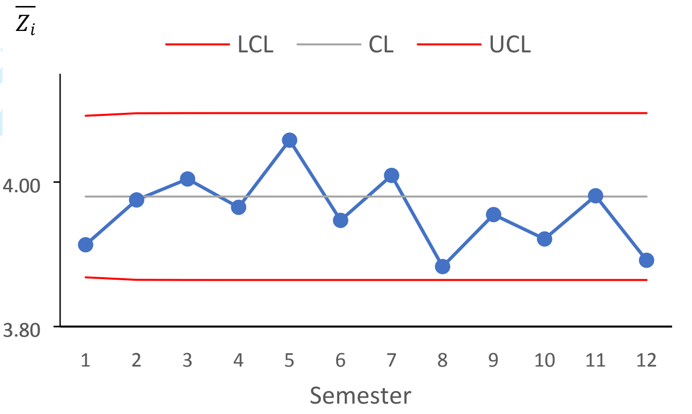


Figure 7f. The EWMA (λ=0.75) CC

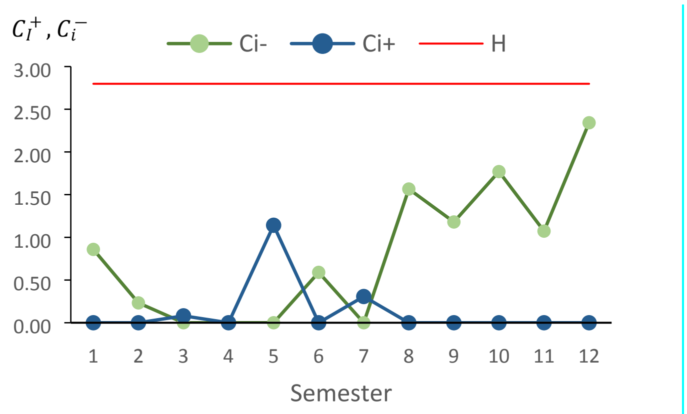


Figure 7g. The CUSUM $\overline{X}$ (K=0.4) CC

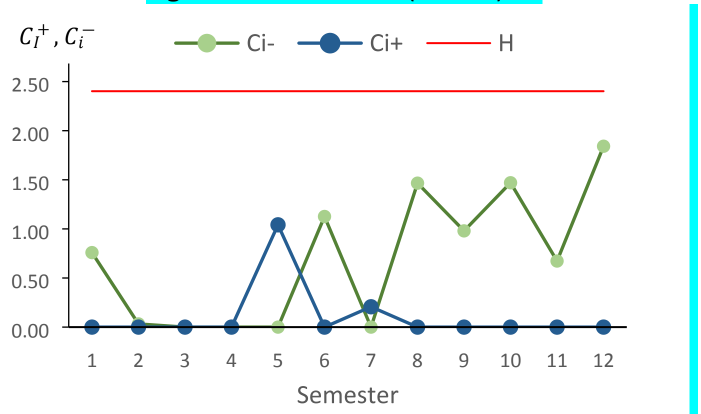


Figure 7h. The CUSUM $\overline{X}$ (K=0.5) CC