Project monitoring by dynamic statistical control charts

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Abstract

Project monitoring activities are fundamental to assure a timely identification of unacceptable project's deviations from the baseline, so that corrective actions may be taken to bring the project back in line with its objectives. Regarding this, the most used approach is the Earned Value Management (EVM) technique. However, traditional EVM metrics do not allow the Project Manager (PM) to recognize if project deviations are due to the natural project variability or to systemic and undiscovered causes that are moving the project to unacceptable out-of-controls. With this recognition, a statistical project control system based on the use of dynamic Shewhart's and CUmulative SUM (CUSUM) control charts is proposed in the present paper to deal with the project monitoring problem. The dynamic design is based on the update of charts' parameters as new data become available over time and makes charts able to be used since the initial phase of the project execution when available measurements on observed variables are still only a few. The efficaciousness and robustness of the designed statistical-based approach are demonstrated by its application to a set of real projects.

Keywords: Project monitoring; Earned Value Management; Dynamic control charts; Shewhart's and CUSUM control charts.

1. Introduction

According to the Project Management BOdy of Knowledge (PMBOK) Guide (2017), the "monitoring and controlling process group consists of those processes required to track, review, and regulate the progress and performance of the project, identify any areas in which changes to the plan are required, and initiate the corresponding changes". Therefore, project monitoring and controlling activities take place in parallel with the project execution to assure that the project is within acceptable variances of cost, schedule, and scope with respect to plans. If an unacceptable variance is observed, appropriate corrective actions are to be taken to bring the project in line with its aims and constraints.

Over the last decades, the project monitoring and control problem has been widely researched in the literature, and techniques able to support the Project Manager (PM) in detecting project deviations as well as in making the appropriate decisions at their occurrence have been investigated. Regarding this, the most widely used project monitoring approach is the Earned Value Management (EVM) method (Kauffmann, Keating, & Considine, 2002; Anbari, 2003; Kim, Wells, & Duffey, 2003; PMBOK Guide, 2017; Ong, Wang, & Zainon, 2016). Introduced in the 60s by the U.S. Department of Defence, the EVM method is based on three different metrics, i.e. the Planned Value (PV), the Actual Cost (AC) and the Earned Value (EV). As defined in (PMBOK Guide, 2017):

- the PV (or Budgeted Cost of Work Scheduled-BCWS) is the authorized budget assigned to scheduled work;
- the AC (or Actual Cost of Work Performed-ACWP) is the cost actually incurred for the work performed on a given activity, during a specific time period;
- the EV (or Budgeted Cost of Work Performed-BCWP) is a measure of work performed, expressed in terms of authorized budget for that work.

Afterward, further metrics are derived from PV, AC, and EV to highlight the project deviation in respect to the approved baseline. Some of the aforementioned derived metrics are listed below.

- The Schedule Variance (SV) is a measure of the schedule performance expressed as the difference between EV and PV. SV highlights whether the project is behind (SV<0) or ahead (SV>0) of schedule.
- The Cost Variance (CV) is the amount of budget deficit or surplus at a given point in time, expressed as the difference between EV and AC. A positive value of CV indicates that the

amount earned by the performed work is higher than the one actually spent, whereas a negative value of CV indicates that it has been spent more than the budget available for the performed work.

- The Schedule Performance Index (SPI) is a measure of the schedule efficiency expressed as the ratio of EV to PV. It measures how efficiently the project team is using its time. An SPI>1 indicates that the project is ahead of schedule since more work has been completed compared to the planned one.
- The Cost Performance Index (CPI) is a measure of the cost efficiency of budgeted resources, expressed as the ratio of EV to AC. A CPI>1 indicates that the cost for completing the work is less than the planned one.

During the project execution, EVM metrics previously described supporting the PM in the identification of project deviations from the baseline. They are simple to use, but they do not explicitly take into account the uncertainty that affects project development. Actually, EVM metrics simply verify whether and how the project deviates from the baseline in terms of time and cost. On the other hand, they do not provide any information about the intrinsic variability of the process (considered as acceptable) or the occurrence of an unexpected situation that may affect the current and future project performance. Therefore, on the basis of the traditional EVM metrics, the PM is not able to recognize if project deviations are due to the natural project variability or to some external cause, which might distort the initial forecasts. Essentially, the lack of guidelines (about reasonable tolerance limits able to discriminate between acceptable and unacceptable performance variations) makes the use of EVM mainly based on the PM's experience and knowledge. With this recognition, a statistical project control system based on the use of dynamic Shewhart's and CUmulative SUM (CUSUM) (Page, 1954) control charts is proposed in the present paper to monitor SPI and CPI values. Differently from control charts traditionally used in the manufacturing field and only recently in project monitoring, the dynamic design is based on the update of charts' parameters as new data become available over time. Therefore, such a dynamic feature makes charts able to be used since the initial phase of the project execution, when available measurements on observed variables are still only few. In addition, to the best of the authors' knowledge, this is the first attempt in the literature to apply CUSUM to deal with the project monitoring problem. The application of the proposed statistically-based approach to a set of real projects demonstrates the efficaciousness and robustness of the combined use of the Shewhart's control charts for individual measurements and moving range along with the CUSUM chart to improve the whole project monitoring process.

The remainder of the paper is organized as follows. The literature review is reported in Section 2 whereas a brief explanation of Statistical Process Control (SPC) charts is given in Section 3. Afterward, the designed statistically-based approach to project monitoring is detailed in Section 4 and the application cases reported in Section 5. Conclusions are finally drawn in Section 6.

2. Literature review

EVM has been widely researched in the literature as a powerful technique for project monitoring. Beyond traditional applications of EVM, many contributions propose statistical analyses with the aim of improving the accuracy of estimates at completion, in terms of both project's cost and time (Chen, 2014). In (Narbaev & De Marco, 2014a, 2014b), authors propose a new cost estimate at completion methodology to forecast the final cost of ongoing projects. In particular, a new regression approach is used and different growth models (i.e. logistic, Gompertz, Bass, and Weibull) (Christensen, Antolini, & McKinney, 1992) are tested to describe the cost expenditure behavior of construction projects. The functional form and parameters of all these models reflect the nature of physical improvement progress and satisfy the requirements for a typical s-shaped cost pattern of construction projects. Moslemi Naeni, Shadrokh, and Salehipour (2011) propose a fuzzy-based approach to estimate the project's cost and time at completion. Plaza and Turetken (2009) investigate the effect of the learning process on the project team performance and include such aspects into the estimate of the project's time at completion. Colin et al. (2015) take into account the multivariate nature of EVM and propose a multivariate model that implements a principal component analysis on a simulated schedule control reference. In (Brandon, 1998) and (Khamooshi & Golafhani, 2014), enhanced EVM-based approaches are suggested to explicitly take into account the uncertainty on activities' costs and duration. Within the EVM framework, Caron, Ruggeri, and Merli (2013) develop a Bayesian model to calculate a confidence interval for the estimate of both the project's cost and schedule at completion. In order to estimate the time at completion, Lipke (2003) introduces the Earned Schedule (ES) concept to overcome discrepancies between traditional SV and SPI metrics. Successively, Lipke et al. (2009) estimate the project's cost and time at completion on the basis of data arising from the application of the EVM technique. Therefore, expected values and related confidence limits are calculated at every tracking period. Warburton, De Marco, and Sciuto (2017) investigate the use of nonlinear cost growth models in generalized ES method to provides more accurate project duration estimates at completion. Referring to the construction sector, Martens and Vanhoucke (2018) empirically validate three types of analytical tolerance limits for project schedule control using EVM metrics and propose a novel approach to construct analytical tolerance limits that incorporate activity risk information.

Statistical Process Control (SPC) charts have been extensively used in the manufacturing field, whereas their application to project monitoring is quite recent. In this regard, the first work is proposed by Lipke and Vaughn's (2000), who suggest Shewhart's charts for individual measurements and moving the range to control the indicators (1/CPI) and (1/SPI) related to a software project. Later, Bauch and Chung (2001) make use of the historical data of 20 similar projects to calculate, at every tracking period, the central line and the tolerance limits of the Shewhart's chart. Once designed, the chart is statically used to verify the performance of similar projects. However, the same authors highlight how a sufficient number of reasonably similar projects may not exist. Namely, every project is unique by definition and unlikely comparable to others even if similar. Wang et al. (2006) observe the CPI and SPI values of six similar software projects and verify the Normal distribution of collected data by the Skewness-Kurtosis test. Traditional Shewhart's charts are then designed to monitor CPI and SPI of a new eighteen-month project. Leu and Lin (2008) employ the traditional Shewhart's charts for individual measurements and moving range into the EVM technique and provide a normalizing transformation of raw project data. A database of 73 similar projects is used for the development of control charts where controlled parameters are the traditional CPI and SPI metrics. Also, Aliverdi, Moslemi Naeni, and Salehipour (2013) focus on the SPI and CPI monitoring by means of the traditional Shewhart's charts. Referring to a single project, authors observe the aforementioned indicators for a thirty-month period, then they propose the Box-Cox and Johnson transformations to normalize data, and finally, they use charts developed on the basis of data collected during the thirty-month period to monitor the remaining ten months of the project. Therefore, the method requires a high number of records to provide estimates on the future project development. As a consequence, it is not usable for short-term projects.

3. Statistical Process Control (SPC) charts

Statistical control charts are a powerful and widely used tool to verify whether a manufacturing process maintains stationary conditions over time (Woodall & Montgomery, 2014). Their easy implementation and interpretation, as well as their flexibility, have increasingly extended the use of control charts from the original manufacturing field to all sectors of the production and service supply, also thanks to the spread of quality paradigm, which requires the use of appropriate control techniques (Tsung, Zhou, & Jiang, 2007; Woodall, 2006).

Referring to a process wherein a measurable feature (i.e. x) has to be monitored over time, Shewhart's charts of the sample mean $\overline{X}$ and sample range R are the most used ones. Specifically, the $\overline{X}$ chart is used to monitor the steady-state condition of the process mean, whereas the R chart controls the process variability. Static $\overline{X}$ and R charts are designed based on an initial sampling stage to collect measurements on x followed by the calculation of control limits. Therefore, mean values and ranges of samples, periodically and randomly selected, are plotted on the two aforementioned charts in order to verify whether they fall within the lower and upper control limits (i.e. LCL and UCL respectively). If the latter does not occur, then the process is considered out-of-control, namely some unexpected cause occurred and implied a change of the considered variable, resulting in a shift of its variance and/or mean value. Apart from the economic chart design and the adaptive control charts (Lorenzen & Vance, 1986; Inghilleri, Lupo, & Passannanti, 2015), the statistical design of the $\overline{X}$ chart is based on the definition of the probability of errors of type I (i.e. α) and II (i.e. β) respectively (Duncan, 1974). From risks α and β, the frequency of a wrong interpretation of data is computed. Such frequency is measured in terms of the average number of samples randomly selected between two consecutive errors of the same type (i.e. L_a from α and L_r from β). In practical applications, α is usually set equal to 0.0027, and the control limits are symmetrically located at $\left(\pm 3 \cdot \sigma_{\bar{x}}\right)$ from the mean line $\overline{X}$ under the hypothesis of Normally distributed variables. $\sigma_{\bar{x}}$ is the standard deviation of samples means. As concerns the R chart, control limits are located on the basis of some proper parameters (i.e. D_3 and D_4) (Duncan, 1974). The sample size may be computed by setting the mean shift corresponding to the error β. However, in the project monitoring process, the sample size is always one for every variable observed (e.g. CPI, SPI, etc..). As a consequence, a mean chart for individual measurements needs to be used, whereas the variability of the process is controlled by means of a chart for moving range.

Apart from those proposed by Shewhart, literature contributions on SPC suggest further control charts, everyone having some specific characteristics (Montgomery, 2013). Among them, the CUSUM chart (Page, 1954) reports the cumulative sum of differences between sample means (or single values) and the reference value k. At the i^{th} sample, let cum_sum_i and x_i be the cumulative sum and the measurement on the observed variable x respectively. Afterward, the following equation (1) holds when downward protection is required.

$$cum\_sum_i = min\{cum\_sum_{i-1} + (x_i - k);0\} \tag{1}$$

On the other hand, the min operator in (1) is replaced by the max operator when upward protection is required. The process is deemed to be out-of-control when the cumulative sum exceeds a given threshold value h. Therefore, the design of the CUSUM chart consists in determining the sample size and the threshold value h. To this aim, the Kemp nomogram (Kemp, 1962) is used (**Figure 1**). Specifically, the target value x_a and the critical value x_r are to be firstly specified. Afterward, risks α and β, expressed in terms of L_a and L_r respectively, are defined in correspondence to x_a and x_r. Finally, the sample size n and the parameter h are determined by tracing the line through L_r and L_a, and assuming k=(x_a+x_r)/2.

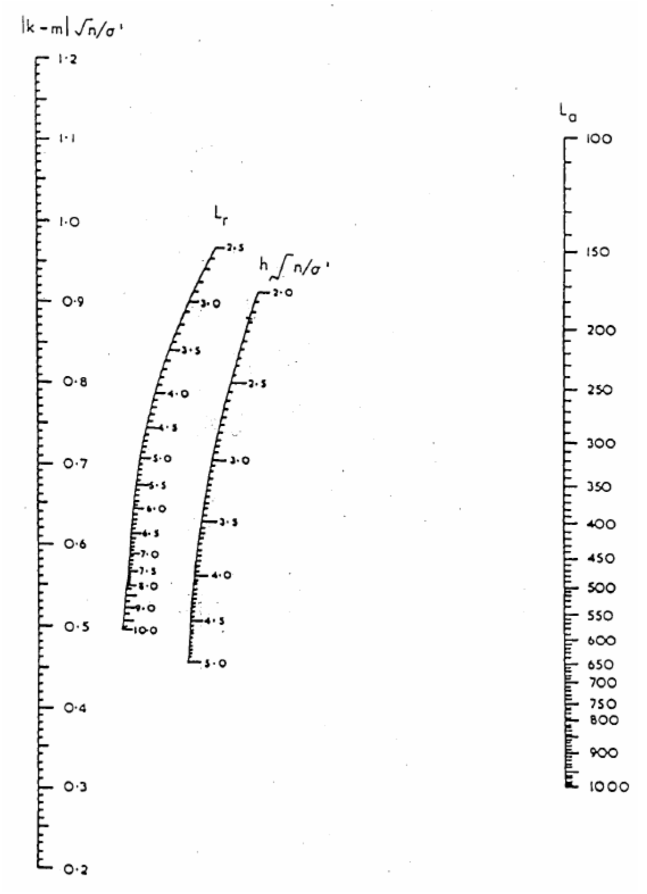

Figure 1: Nomogram of Kemp for the design of the CUSUM chart (Kemp, 1962)

If the sample size is constrained (such as in the project monitoring problem where n=1 for every observed variable), only L_a or L_r may be set, whereas the other value will be derived.

4. Design of SPC charts for project monitoring

Aiming to accurately locate control limits, the application of statistical control charts is based on the knowledge of the probability density function of every observed variable, traditionally assumed to be distributed as a Normal. Nevertheless, the robustness of control charts has also been proven when the traditional assumption about the Normal distribution of data does not hold (Montgomery, 2013). Actually, the only consequence of dealing with non-Normal distributed data is a slight increase in errors of type I and II. Despite that, the main part of literature contributions on SPC suggests a normalizing transformation of data to trace back to Normal distributions. However, performing whatever normalizing transformation requires a huge number of data. In regard to this, data available for the statistical project monitoring are generally poor, so that their eventual non-Normal distribution cannot be verified to promptly perform a normalizing transformation. To overcome such a problem, Aliverdi et al. (2013) make use of the first thirty monitoring months of a project to verify the distribution of data, perform the required transformation and design the traditional Shewhart's control charts to monitor the remaining ten months of the same project. Nevertheless, such an approach has two main drawbacks. On the one hand, it is based on the assumption that the project is under control over the thirty-month period used to collect measurements on CPI and SPI. On the other hand, the developed charts are used to monitor only the final phase of the project. In this regard, it is recognized how corrective actions are more useful and effective if taken as soon as possible.

Conversely, the proposed dynamic design allows the use of statistical control charts since the initial phase of the project execution, when data on observed variables are still sparse. Dynamic control charts are updated as the project goes ahead and new measurements become available. At a generic tracking period, collected data are used to estimate charts' parameters and to control the next measurement. More specifically, the first five measurements on SPI and CPI are firstly used to estimate the mean value and the standard deviation of distributions related to SPI and CPI. Afterward, the aforementioned values are used to compute the control limits of Shewhart's charts and the threshold value h of CUSUM for the sixth observation. When the sixth observation is obtained, a new and more accurate estimate of the distributions' parameters is obtained as well, and the new calculated limits and threshold h will be used for the seventh observation, and so on. Proceeding in such a way, more and more precise and reliable estimates of the charts' parameters will be obtained. In addition, the CUSUM chart is only designed for downward protection because SPI and CPI values smaller than one are undesired. Therefore, the target value x_a is set equal to the desired one (i.e. $x_a = 1$) for both SPI and CPI, whereas (x_a - x_r) is set equal to the standard deviation of the first five measurements, and L_r equal to 4.5.

5. Application cases: results

In order to verify the efficaciousness of the proposed statistically-based project monitoring approach, the OR-AS database has been used (Batselier & Vanhoucke, 2015; Vanhoucke, Coelho, & Batselier, 2016). For research purposes, such a database contains baseline scheduling data (network, resources, etc..) and EVM metrics of a wide list of real projects, covering different fields. The website is continuously under construction, and it currently includes 125 projects, both completed and in progress, whose data were obtained directly from the actual project owner. Projects monitored by means of the proposed dynamic Shewhart's and CUSUM charts have been randomly selected from the aforementioned database, considering only the ones characterized by fifteen tracking periods at least. Finally, three projects have been chosen. Related generic data are synthesized in **Table 1**. Please, refer to the database for CPI and SPI values (http://www.or-as.be/research/database).

Project name	Project description	# Activities	Planned duration	Budget at completion	Tracking periods
Brussels Finance Tower	The project consists of two parts: the renovation of the existing tower and the construction of a new office building next to it.	55	425 days*	15,440,865 €	18
Building a House	The building of a rather spacious house somewhere in Flanders.	32	195 days*	484,398 €	41
Building a Dream	A young family building the house of their dreams.	33	145 days*	241,015 €	41

*Standard eight-hour working days

Table 1: Data for selected projects (Batselier & Vanhoucke, 2015; Vanhoucke et al., 2016)

As concerns, the Brussel Finance Tower project (**Figure 2**), both the $\overline{\mathrm{X}}$ and R charts highlight an out-of-control of CPI at the 11th point. The good value of CPI (i.e. 1.0496) presumably means that none corrective action is to be implemented but it only highlights incurred costs lower than the ones planned for the considered tracking period. CUSUM does not show any out-of-control situation at the 11th point. Actually, the chart is designed for downward protection of CPI, so that increasing values are not taken into account. Instead, the next descendant trend of CPI is evident, and an out-of-control is observed at the 15th point. The latter should be investigated by the PM. As regards SPI, none warning situation is highlighted.

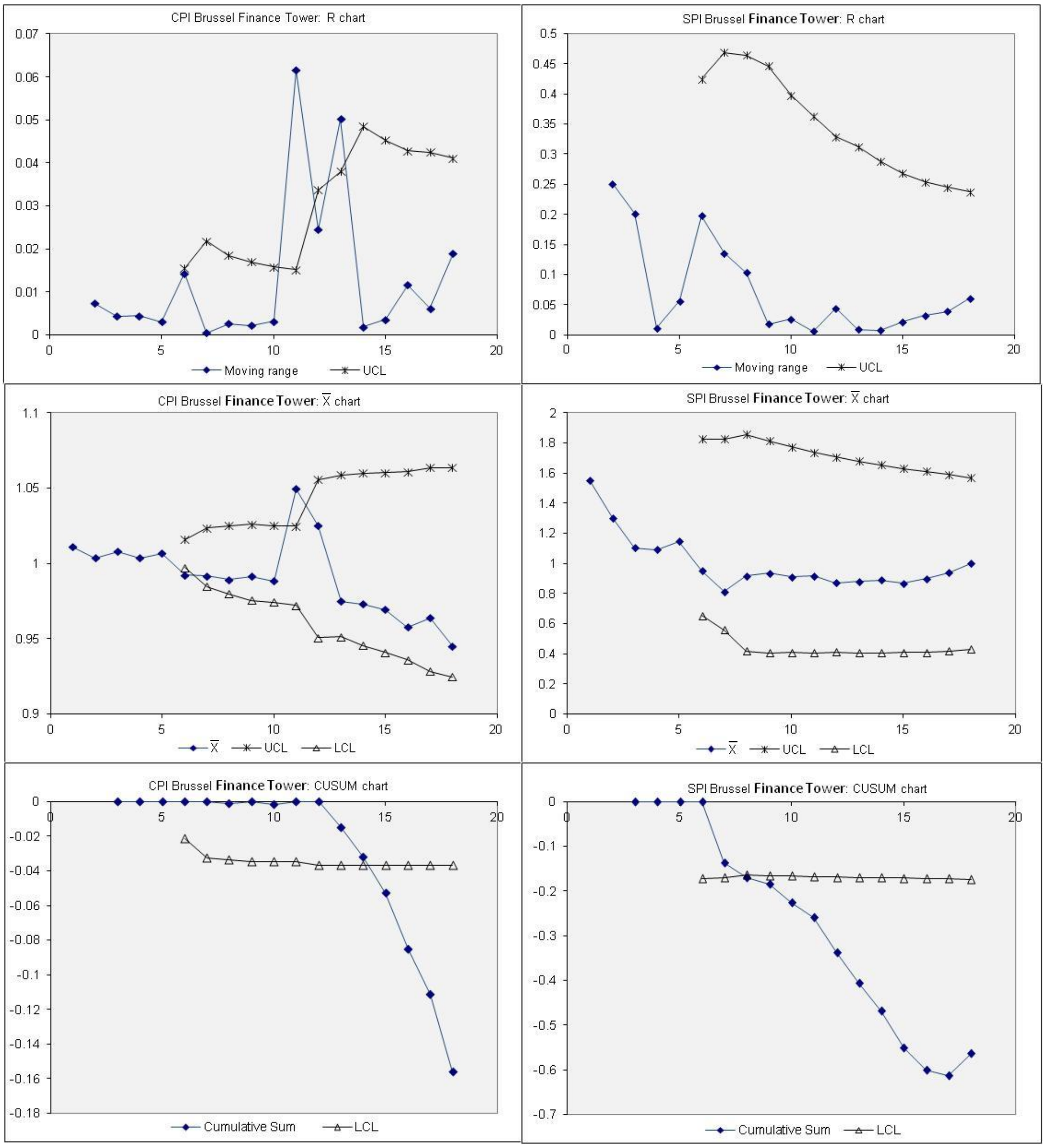

Figure 2: Shewhart's and CUSUM charts of the project Brussel Finance Tower

Referring to CPI of the project Building a House (**Figure 3**), the R chart does not show any out-of-control (the run test cannot be performed on the moving range chart). The $\overline{X}$ chart does not detect any point outside the control limits, but the run test proves that the project is out-of-control at the 12th point because of six consecutive descendent measurements. CUSUM highlights the same trend with a slight delay. Therefore, a systemic cause of deviation appears to be occurring, causing the project to move progressively away from the baseline. In addition, the next trend of CPI could presumably arise from the implementation of corrective actions. For the SPI metric, all charts immediately show an out-of-control because of the considerably small value of SPI (i.e. 0.387). Successively, the SPI trend goes back to values almost equal to one. Such a trend of SPI could be justified by the occurrence of an extraordinary event which causes the reduction of SPI up to the out-of-control situation, and the implementation of consequent corrective actions. However, the project still appears to be out-of-control in next periods, as highlighted by the run test on the $\overline{X}$ chart and confirmed by the CUSUM.

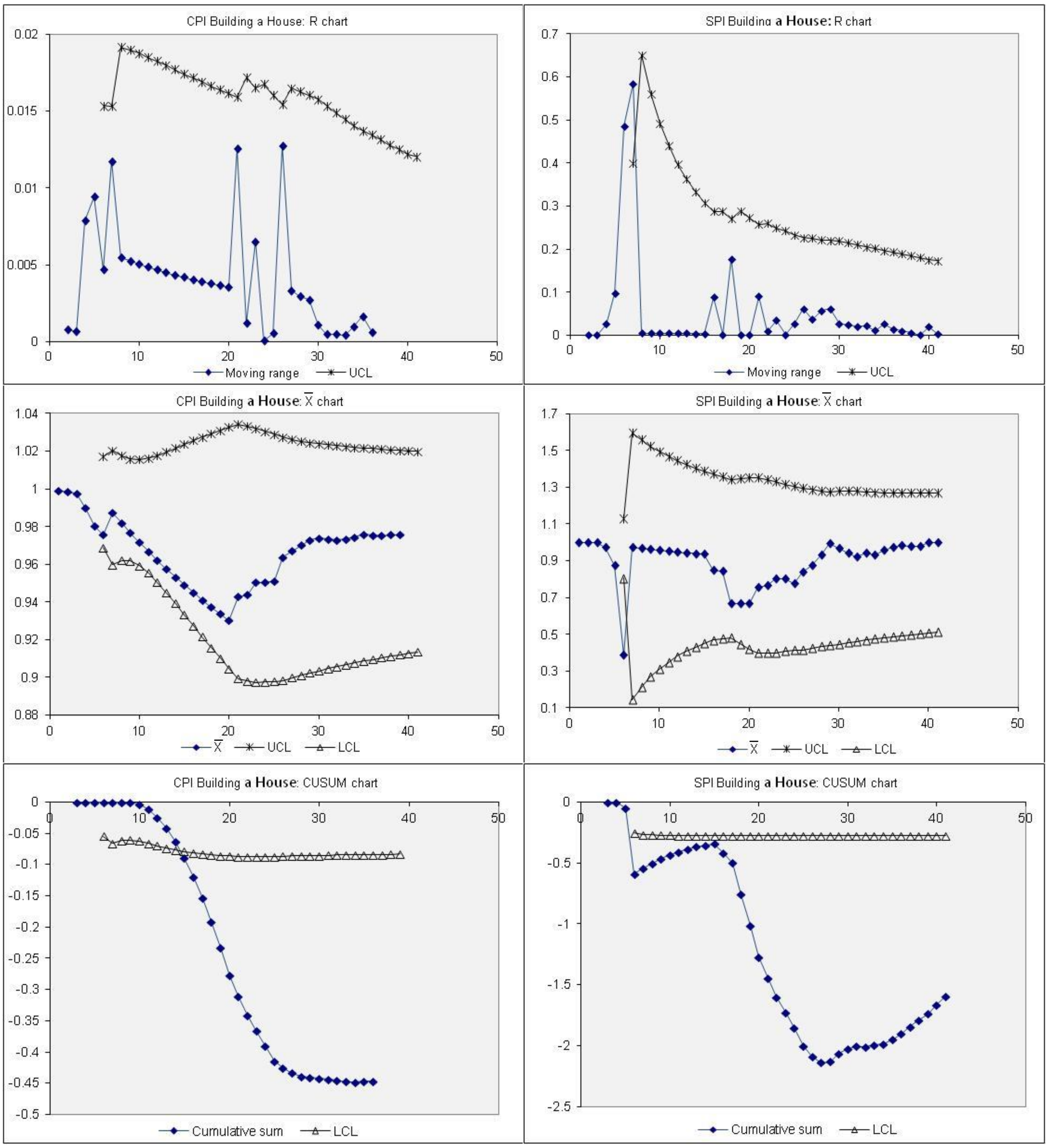

Figure 3: Shewhart's and CUSUM charts of the project Building a House

With relation to the project Building a Dream (**Figure 4**), the $\overline{X}$ and R charts do not detect any out-of-control of variables, neither CPI nor SPI. On the other hand, the two CUSUM charts immediately show how CPI and SPI values are meaningfully smaller than the desired ones. The latter proves that a systemic cause affects project performance.

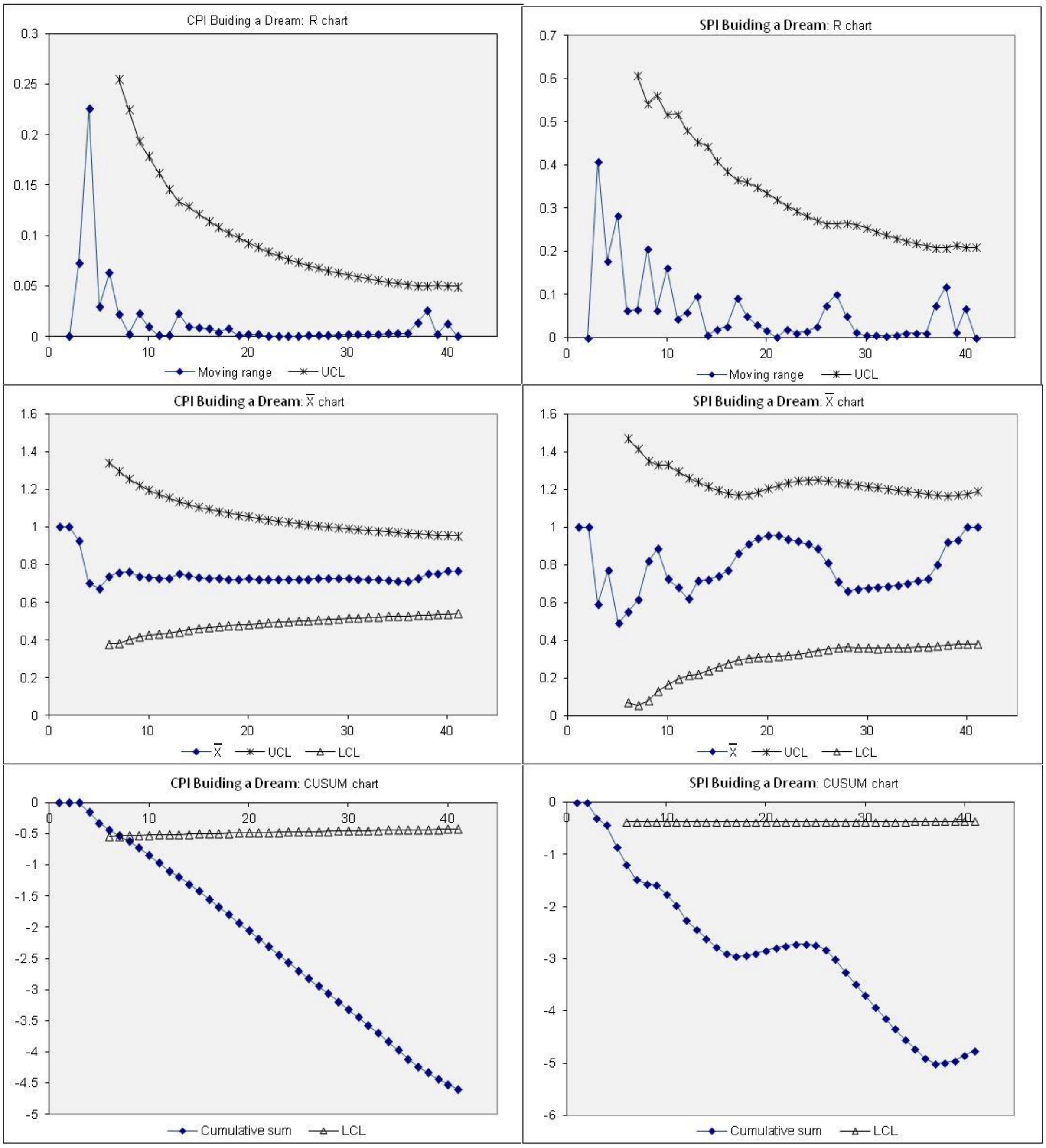

Figure 4: Shewhart's and CUSUM charts of the project Building a Dream

The fourth project analyzed is the one reported by Aliverdi et al. (2013) with the aim of comparing their approach to the one proposed in the present paper. In this regard, let's remind that Aliverdi et al. (2013) design the traditional static Shewhart's control charts on the basis of data collected during a thirty-month period when the process is assumed in control. Afterward, they use the designed charts to monitor the remaining ten months of the same project. On the other hand, results obtained by the dynamic control charts here proposed and applied to the whole project duration are reported in **Figure 5**.

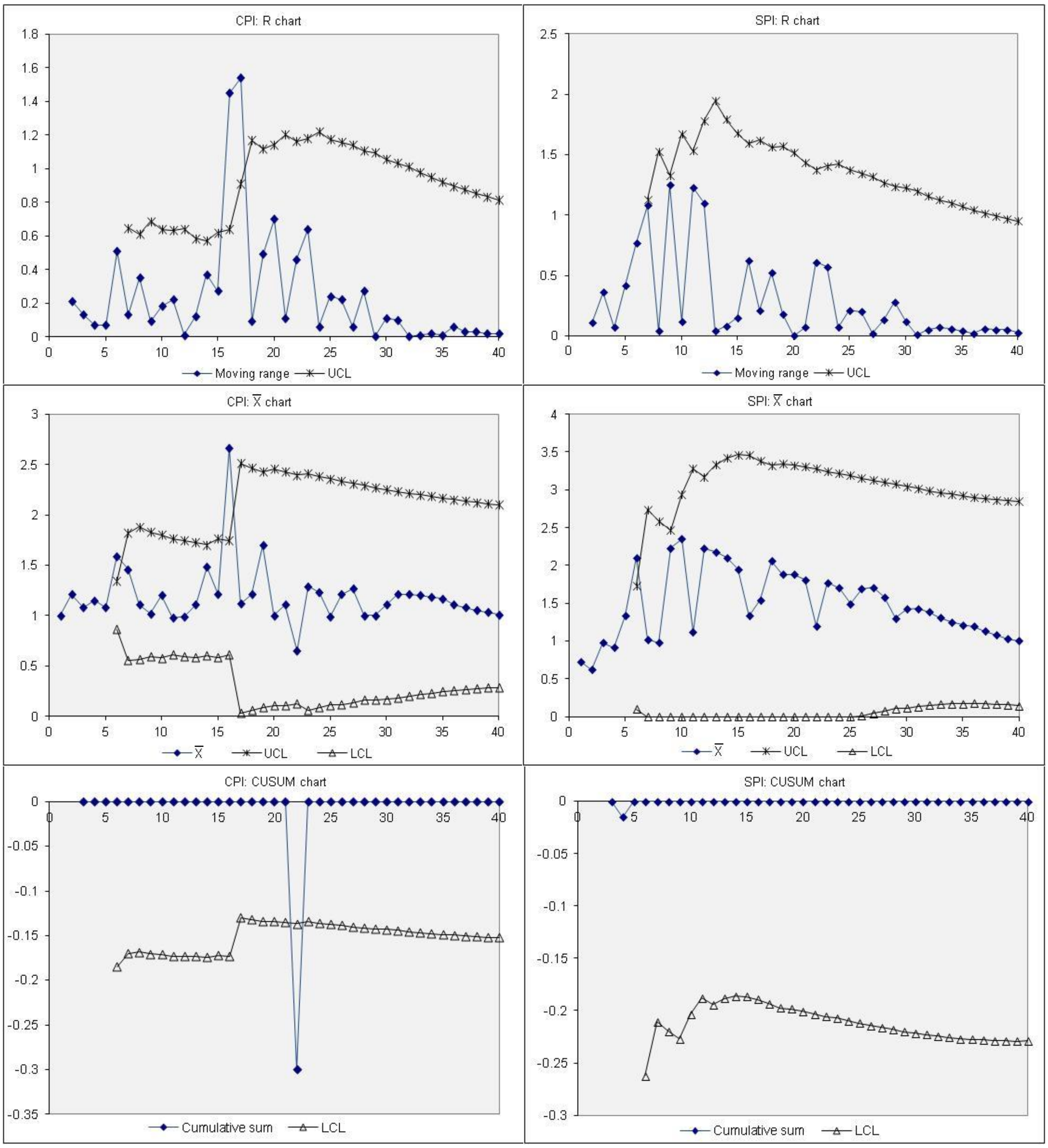

Figure 5: Shewhart's and CUSUM charts for CPI and SPI values reported in Aliverdi et al. (2013)

As regards SPI, Aliverdi et al. (2013) detect an out-of-control at point 37 as a result of the run test on the $\overline{X}$ chart. The here designed dynamic moving range and CUSUM charts (**Figure 5**) do not highlight any warning situation, whereas the sixth point is outside the control limits in the $\overline{X}$ chart. In addition, a descendent trend on which paying further attention could be noticed much earlier than the out-of-control point identified by Aliverdi et al. (2013). Referring to CPI, Aliverdi et al. (2013) consider the project in control during the last ten months when the charts are applied. Instead, the dynamic $\overline{X}$ and R charts already identify two out-of-control before the

30th point. A further warning situation is identified by the CUSUM at the 22nd measurement because of the small value of CPI (i.e. 0.65).

From the obtained results, one can state that the CUSUM chart often allows detecting out-of-control situations which the $\overline{X}$ and R charts disregard. In addition, the way it is designed (i.e. downward protection) allows focussing on small values of CPI and SPI metrics. Actually, values higher than one do not represent a warning situation to pay attention on.

6. Conclusions

The traditional Earned Value Management (EVM) method is simple to be implemented although it does not take explicitly into account the uncertainty that affects project performance. At a generic tracking period, EVM merely verifies whether and how the project deviates from the baseline. However, it does not indicate if deviations are within the expected project variability, considered as acceptable, or if systemic and undiscovered causes are taking place so moving the project out-of-control. In order to explicitly take into account such uncertainty, the use of traditional statistical control charts has been lately proposed in the literature to deal with the project monitoring problem. The present work tries to overcome some limitations of previous contributions by the proposal of dynamic control charts, which may effectively support the Project Manager (PM) since the initial phase of the project execution when available data are still few. In particular, the $\overline{X}$ chart for individual measurements as well as the one for moving range of Shewhart along with the CUSUM chart has been dynamically designed to monitor CPI and SPI values. Because of their dynamic feature, charts' parameters are updated over time as new data become available. Referring to Shewhart's charts, the PM has to properly interpret the obtained results, since the position of control limits is not very reliable at the beginning of the monitoring phase. The latter means that the PM needs to check those values plotted very close to the control limits and to monitor the control limits trend. Actually, highly variable limits may be a consequence of unreliable estimates because of the availability of few data. On the other hand, a stable trend means that estimates are more reliable.

The proposed statistically-based approach to project monitoring has been applied to a set of real projects with the aim of proving the efficacy of the combined use of Shewhart's and CUSUM control charts to detect out-of-control situations to pay attention to. In particular, the obtained results have shown that the use of the CUSUM control chart improves the efficacy of the statistical approach based on traditional Shewhart's charts only.

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