Statistical Process Control for Software: Fill the Gap

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1. Introduction

The characteristic of software processes, unlike manufacturing ones, is that they have a very high human-centered component and are primarily based on cognitive activities. As so, each time a software process is executed, inputs and outputs may vary, as well as the process performances. This phenomena is better identified in literature with the terminology of "Process Diversity" (IEEE, 2000). Given the characteristics of a software process, its intrinsic diversity implies the difficulty to predict, monitor and improve it, unlike what happens in other contexts. In spite of the previous observations, Software Process Improvement (SPI) is a very important activity that cannot be neglected. To face these problems, the software engineering community stresses the use of measurement based approaches such as QIP/GQM (Basili et al., 1994) and time series analysis: the first approach is usually used to determine what improvement is needed; the time series analysis is adopted to monitor process performances. As so, it supports decision making in terms of when the process should be improved, and provides a manner to verify the effectiveness of the improvement itself.
A technique for time series analysis, well-established in literature, which has given insightful results in the manufacturing contexts, although not yet in software process ones is known as Statistical Process Control (SPC) (Shewhart, 1980; Shewhart, 1986). The technique was originally developed by Shewhart in the 1920s and then used in many other contexts. The basic idea it relies on consists in the use of so called "control charts" together with their indicators, called run tests, to: establish operational limits for acceptable process variation; monitor and evaluate process performances evolution in time. In general, process performance variations are mainly due to two types of causes classified as follows:

- Common cause variations: the result of normal interactions of people, machines, environment, techniques used and so on.
- Assignable cause variations: arise from events that are not part of the process and make it unstable.

In this sense, the statistically based approach, SPC, helps determine if a process is stable or not by discriminating between common cause variation and assignable cause variation. We can classify a process as "stable" or "under control" if only common causes occur. More precisely, in SPC data points representing measures of process performances are collected.

These values are then compared to the values of central tendency, upper and lower limit of admissible performance variations.
While SPC is a well established technique in manufacturing contexts, there are only few works in literature (Card, 1994; Florac et al., 2000; Weller, 2000(a); Weller, 2000(b); Florence, 2001; Sargut & Demirors, 2006; Weller, & Card. 2008; Raczynski & Curtis, 2008) that present successful outcomes of SPC adoption to software. In each case, not only are there few cases of successful applications but they don't clearly illustrate the meaning of control charts and related indicators in the context of software process application.
Given the above considerations, the aim of this work is to generalize and put together the experiences collected by the authors in previous studies on the use of Statistical Process Control in the software context (Baldassarre et al, 2004; Baldassarre et al, 2005; Caivano 2005; Boffoli, 2006; Baldassarre et al, 2008; Baldassarre et al, 2009) and present the resulting stepwise approach that: starting from stability tests, known in literature, selects the most suitable ones for software processes (tests set), reinterprets them from a software process perspective (tests interpretation) and suggest a recalculation strategy for tuning the SPC control limits.
The paper is organized as follows: section 2 briefly presents SPC concepts and its peculiarities; section 3 discusses the main differences and lacks of SPC for software and presents the approach proposed by the authors; finally, in section 4 conclusions are drawn.

2. Statistical Process Control: Pills

Statistical Process Control (SPC) (Shewhart, 1980; Shewhart, 1986) is a technique for time series analysis. It was developed by Shewhart in the 1920s and then used in many contexts. It uses several "control charts" together with their indicators to establish operational limits for acceptable process variation. By using few data points, it is able to dynamically determine an upper and lower control limit of acceptable process performance variability. Such peculiarity makes SPC a suitable instrument to detect process performance variations. Process performance variations are mainly due to: common cause variations (the result of normal interactions of people, machines, environment, techniques used and so on); assignable cause variations (arise from events that are not part of the process and make it unstable). A process can be described by measurable characteristics that vary in time due to common or assignable cause variations. If the variation in process performances is only due to common causes, the process is said to be stable and its behavior is predictable within a certain error range; otherwise an assignable cause (external to the process) is assumed to be present and the process is considered unstable. A control chart usually adopts an indicator of the process performances central tendency (CL), an upper control limit (UCL = CL+3sigma) and a lower control limit (LCL = CL-3sigma). Process performances are tracked overtime on a control chart, and if one or more of the values fall outside these limits, or exhibit a "non random" behavior, an assignable cause is assumed to be present.

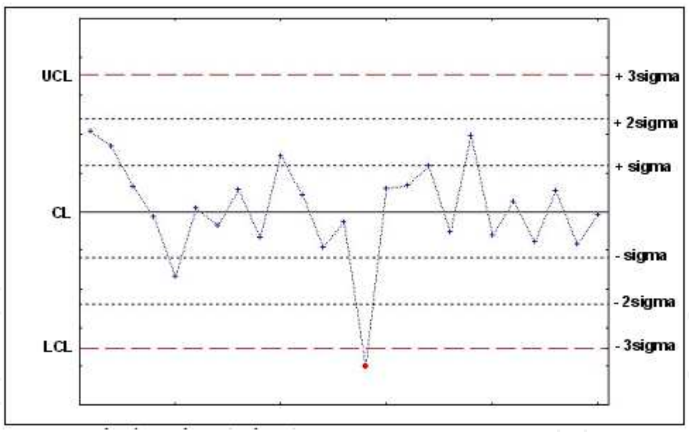


Fig. 1. Example of SPC charts (X charts)

"Sigma" is calculated by using a set of factors tabulated by statisticians (for more details refer to (Wheeler & Chambers, 1992)) and it is based on statistical reasoning, simulations carried out and upon the heuristic experience that: "it works". A good theoretical model for a control chart is the normal distribution shown in figure 2 where: the percentage values reported express the percentage of observations that fall in the corresponding area; μ is the theoretical mean; σ is the theoretical standard deviation. In the [μ-3σ, μ+3σ] interval, fall 99.73% (i.e. 2.14 + 13.59 + 34.13 + 34.13 + 13.59 + 2.14) of the total observations. Thus only the 0,27 % of the observations is admissible to fall outside the [μ-3σ, μ+3σ] interval.

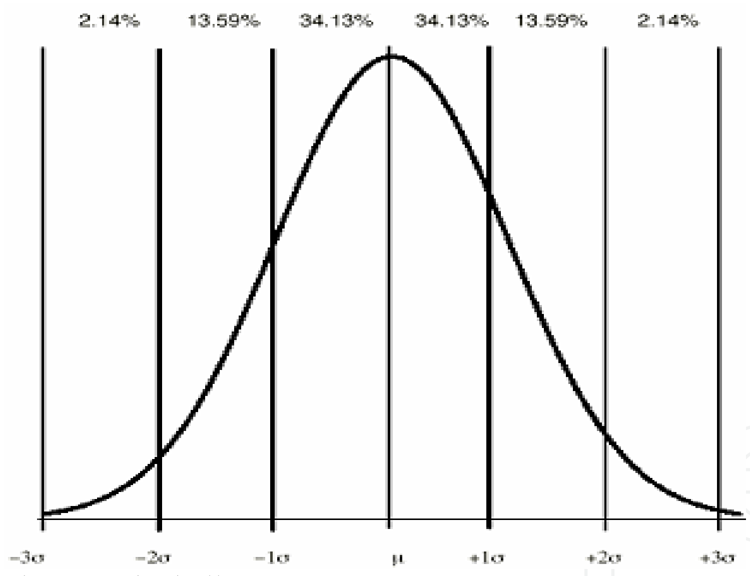


Fig. 2. Normal distribution, the bell curve

If we consider sigma in place of σ, the meaning and rational behind a control chart results clear. For completeness it is necessary to say that the normal distribution is only a good theoretical model but, simulations carried out have shown that independently from the data distribution, the following rules of thumb work:

- Rule1: from 60% to 75% of the observations fall in the [CL-sigma, CL+1sigma]
- Rule2: from 90% to 98% of the observations fall in the [CL-2sigma, CL+2sigma]
- Rule3: from 99% to 100% of the observations fall in the [CL-3sigma, CL+3sigma]

The control limits carried out using SPC are based on a process observation and they are expression of it. They are not the result of expert judgment and, furthermore, they can be clearly obtained.
In general, control charts are used as follows: samples are taken from the process, statistics (for example, average and range) are calculated and plotted on charts, and the results are interpreted with respect to process limits or, as they are known in SPC terminology, control limits. Control limits are the limits within which the process operates under normal conditions. They tell us how far we can expect sample values to stray from the average given the inherent variability of the process or, to use the SPC terms, the magnitude of common-cause variation. Data points beyond the control limits or other unusual patterns indicate a special-cause variation.

3. SPC for Software

Software processes and manufacturing ones present deep differences that the use of SPC in software cannot exempt from considering. Moreover, according to the discussions in (Jalote, 2002(a); Eickelmann & Anant, 2003) we can consider three main differences between manufacturing and software processes that have to be kept in mind in order to assure a more appropriate use of SPC in software context in terms of control charts, run test indicators, anomalies interpretation and control limits calculation.

Measurement of Software Processes. In manufacturing, the observed and actual number of defects is not significantly different. In software development, these two numbers routinely vary significantly. Possible causes for extreme variation in software measurement include the following:

- People are the software production process.
- Software measurement might introduce more variation than the process itself.
- Size metrics do not count discrete and identical units.

Such extreme variations in software processes need different indicators for the anomalies detection and more specific interpretations.

Product Control and Product Rework. The primary focus of using SPC control charts in manufacturing is to bring the process back in control by removing assignable causes and minimize as much as possible the future production losses. In the manufacturing process when an anomaly occurs the products usually do not conform to the expected standards and therefore, must be discarded. On the other hand, in the software process the product can be “reworked”. For example, when using control charts for an inspection process, if a point falls outside the control limits, besides the process improvement actions like improving the checklist, inevitably, product improvement actions like re-reviews, scheduling extra testing also occurs. With software processes, besides improving the process, an important objective of using control charts is to also control the product. In (Gardiner & Montgomery, 1987), which is perhaps the first paper on the use of SPC in software, Gardiner and Montgomery suggest "rework" as one of the three actions that management should carry out if a point falls outside the control limits. The use described in (Ebenau, 1994) clearly shows this aspect of product control. The survey of high maturity organizations also indicates that project managers also use control charts for project-level control (Jalote, 2002(b)). Due to this product-control, project managers are more likely to want test indicators and interpretations that highlight potential warning signals, rather than risk to miss such signals, even if it means more false alarms.

Shutdown and Startup is “Cheaper”. The cost parameters that affect the selection of control limits are likely to be quite different in software processes. For example, if a manufacturing process has to be stopped (perhaps because a point falls outside the control limits), the cost of doing so can be quite high. In software, on the other hand, the cost of stopping a process is minimal as elaborate "shutdown" and "startup" activities are not needed. Similarly, the cost of evaluating a point that falls outside the control limits is likely to be very different in software processes as compared to manufacturing ones. For these reasons the control limits could be recalculated more often than in manufacturing processes.
Due to these differences, it is reasonable to assume that, to get the best results, control charts, the use of the indicators and their interpretation, as well as the tuning of process limits, will need to be adapted to take into account the characteristics of software processes.

Finally, in spite of the rather simple concepts underlying statistical process control, it is rarely straightforward to implement (Card, 1994). The main lacks for software processes are listed below:

Focus on individual or small events. The indicators generally used in SPC highlight assignable causes related to the individual events. However the high variability of a software process and its predominant human factor make such indicators ineffective because they usually discover occasional variations due to passing phenomena that should be managed as false positives (false alarms).
Therefore the SPC indicators, in software processes, should detect the assignable variations and then also interpret them if occasional variations (as false positives) or occurred changes in the process (in the manufacturing processes the passing phenomena are very rare). For such reasons the control charts should be constructed with a view toward detecting process trends rather than identifying individual nonconforming events (Figure 3).

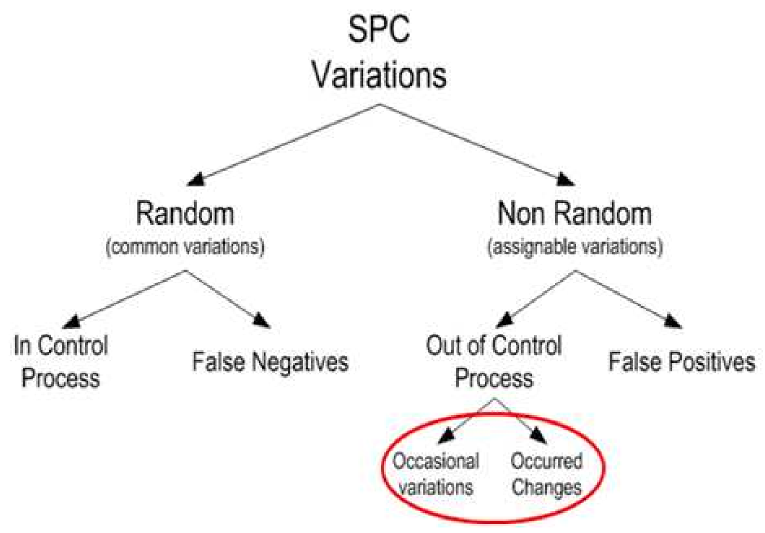


Fig. 3. SPC variations tree

Failure to investigate and act. Statistical process control only signals that a problem may exist. If you don't follow through with a detailed investigation, like an audit, and follow-up corrective action, there is no benefit in using it. In these sense a larger set of anomalies indicators and a more precise anomalies interpretation is necessary.

Incorrect computation of control limits. Several formulas exist for computing control limits and analyzing distributions in different situations. But although they are straightforward, without proper background, it is easy to make mistakes. Such mistakes might concern:

- the correct calculation of control limits
- the appropriate timing for the recalculation of control limits ("tuning" activities)

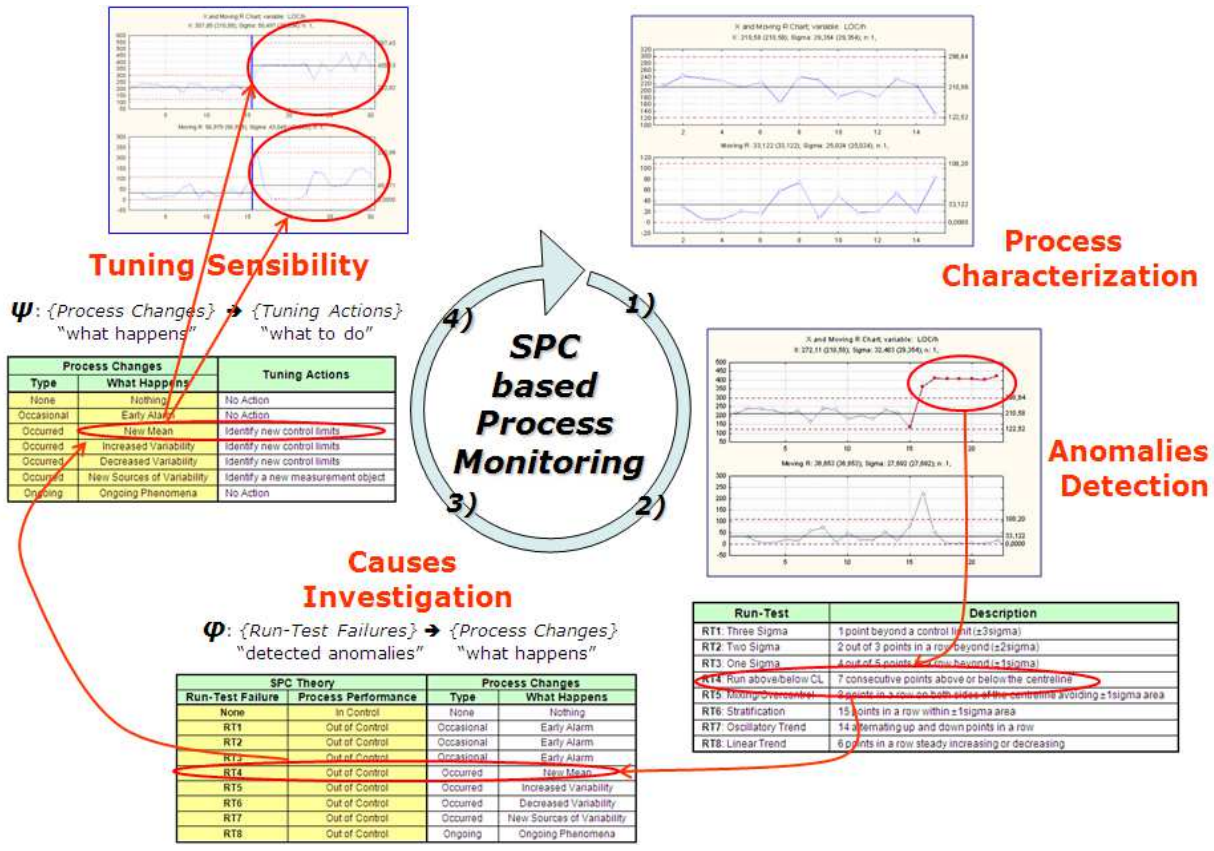
In order to mitigate such differences and face these issues, in the past the authors have proposed and experimented an SPC framework for software processes (Baldassarre et al., 2007). Such framework, based on the software process peculiarities, proposes the most appropriate control charts, a set of indicators (run-test set) and related interpretations (run-test interpretation) in order to effectively monitor process variability. When such indicators are used, SPC is able to discover software process variations and discriminate between them. For these reasons such indicators:

- are able to detect process trends rather than identify individual nonconforming events (i.e. occasional variations that in software processes would be considered like the false alarms)
- enable to discover assignable variations and address some quality information about "what happens" in the process. Thereby such framework supports the manager during the causes-investigation activities.

Furthermore, our framework faces problems related to incorrect computation of control limits and proposes "when" and "how" to recalculate the SPC control limits (the "tuning" activities) that supports manager in:

- Choosing the control charts and measurement object to use in SPC analysis
- Selecting the appropriate data-points, building the Reference Set and calculating the control limits needed for monitoring process variations
- Monitoring the process variations and detecting run-tests failures
- Evaluating the assignable events occurred and then undertaking the appropriate actions (for example recalculating the control limits)

Figure 4 summarizes the steps for applying the framework: first, process characterization is carried out, i.e. a process characteristic to monitor is observed over time, and related data points are collected; the appropriate control chart is selected and upper and lower control limits are calculated (Step 1); secondly anomaly detection occurs, i.e. each new data point observed is plotted on the chart, keeping control limits and central line the same; the set of run tests (RT1…RT8) is executed and anomalies are detected each time a test fails (Step 2); at this point, causes investigation is carried out, i.e. the cause of the anomaly pointed out is investigated in order to provide an interpretation (Step 3). Finally, according to the process changes occurred and identified in the previous step, appropriate tuning actions are applied to tune the sensibility of the monitoring activity and adapt it to the new process performances (Step 4).



ψ: {Process Changes} ➔ {Tuning Actions}
"what happens" "what to do"

Process Changes		Tuning Actions
Type	What Happens	
None	Nothing	No Action
Occasional	Early Alarm	No Action
Occurred	New Mean	Identify new control limits
Occurred	Increased Variability	Identify new control limits
Occurred	Decreased Variability	Identify new control limits
Occurred	New Sources of Variability	Identify a new measurement object
Ongoing	Ongoing Phenomena	No Action

Run-Test	Description
RT1: Three Sigma	1 point beyond a control limit (±3sigma)
RT2: Two Sigma	2 out of 3 points in a row beyond (±2sigma)
RT3: One Sigma	4 out of 5 points in a row beyond (±1sigma)
RT4: Run above/below CL	7 consecutive points above or below the centreline
RT5: Mixing/Overcontrol	8 points in a row on both sides of the centreline avoiding ±1sigma area
RT6: Stratification	15 points in a row within ±1sigma area
RT7: Oscillatory Trend	14 alternating up and down points in a row
RT8: Linear Trend	6 points in a row steady increasing or decreasing

φ: {Run-Test Failures} ➔ {Process Changes}
"detected anomalies" "what happens"

SPC Theory		Process Changes	
Run-Test Failure	Process Performance	Type	What Happens
None	In Control	None	Nothing
RT1	Out of Control	Occasional	Early Alarm
RT2	Out of Control	Occasional	Early Alarm
RT3	Out of Control	Occasional	Early Alarm
RT4	Out of Control	Occurred	New Mean
RT5	Out of Control	Occurred	Increased Variability
RT6	Out of Control	Occurred	Decreased Variability
RT7	Out of Control	Occurred	New Sources of Variability
RT8	Out of Control	Ongoing	Ongoing Phenomena

Fig. 4. SPC based Process Monitoring guidelines

3.1 Process Characterization

A reference set must be determined in order to characterize a process, i.e. a set of observations that represent the process performances and do not suffer from exceptional causes. In short, the reference set provides a reference point to compare the future performances with. After determining the reference set, each following observation must be traced on the control chart obtained and then the set of tests included in the test set must be carried out in order to identify if eventual exceptional causes come up. More precisely, the following two steps are executed:

- Identify the measurement object
- Identify the reference set

Identify the measurement object. The process to evaluate is identified along with the measurement characteristics that describe the performances of interest. The most appropriate control charts for the phenomena being observed are selected. There are charts for variables data (measurement data such as length, width, thickness, and moisture content) and charts for attributes data ("counts" data such as number of defective units in a sample).

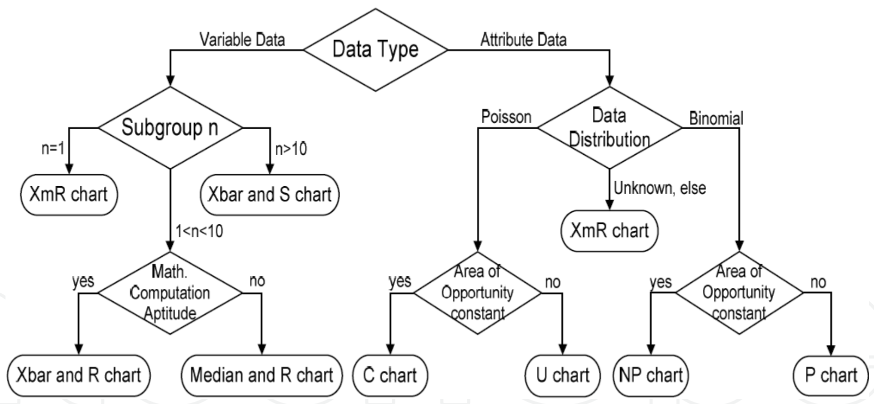


Fig. 5. Decision Tree for Control Chart Selection

In software processes, where data points are not so frequent, generally, each data point is individually plotted and evaluated. Hence, charts that work on single observation points (like the XmR or the U charts) are more suitable for software (Gadiner & Montgomery, 1987; Weller, 2000(a); Zultner, 1999) and are the most commonly used charts, as reported in the survey (Radice, 2000). On the other hand, in manufacturing, the Xbar-R charts, which employ a sampling based technique, is most commonly used. Consequently, modeling and analysis for selecting control limits optimal performance has also focused on Xbar-R charts.

Identify the Reference Set. Identifying the "reference set" is a mandatory activity for correctly monitoring and evaluating the evolution of process performances in time. It consists in a set of observations of the measurement characteristics of interest. The set expresses the "normal" process behaviour, i.e. the process performances supposing that the variations are determined only by common causes. As so, first, process performances in time must be measured and, CL and control limits must be calculated. The observations collected are then traced on the control charts and the tests included in the test set are carried out. If no anomalies are detected, the process can be considered stable during the observation period. The observations collected along with the CL and control limits values become the reference set. If one of the tests points out anomalies, then the process is not stable. As so, it must be further investigated. The exceptional causes, if present, need to be eliminated from the process and, the CL and control limits must be recalculated. This is repeated until a period of observed data points indicate a stable process, i.e. until a new reference set can be determined.

In an X chart: each point represents a single value of the measurable process characteristic under observation; CLX is calculated as the average of the all available values; UCLX and LCLX are set at 3sigmaX around the CLX; sigmaX is the estimated standard deviation of the observed sample of values calculated by using a set of factors tabulated by statisticians (for more details refer to (Wheeler & Chambers, 1992; Park, 2007)). In a mR chart: each point represents a moving range (i.e. the absolute difference between a successive pair of observations); CLmR, is the average of the moving ranges; UCLmR = CLmR+3sigmamR and LCLmR=0; sigmamR is the estimated standard deviation of the moving ranges sample.
For example, given a set of 15 observations X = {213.875, 243.600, 237.176, 230.700, 209.826, 226.375, 167.765, 242.333, 233.250, 183.400, 201.882, 182.133, 235.000, 216.800, 134.545}, the following values are determined:

$$\overline{mR} = \frac{1}{m-1} \times \sum_{i=1\ldots m-1} |x_{i-1} - x_i| = 33.11$$

$3sigma_X = 2{,}660 * \overline{mR} = 88.07$

$CL_X = \overline{X} = 210.58$

$UCL_X = \overline{X} + 2{,}660 * \overline{mR} = 298.64$

$LCL_X = \overline{X} - 2{,}660 * \overline{mR} = 122.52$

$CL_{mR} = \overline{mR} = 33{,}11$

$UCL_{mR} = 3{,}268 * \overline{mR} = 108{,}2$

$LCL_{mR} = 0$

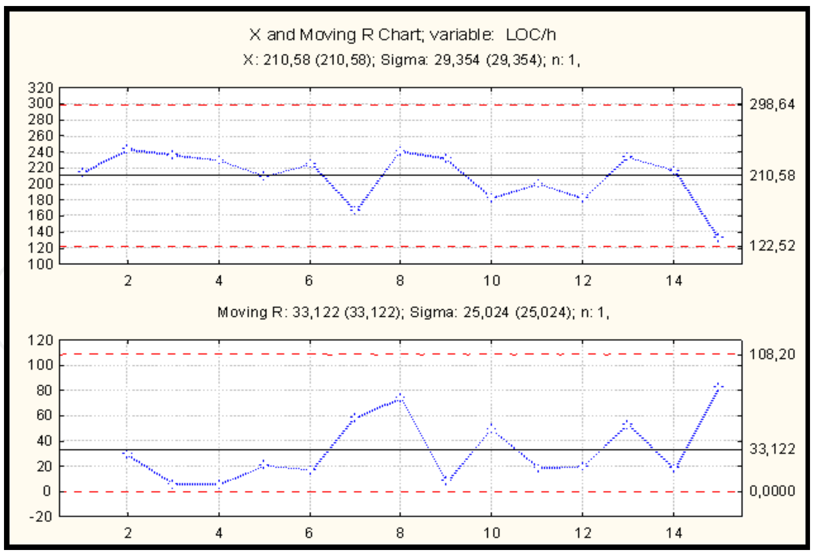


Fig. 6. Example of Individual and moving ranges charts (XmR charts)

3.2 Anomalies Detection

In software processes, one should look for systematic patterns of points instead of single point exceptions, because such patterns emphasize that the process performance has shifted or is shifting. This surely leads to more insightful remarks and observations. There is a set of tests for such patterns referred to as "run rules" or "run tests" (see (AT&T, 1956; Nelson, 1984; Nelson, Grant & Leavenworth, 1980; Shirland, 1993)) that aren't well known (or used) in the software engineering community.

Run-Test	Description
RT1: Three Sigma	1 point beyond a control limit (±3sigma)
RT2: Two Sigma	2 out of 3 points in a row beyond (±2sigma)
RT3: One Sigma	4 out of 5 points in a row beyond (±1sigma)
RT4: Run above/below CL	7 consecutive points above or below the centreline
RT5: Mixing/Overcontrol	8 points in a row on both sides of the centreline avoiding ±1sigma area
RT6: Stratification	15 points in a row within ±1sigma area
RT7: Oscillatory Trend	14 alternating up and down points in a row
RT8: Linear Trend	6 points in a row steadily increasing or decreasing

Table 1. Run-Test Set Details

As sigma, the run rules are based on "statistical" reasoning. For example, the probability of any observation in an X control chart falling above the CL is at a glance equal to 0.51. Thus, the probability that two consecutive observations will fall above the CL is equal to 0.5 times 0.5 = 0.25. Accordingly, the probability that 9 consecutive observations (or a run of 9 points) will fall on the same side of the CL is equal to 0.5^9 =0.00195. Note that this is approximately the probability with which an observation can be expected to fall outside the 3-times sigma limits. Therefore, one could look for 9 consecutive observations on the same side of the CL as another indication of an out-of-control condition. Duncan (Duncan, 1986) provides details concerning the "statistical" interpretation of the other tests presented in this paragraph.

In order to simplify the test execution, the chart area is conventionally divided in three zones: Zone A is defined as the area between 2 and 3 times sigma above and below the center line; Zone B is defined as the area between 1 and 2 times sigma, and Zone C is defined as the area between the center line and 1 times sigma. For the execution of the zone based tests, the distribution of the values in the charts need to be assumed as symmetrical around the mean. This is not the case for mR charts and thus, in general, all the zone based tests are not applicable to R chart (see Figure 7 for applicability). Although this is a shared opinion, someone (Wheeler & Chambers, 1992) states that these tests help process monitoring. Furthermore, according to (Jalote, 2000(a)), managers are more likely to want warning signals to be pointed out, rather than missing them, even if it means risking for false alarms.

The presented framework points out which SPC tests may be applied to which control charts. It presents, interprets and organizes tests in order to manage software processes. Although in the software engineering community only “a point falling outside control limits” test is usually used for testing process stability, we are of the opinion that the SPC based software process monitoring should be based on the following tests that we have rearranged in three conceptual classes according to the type of information they provide (Figure 6). When one or more of these tests is positive, it is reasonable to believe that the process may no longer be under control, i.e. an assignable cause is assumed to be present. For completeness and clearness it is the case to point out that the first 4 tests among those that follow are also referred to as “detection rules” and are the most (and often the only ones) used tests (Wheeler & Chambers, 1992; Florac et al., 1997) within the software engineering community.

[1] provided (1) that the process is in control (i.e., that the centre line value is equal to the population mean), (2) that consecutive sample means are independent, and (3) that the distribution of means follows the normal distribution.

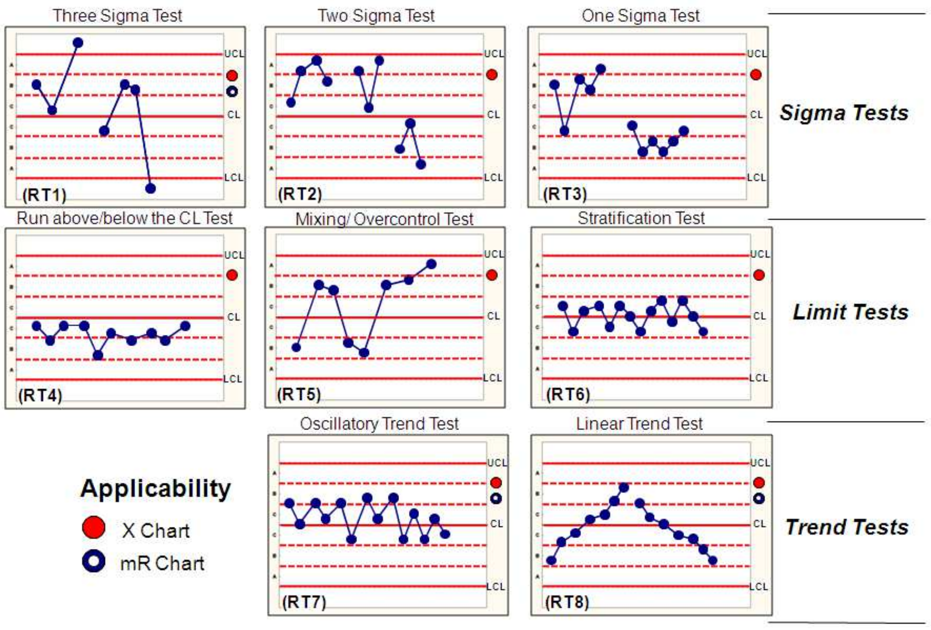


Fig. 7. Run-tests set

3.2.1 Sigma Tests

These tests point out the possible presence of an assignable cause. The three sigma test can be applied to both, X and R charts. The One and Two sigma tests are Zone Tests and thus they should not be applied to R the chart due to its lack of symmetry around the mean.

1. Three Sigma Test (Extreme Points Test): The existence of a single point beyond a control limit signals the presence of an out-of -control condition, i.e. the presence of an assignable cause.
2. Two Sigma Test: This test watches for two out of three points in a row in Zone A or beyond. The existence of two of any three successive points that fall on the same side of, and more than two sigma units away from, the central line, signals the presence of an out-of -control condition. This test provides an "early warning" of a process shift.
3. One Sigma Test: This test watches for four out of five subgroups in a row in Zone B or beyond. The existence of four of any five successive points that fall on the same side of, and more than one sigma unit away from, the central line, signals the presence of an out-of-control condition. Like the previous test, this test may be considered to be an "early warning indicator" of a potential shift in process performance.

The three sigma test is the most (and often the “only” one) used test in software engineering literature.

3.2.2 Limit Tests

All the tests included in this class use chart Zones and thus they are applicable to the X charts only.

1. Run above or below the Centerline Test: This test watches for 7, 8 or 9 consecutive observations above or below the centerline. The presence of such a run indicates

that the evidence is strong and that the process mean or variability has shifted from the centerline.

2. Mixing/Overcontrol Test: Also called the Avoidance of Zone C Test. This test watches for eight subgroups in a row on both sides of the centerline avoiding Zone C. The rule is: Eight successive points on either side of the centerline avoiding Zone C, signals an out-of-control condition.
3. Stratification Test: Also known as the Reduced Variability Test. This test watches for fifteen subgroups in a row in Zone C, above and below the centerline. When 15 successive points on the X chart fall in Zone C, to either side of the centerline, an out-of control condition is signaled.

3.2.3 Trend Tests
This class of tests point out a trend resulting in a process performance shift. Neither the chart centerline nor the zones come into play for these tests and thus they may be applied to both X and R charts.

1. Oscillatory Trend Test: it watches for fourteen alternating up or down observations in a row. When 14 successive points oscillate up and down, a systematic trend in the process is signaled.
2. Linear Trend Test: it watches for six observations in a row steadily increasing or decreasing. It fails when there is a systematic increasing or decreasing trend in the process.

3.3 Causes Investigation
SPC is only able to detect whether the process performance is “out of control” and if an anomaly exists. It doesn’t support the manager during the causes investigation and the selection of the appropriate corrective actions. This solution extends the SPC-theory by providing a specific interpretation (Table 2) of the anomaly for each run test failure (section 3.2) from the software process point of view, and suggesting possible causes that make the process “Out of Control” (Baldassarre, 2004). More precisely, the authors have arranged and interpreted the selected SPC indicators (Table 1) in logical classes: sigma (RT1, RT2, RT3), limit (RT4, RT5, RT6) and trend (RT7, RT8), for details refer to (Baldassarre, 2004).

3.3.1 Sigma Tests
They provide an “early” alarm indicator that must stimulate searching for possible assignable causes and, if the case, identify and eliminate them. One and Two sigma tests point out a potential anomalous “trend” that “may” undertake assignable causes. In general, due to the high variance in software processes especially when we manage individual rather than sample data, the faults highlighted by these tests could be numerous but less meaningful than in manufacturing contexts. For example, in a manufacturing process a party of poor quality raw material may be a potential assignable cause that must be investigated and removed. In a software process, a possible assignable cause may be an excessive computer crash due to a malfunctioning peripheral but also to a headache of the developer. Different considerations could be made if the point on the chart represents a group of observations, such as the productivity of a development team. In this case the

peaks accountable to a single developer's behavior are smoothened. Therefore, the point on the charts may express a general behavior determined by an assignable cause.
Similar considerations can be made on the use of *Three sigma test*, based on a single observation that falls outside limits, rather than *One or Two sigma* tests, that refer to a sequence of observations and thus to a "potential behavioral trend".

3.3.2 Limit Tests

This class of tests point out an occurred shift in process performances. They highlight the need to recalculate the control limits when the actual ones are inadequate, because they are too tiny or larger than required. In software process monitoring and improvement we represent a measurable characteristic that expresses human related activity outcomes (time spent, productivity, defect found during inspection etc.) on a control chart. Thus while a single point falling outside control limits can be interpreted as the result of a random cause, a "sequence" of points means that something has changed within the process.
The *Run above or below the Centerline Test* watches for 8 points on one side of the central line. If this pattern is detected, then there is strong evidence that the software process performance has changed in better or worse. The longer the sequence is, the stronger the evidence is.
A failure of the *Mixing/Overcontrol Test* could mean more than one process being plotted on a single chart (mixing) or perhaps over control (hyper-adjustment) of the process. In software process this test failure highlights that the process is becoming less predictable than in the past. Typically this occurs immediately after an induced improvement, and continues until the improvement is fully acquired by the developers or organization.
A failure of the *Stratification Test* can arise from a change (decrease) in process variability that has not been properly accounted for in the X chart control limits. From the software process point of view this is a typical behavior of process when a maturity effect is identified. Introduction of a new technology in a software process is usually followed by, an unstable period until developers become more confidant and performance variability decreases. Substantially, although in SPC theory this test highlights the presence of an assignable cause, in software process the interpretation of this test may be positive: the process is becoming more stable and predictable than in the past.

3.3.3 Trend Tests

While the previous tests class points out the presence of an occurred shift, this one highlights an ongoing or just occurred phenomena that represents an ongoing shift that needs to be investigated. Typically, a failure in this test class can be the result of both spontaneous or induced process improvement initiatives. The tests will be briefly commented.
When the *Oscillatory Trend Test* is positive, two systematically alternating causes are producing different results. For example, we may monitor the productivity of two alternating developer teams, or monitor the quality for two different (alternating) shifts. As a consequence the measurable characteristic observed must be investigated in a more straightforward way in order to isolate the two causes. Probably, when this test fails we are observing the wrong characteristic or the right one measured in a wrong way.
The *Linear Trend Test* fails when there is a systematic increasing or decreasing trend in the process. This behavior is common and frequent in software processes. It is the result of an

induced process improvement, such as the introduction of a new technology, or a spontaneous one, such as the maturation effect. This test, give insightful remarks when it fails on R chart and it is interpreted jointly between X and R charts. For example:

- If R chart shows a decreasing trend as in Figure 8(d), a possible interpretation is that the process is going asymptotically towards a new stability point: better as in Figure 8(b) or worse than actual Figure 8(a). If this is the case, this test failure should be followed by a limit test failure (typically test 4) on X chart. Another situation is represented in Figure 8(c) i.e. a process is going towards a more stable situation around the central line, after a strong period of destabilization.
- If R chart shows an increasing trend, as in Figure 9(d), then the process is becoming unstable, its performance are changing in a turbulent manner and it is far from reaching a new point of stability (see as in Figure 9(a, b, c). Typically this test failure occurs together with test 5 failure on X chart.

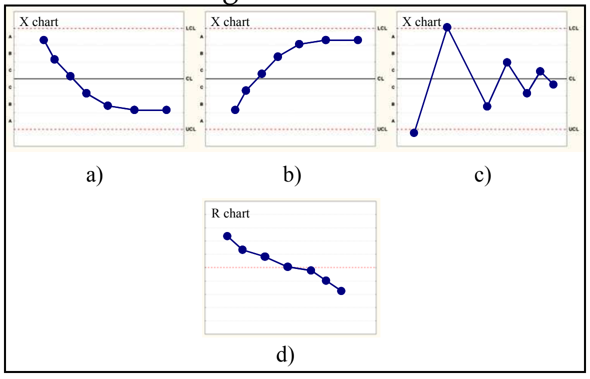


Fig. 8. Decreasing linear trend test interpretation

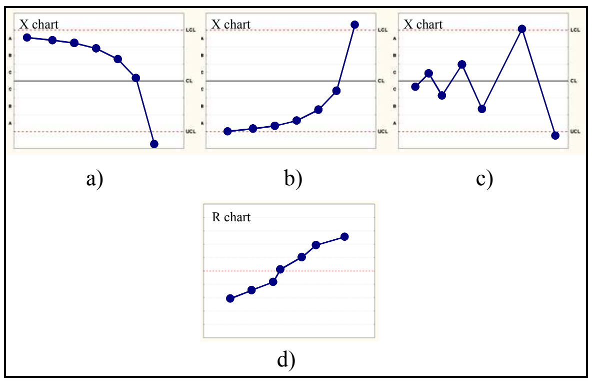


Fig. 9. Increasing linear trend test interpretation

As so, according to the interpretations given, we are able to define the following function:

φ: {Run-Test Failures} ➔ {Process Changes}
"detected anomalies" "what happens"

SPC Theory		Process Changes	
Run-Test Failure	**Process Performance**	**Type**	**What Happens**
None	In Control	None	Nothing
RT1	Out of Control	Occasional	Early Alarm
RT2	Out of Control	Occasional	Early Alarm
RT3	Out of Control	Occasional	Early Alarm
RT4	Out of Control	Occurred	New Mean
RT5	Out of Control	Occurred	Increased Variability
RT6	Out of Control	Occurred	Decreased Variability
RT7	Out of Control	Occurred	New Sources of Variability
RT8	Out of Control	Ongoing	Ongoing Phenomena

Table 2. Run-Test Interpretation Details.

For each run-test failure, φ is able to relate the "detected anomalies" to "what happens" within the process and suggest their cause.

3.4 Tuning Sensibility

SPC control limits need to be recalibrated according to relevant process performance changes. The sensibility of the monitoring activity has to be tuned continuously. The risk of not tuning sensibility is to miss anomalies as the result of using larger limits than necessary or having several false alarms.

- The monitoring activity based on SPC is carried out with control limits as baselines within which the process can vary randomly. Process is monitored according to specific characteristics (known as measurement objects) selected by the manager.
- Even when control limits are well estimated they can become obsolete due to process performance changes.
- Control limits are too tight, too wide, or the central line is no longer representative of the average process performances.
- Measurement object is no longer representative, the measures used may no longer express process variability.

In both cases it is necessary to:

1. identify when a relevant process performance change occurs;
2. tune the control model (i.e. recalibrate control limits) according to performance changes.

Point (1) follows from the experience acquired during empirical validation of the SPC approach in a previous study (Baldassarre et al., 2004). Following to this experience we have generalized a set of relations between "what happens" in the process and what the best actions to undertake are (Table 3).

Process Changes		**Tuning Actions**
Type	**What Happens**	
None	Nothing	No Action
Occasional	Early Alarm	No Action
Occurred	New Mean	Identify new control limits (new reference set)
Occurred	Increased Variability	Identify new control limits (new reference set)
Occurred	Decreased Variability	Identify new control limits (new reference set)
Occurred	New Sources of Variability	Identify a new measurement object
Ongoing	Ongoing Phenomena	No Action

Table 3. Relationship between Process Changes and the necessary SPC Tuning Actions.

According to such relations and to "Process Changes" described through the "run-test interpretation" we have defined the following function:

$$\underset{\text{“what happens”}}{\boldsymbol{\psi}: \{\textit{Process Changes}\}} \rightarrow \underset{\text{“what to do”}}{\{\textit{Tuning Actions}\}}$$

Ψ is defined so that it assigns the appropriate tuning actions needed to update the SPC settings preserving the sensibility of monitoring.
Thus ψ can be defined as follows:

- if the process change is "Occasional", the process performance:
    - should be the same as in the past if assignable causes have been detected and removed or, if this is not the case, further observations are needed to exhibit the new process performance;
    - is probably changing due to the fact that assignable causes were made part of the process. In this case further observations have to be collected.

In both cases the control limits and the measurement objects remain the same.

- if the process change is "Occurred":
    - if process mean or variability are changed then the control limits should always be recalculated in order to determine a new reference set that expresses the new process performance. The candidate points to be included in the reference set are those responsible for the test failure.
    - if there is a new source of variability then the different sources must be identified, separated and tracked on different charts.
- if the process change is "Ongoing" additional observations are needed to determine reliable limits for the process because the actual observations express a change in actions and thus, they are not suitable for a reference set. In this case "no action" is advisable.

Point (2) derives from composing functions φ and ψ, in ρ = ψoφ:

$$\underset{\text{“detected anomalies”}}{\boldsymbol{\rho}: \{\textit{Run-Test Failures}\}} \rightarrow \underset{\text{“what to do”}}{\{\textit{Tuning Actions}\}}$$

ρ for each statistical "signal" suggests the suitable action to undertake to preserve monitoring sensibility (Table 4).
Section 2, therefore, outlines a quick and effective solution that takes into account the issue of process monitoring, allows to identify anomalies, suggests the most appropriate tuning actions and preserves the monitoring model in use.

Run-Test Failure	**Tuning Actions**
None	No Action
RT1	No Action
RT2	No Action
RT3	No Action
RT4	Identify a new control limits
RT5	Identify a new control limits
RT6	Identify a new control limits
RT7	Identify a new measurement object
RT8	No Action

Table 4. Relationship between the Signals and the SPC Tuning Actions

Let us now apply these concepts to the explanatory figures 10 and 11. We can see that RT1, RT2, and RT3 are classified as "occasional" process changes. They detect an early alarm, and according to ψ do not require any tuning action. On the other hand, RT4 and RT5 are classified as "occurred" process changes because the process mean has changed (RT4) and the process variability, considering the limits in use, has also increased (RT5) as can clearly be seen in figure 10. Indeed, the observed data points, from 16 on, no longer fall within the fixed limits. Consequently, in accordance to ψ and to the guidelines in table 4, new control limits must be calculated. Figure 11 shows the result of the tuning action, i.e. the new control limits calculated from data points 16-30.

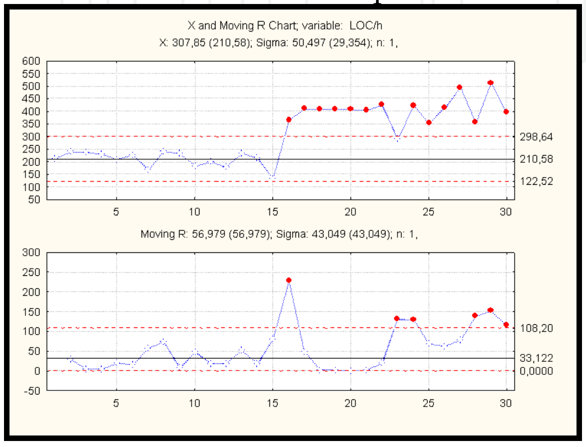


Fig. 10. RT4 and RT5 suggesting a shift in process performances

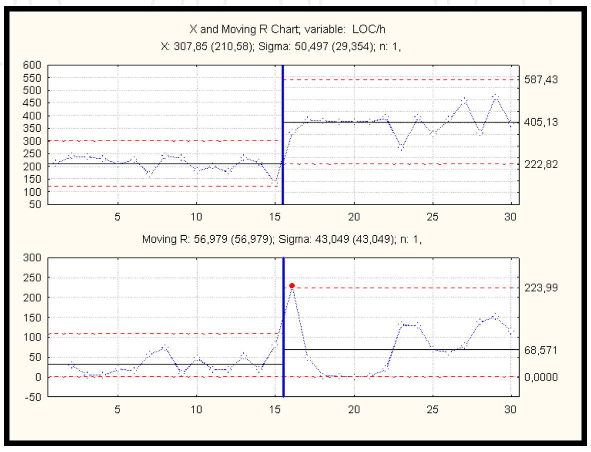


Fig. 11. new control limits calculated from data points 16-30

4. Discussion and final remarks

The presented framework, starting from the analysis of the Statistical Process Control as commonly used in the manufacturing contexts, and based on the issues that characterize software production, presents a set of evolutions and improvements that allow to:

- take into account the trends of observations rather than exclusively considering, single data points, even if anomalous. Indeed, in software and in human intensive processes, the behavioural trends are more significant than the single observations. Furthermore, in software, a single event such as an observation that falls outside the limits is not as critical as an observation in the manufacturing context. Indeed, in the latter case, an observation out of the limits is most likely an indicator that leads to discarding part of the production and stopping the production chain to avoid further relevant economical losses. Fortunately, in software it is possible to "rework" rather than discard the work already produced. The framework presented in this paper on one hand implies Run Tests that focus on a long-sequence of events (Limit and Trend tests) and, on the other, reinterprets the Run Tests based on a short-sequence (Sigma Test) reorganizing them in meaning and effect.
- make up for the lacks of SPC in the investigation phase of the anomalies and in identifying appropriate interventions to make the monitored process stable again. In this sense, it foresees a function φ that, based on the anomalies detected by the Run-Tests, determines what happens in the process, i.e. identifies the changes

occurred or taking place. As so, focused and specific actions can be identified and carried out in order to regain a stable process.

- adapt the sensibility of monitoring actions with respect to the actual performances of the monitored process. This characteristic is particularly important in pursuing the effectiveness of monitoring. The current literature does not present useful guidelines for determining when the control limits should be recalculated, in that they are no longer representative of the process performances. Consequently an incorrect use of SPC occurs, based on inadequate control limits which lead to ineffective monitoring and control actions: too wide limits do not allow to promptly raise significant variations, while too narrow ones determine numerous false alarms. The proposed framework foresees the ψ function that associates Tuning Actions, expression of "what to do", to Process Changes, the expression of "what happens". This assures a dynamic and continuous calibration of monitoring based on the actual observed process performances.

The framework represents an alternative to other software process monitoring techniques, which can generally be considered as based on expert judgment, use measures collected in time, and subject to subjective evaluations. In this sense, it is interesting to point out that the framework:

- makes it possible to characterize process performances, even without having any previous knowledge, by determining a reference set through a deterministic procedure. Note that lack of previous knowledge usually occurs for innovative processes, or for processes that are used in different contexts with different maturity levels, or refer to various application domains (technical rather than business). Moreover, in our framework, control limits are not an expert-based estimation, but an actual expression of the process itself.
- provides a conceptual manner for defining process anomalies and, at the same time, an operational means for identifying them. Without such instruments (conceptual and operational) the interpretation of a trend rather than a single observation would completely rely on the project manager, who may not necessarily have the previous knowledge needed and thus, may neglect important events or focus on irrelevant ones resulting in ineffective monitoring.
- represents an objective rather than subjective tool, a clear reference point, follows rom explicit reasoning and based on a solid theoretic model (SPC).

Nevertheless, software process monitoring still represents an open issue. As discussed in (Baldassarre et al., 2007), there are many aspects related to software process measurement such as the difficulty of collecting metrics, their reliability and the selection of monitored process characteristics (Sargut & Demirors, 2006); the violation of assumptions underlying SPC (Raczynski & Curtis, 2008); predominance of human factors in software processes that can impact on the SPC-theory and monitoring effectiveness [17]. All these aspects leave much space for subjective management decisions that can influence the success/failure of monitoring activities. Given these limitations, this framework is not intended as the solution to monitoring problems, nor as a silver bullet for applying SPC to software processes.
Rather, it should be considered as a perspective on how SPC can contribute to practically solve some monitoring issues according to the authors' experience from the trench in real industrial software projects. It can be seen as a contribution for guiding practitioners

towards a more disciplined use of SPC starting from understanding how it can really address software process monitoring. In this way operational, practical issues and pitfalls of SPC can be faced more systematically.

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