Journal of Quality Engineering and Production Optimization

Vol. 7, No. 1, Winter & Spring 2022

http://jqepo.shahed.ac.ir

Research Paper

DOI: 10.22070/JQEPO.2022.15415.1215

Improving Earned Value Management and Earned Schedule by Statistical Quality Control Charts Considering the Dependence between Cost and Schedule

Mohammad Sheikhalishahi[1] , Saeed Abdolhossein Zadeh[1], Azam Sardarabadi[1], Saba Naeimi[1]

[1] *School of Industrial and Systems Engineering, College of Engineering, University of Tehran, Iran*

*** Corresponding Author:** *Mohammad Sheikhalishahi (Email: m.alishahi@ut.ac.ir)*

Abstract *– Earned Value Management (EVM) is a technique that provides decision-makers with efficient control, analysis, and monitoring of the performance as well as the progress of a project to prevent delays and cost overruns. Earned Schedule (ES), as an extension of EVM, is introduced to deal with the problems of EVM schedule performance indicators. Using statistical quality control principles has proved to enhance the efficiency of EVM and ES. In previous approaches, schedule and cost indicators were considered independent indices, and thus the relationship between these two variables was ignored. The failure to take into account the dependency between dependent parameters can result in unrealistic and misleading results. Therefore, in the proposed approach, the relationship between two basic elements of EVM and ES, i.e. time and cost is also considered in order to more precisely analyze the results obtained from these methods. This paper proposes a multivariate quality control chart (MQCC) alongside univariate quality control charts (UQCCs) for analyzing, managing, and monitoring projects to improve the capability, accuracy, and efficiency of EVM and ES. Furthermore, to show the applicability and superiority of the proposed approach, three construction projects as case studies were applied. . The results show considerable improvement.*

Keywords*– Earned Value Management; Earned Schedule; Variation; Statistical Quality Control Charts; Multivariate Quality Control Chart.*

I. INTRODUCTION

Due to the complexity of implementing projects and also existing uncertainty in today's complicated environment, the key factor for a project's success is project management (PM). PM gains even more significance when the project is under pressure to be completed according to the agreed scope, time, and cost. Several conventional methods are utilized to monitor and report the progress of projects. Some of these models depend on the information associated with activities, whereas others are related to the work type. As a consequence, it is expected that, for certain real world situations, some of these techniques will create measures that may require control actions while others possibly may fail to do so (Al-Jibouri, 2003). For instance, traditional strategies for estimating project costs which are dependent on thorough information prepared for a particular project (e.g., bottom-up estimate or inside view) tend to result in cost overruns (Kim and Reinschmidt, 2011). Cost overruns in projects are persistently observed irrespective of project type and location. Flyvbjerg (2013) argued that there is no indication of improvement in cost prediction accuracy over the past 70 years. Thus, it is vital to have an effective tool to guide the project toward its planned target.

Manuscript Received:6- Feb -2022 & Revised: 17- May -2022 & Accepted: 29- June -2022
ISSN: 2423-3781

A. Earned Value Management and Earned Schedule

Earned Value Management (EVM) (also referred to as EV) is a project management strategy with comprehensive application to measure the progress and performance of a project against the plan at a particular date, as well as to estimate the future performance of the project in an objective manner. For this purpose, EVM incorporates efficiently the management of three key elements of a project, i.e. cost, schedule and scope. In other words, it contributes to a simultaneous time and cost control system to be carried out according to the project's scope. In summary, EVM:

- Measures the time and cost performance features of a project within the project's scope,
- Forecasts the completion time as well as the completion cost of a project, and,
- Calculates the performance and the progress of a project (Moslemi Naeni et al., 2013).

EVM helps managers to identify over-costs and delays by presenting performance variances; but, its shortcoming is that it does not notice whether the overruns are within the limits of acceptable variability of the project or if exist structural and systemic variations over the project life cycle (Pajares and Lopez-Paredes, 2011). The acceptable variability indicates levels of maximum overruns within a particular level of confidence. Indeed, EVM is conducted to complete the project on time-on budget with a satisfactory level of quality (Noori et al., 2008). It also allows for assessing and managing the project's risk by determining project's progress in monetary terms and provides an early warning of performance problems, if any (PMI, 2004). To determine three dimensions for a specific project, three measures have to be calculated: planned value (PV), earned value (EV) and actual cost (AC). More descriptions regarding these measures as well as other indices that result from the combination of these three variables are provided in Table I.

Table I. Evm Variables, Definitions And Formulae

Acronym	*Phrase*	*Definition*	*Formula*
PV (BCWS)	Planned Value	Budgeted cost of work scheduled to be completed up to a given point in time	——
EV (BCWP)	Earned Value	Budgeted cost of work performed during a given time period	——
AC (ACWP)	Actual Cost	Actual cost of work performed during a given time period	——
SV	Schedule Variance	Deviation from the schedule	EV − PV
CV	Cost Variance	Deviation from the expected cost	EV − AC
SPI	Schedule Performance Index	Being delayed/ ahead of schedule	EV/PV
CPI	Cost Performance Index	Having over-costs/being under budget	EV/AC
BAC	Budget At Completion	Planned budget of the project	——
SAC	Schedule At Completion	Initially planned duration of the project	——
PMB	Performance Measurement Baseline	Cumulative PV over time	——
EAC	Estimate At Complete	Manager's projection of total cost of the project at completion	BAC/CPI
ETC	Estimate To Complete	Cost estimate to complete the remaining work of the project	$EAC - AC$
IEAC	Independent Estimate At Completion	Forecasted final cost	$AC_{cumulative} + (BAC - EV_{cumulative})/CPI$
VAC	Variance At Completion	How much over or under budget the project is expected to be	$BAC - EAC$

The three possible results for CPI and SPI are presented in Table II.

Table II. Possible Results For Spi And Cpi

Result	*Condition*
$SPI > 1$ & $SV > 0$	Ahead of the plan
$SPI < 1$ & $SV < 0$	Delayed
$SPI = 1$ & $SV = 0$	Exactly as scheduled
$CPI > 1$ & $CV > 0$	Under budget
$CPI < 1$ & $CV < 0$	Over-costs
$CPI = 1$ & $CV = 0$	Exactly as planned

Figure 1 presents a graphical representation of the parameters of EVM on a cost-time curve (S-curve). By monitoring the procedure of these variables through the project's life cycle, managers will be able to more efficiently control the performance and progress of the project and identify any deviation from the plan to perform corrective actions timely (Zhan et al., 2019).

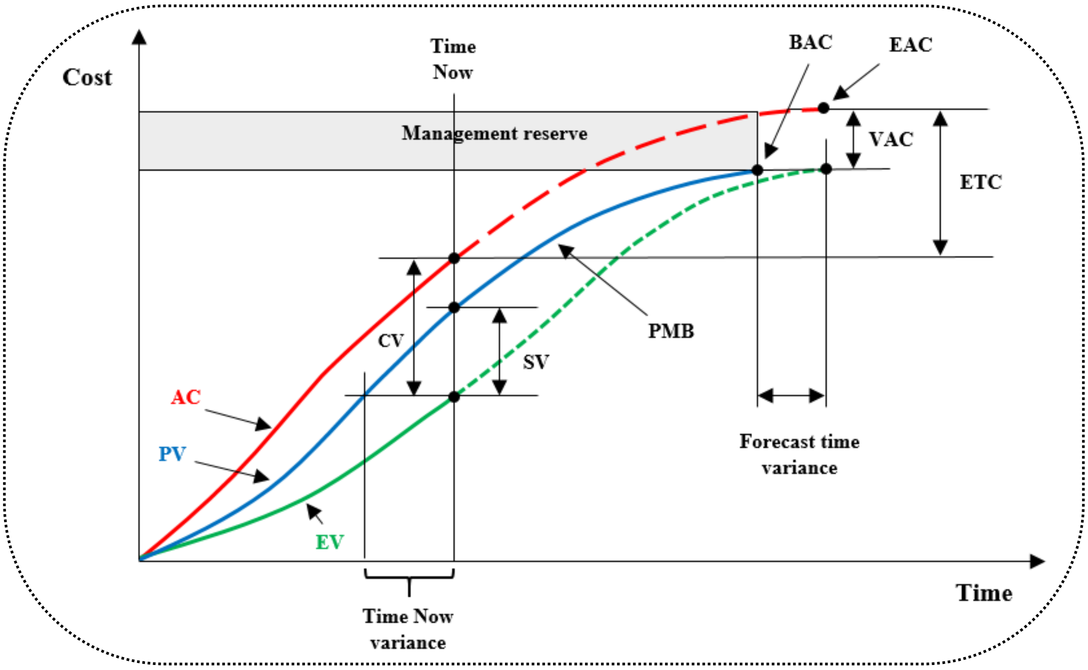


Fig 1. Graphical illustration of EVM variables and variances (Zhan et al., 2019)

As most of a project's effort is usually made in the middle of its life cycle, commonly, the curves are S-shaped (Pajares and Lopez-Paredes, 2011). The PV line is the baseline for the project's cost and shows the anticipated accumulated cost if the project proceeds according to the plan. The concept of Earned Schedule (ES) was developed by Lipke (2003) to deal with these drawbacks of the EVM schedule performance indicators and express schedule indicators in time units. Using ES, the schedule indicators are established that behave properly and are similar to the cost indicators (Henderson, 2007; Lipke, 2003). In this technique, the earned value at a particular point in time is traced forward or backward to the performance baseline or planned value. By reflecting this intersection point on the X-axis (the time scale) the ES is determined (see Figure 2).

In this method, variances are measured horizontally and presented in time units. Therefore, SV is replaced by SV(t), which reflects how many time units the project is delayed or ahead of the plan. ES translates the EV into time increments and calculates the real performance of the project compared to its expected time performance (Vandevoorde and Vanhoucke, 2006). It indicates the time when the current earned value should have been achieved. In order to calculate ES, find t such that $EV \geq PV_t$ and $EV < PV_{t+1}$. We have:

$$ES = t + \frac{(EV - PV_t)}{(PV_{t+1} - PV_t)} \quad (1)$$

Where t shows the number of time periods from the beginning of the project, and EV refers to the earned value at the actual time.

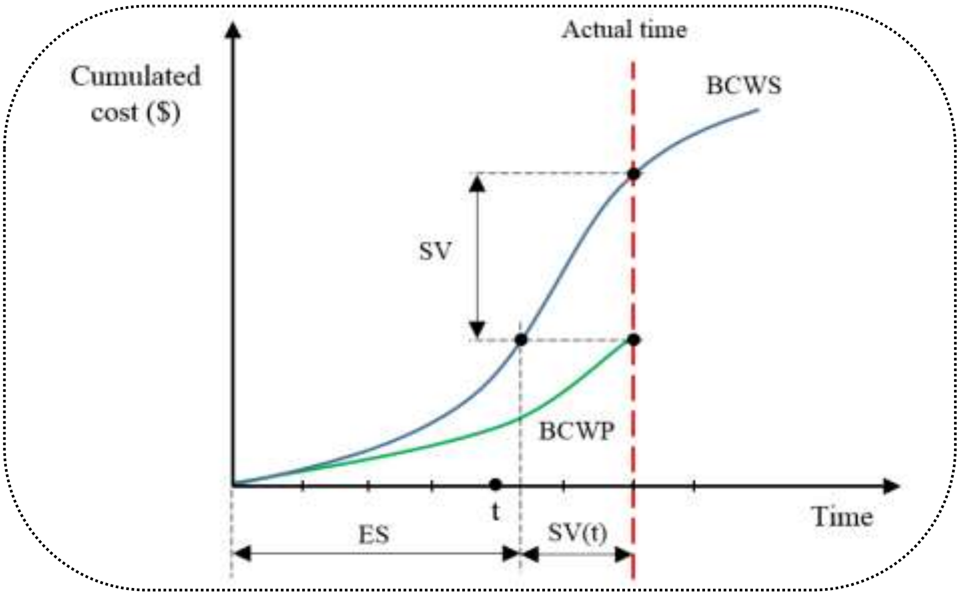


Fig 2. Earned schedule (Vanhoucke, 2016)

With ES calculated, time-based indicators (i.e., schedule variance and schedule performance index) can be determined by the following equations:

$$SV(t) = ES - AT \tag{2}$$

$$SPI(t) = ES/AT \tag{3}$$

Where AT refers to the actual time. Since contrary to the SV, the SV(t) is expressed in time units, its interpretation is easier. For instance, SV(t) > 0 (< 0) shows the number of time units that the project is ahead of (has delayed) its anticipated performance.

Another shortcoming of EVM, as mentioned before, is that it does not provide sufficient information about the amount of acceptable variability for each of the parameters in the project implementation process. SPI or SPI(t) deviation from 1 indicates project deviation from the plan. The conventional methods of monitoring and analyzing a project's progress cannot distinguish variations to this extent (Aliverdi et al., 2013). Therefore, there seems to be a need to establish reliable techniques to reinforce EVM and ES to be capable of considering the significance of different variations. In previous approaches, schedule and cost performance indices were considered independent and the relationship between these two variables was ignored. Note that failure to consider dependency between dependent parameters can lead to unrealistic results (Montgomery, 2007).

To address these deficiencies, this paper proposes using statistical process control charts as support for EVM and ES indicators to better manage and monitor the performance and progress of the project. This integrated methodology detects any deviation of the EVM and ES indices from the acceptable range and helps implement timely corrective actions, if necessary. Moreover, in the proposed approach, dependencies between these parameters are monitored. To the best of our knowledge, no comprehensive research has been done on the use of multivariate statistical quality control chart besides univariate statistical quality control charts to improve the performance of EVM and ES in monitoring the performance and progress of a project.

B. Statistical process control charts

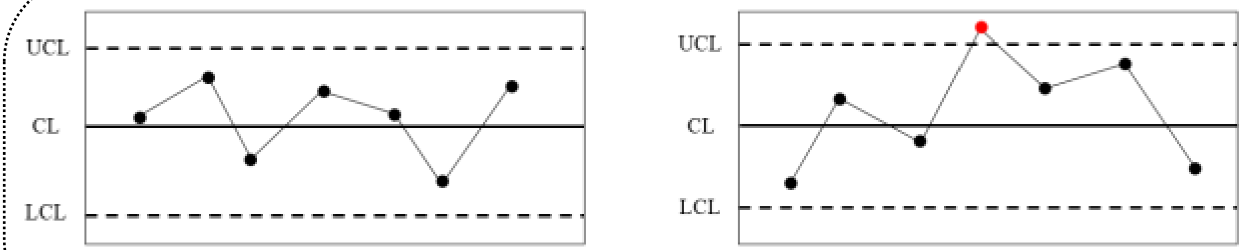
In the mid-1920s, Dr. Walter A. Shewhart developed the fundamentals of SPC (though this is not what it was called at the time) and the associated tool of the 'Control Chart'. A Control chart is one of the useful tools of statistical process control, which monitor the processes over time (Gharib et al., 2021). The main features of a control chart include data points, a centerline (mean value), an upper control limit (UCL), and a lower control limit (LCL). For good and safe control, subsequent data collected should fall within three standard deviations of the mean. Control charts build on this basic idea of statistical analysis by plotting the mean or range of subsequent data against time ().

"Control limits" are determined based on the capability of a particular process, whereas "specification limits" are determined according to the client's needs. Control charts attempt to distinguish between two types of process variation:

Variations within the control limits due to a 'common cause', which are inherent in the process and will always exist.

'Special cause' variations, which stem from external sources and indicate that the process is out of statistical control and something within the process should be changed to fix the problem before defects occur.

Figure 3 illustrates two control charts, one for an under-control process and one for an out-of-control process.



a) Under control b) Out of control

Fig 3. Control chart

XmR or ImR control charts-which are two types of Shewhart control charts-, can effectively be applied for statistically monitoring the duration and cost progress of the projects for two reasons (Aliverdi et al., 2013). Firstly, the relevant EVM variables, i.e. CPI and SPI, are measurable and can also take continuous values. Secondly, these features along with several other EVM parameters are observed at weekly or monthly intervals (i.e., a single measurement in every period) and thus, the number of measurements is very limited. Applying ImR control charts to SPI and CPI measurements determines whether deviations detected in the parameters are common cause variations or special cause ones. ImR control charts are composed of two separate charts: The first chart called 'IX' indicates the value of each measurement, and the second one called moving range, 'MR', monitors the variations between two successive measurements. Eqs. (4)– (9) show how to determine limits for IX and MR charts.

$$UCL_{IX} = \bar{x} + 3(\overline{MR}/_{d_2}) \tag{4}$$

$$CL_{IX} = \bar{x} = \sum_{i=1}^{n} {x_i}/_{n} \tag{5}$$

$$LCL_{IX} = \bar{x} - 3(\overline{MR}/_{d_2}) \tag{6}$$

$$UCL_{MR} = D_4\overline{MR} \tag{7}$$

$$UCL_{MR} = D_4\overline{MR} \tag{8}$$

$$LCL_{MR} = D_3\overline{MR} \tag{9}$$

where x_i denotes individual measurement, $MR_i = x_i - x_{i-1}$ and constants d_2, D_3 and D_4 are known functions of n (Montgomery, 2007). The main advantage of using univariate quality control charts (UQCCs) is that they help realize the behavior of the EVM variables over time (Aliverdi et al., 2013). In monitoring the performance and progress of a project, since the desired situation happens when SPI (or SPI(t)) and CPI are both equal to 1, the center line of Xbar is fixed at 1, and any deviation from the center line must be controlled.

C. Multivariate quality control charts

Nowadays, in industry, due to the automation of measurement and data collection systems, there are many situations in which there is a correlation between two or more quality–process features (Kalgonda and Kulkarni, 2004). Since correlation can have a serious influence on the performance of classical control charts, monitoring these quality characteristics individually can be very misleading (Bersimis et al., 2007; Kalgonda and Kulkarni, 2004). Thus, there is a need to make use of an appropriate tool in order to have a simultaneous observation of these dependent features. This issue has formed the basis for expansive studies performed in the area of multivariate quality control charts (MQCCs) since 1940s (Hotelling, 1947). Several studies have considered multivariate control charts (Ghute and Shirke, 2008; Cerioli, 2010; Fan et al., 2013).

Despite the misleading nature of UQCCs in some situations, they still continue to be practically the typical monitoring tool utilized by industry (Kourti and MacGregor, 1995). However, several multivariate SPC techniques have been developed to deal with the situations in which the process measurements are auto-correlated, among which CUSUM chart introduced by Theodossiou (1993), and EWMA control chart developed by Kramer and Schmid (1997) are two of the most well-known methods. However, using these methods involves some practical drawbacks. A noteworthy shortcoming is the inability of these techniques to find the variable(s) responsible for the signal when the indication of an out-of-control situation is identified (Kalgonda and Kulkarni, 2004).

D. Motivation and significance

The conventional techniques are mainly based on the assumption that the observation vectors are independent. However, this assumption may not be satisfied in some processes, since the characteristics are measured in time order. This autocorrelation can have a significant impact on the performance and effectiveness of control chart procedure. SPI (or SPI(t)) and CPI are two dependent variables, since, clearly, with the increase of time required to finish an activity, the cost of completing that activity increases correspondingly. Therefore, in this paper, the relationship between two basic features of EVM and ES methods, i.e. time and cost is also taken into account in order to more accurately analyze the results obtained from these methods. This paper proposes using MQCC besides UQCCs in the analysis, management, exploration, and monitoring of project performance to enhance the capability and efficiency of EVM and ES. The proposed approach attempts to help managers keep the variations under control and monitor project's performance to prevent cost overruns and delays, and on the other hand to find out the reasons for falling ahead of the plan or having savings (for benchmarking), and in this way enhances the capability and efficiency of EVM and ES.

The plan for the remainder of the paper is as follows. The related literature is reviewed in Section 2. The description of the proposed methodology is presented in Section 3. Section 4 provides the implementation of the methodology in three case studies. Lastly, Section 5 is dedicated to concluding remarks.

II. LITERATURE REVIEW

Several studies have provided a detailed explanation of the methodology as well as the basic principles of EVM and showed the advantages of EVM on the cost and the schedule performances of a project (Moslemi Naeni et al., 2013; Abba and Niel, 2010; PMI, 2005; Cioffi, 2006; Jacob, 2003; Vanhoucke and Vandevoorde, 2007; Lipke, 2004).

Despite the advantages of integrating statistical techniques with EVM to improve the applicability and efficiency of EVM, there have been few studies that have considered these techniques. Lipke (2004 and 2011) focused on the statistical distribution of several cost variables of EVM. He considered the case of non-normally distributed data and presented a technique for approximating the distribution to normal distribution. He also tried to realize whether the normality assumption for the indices is valid. Moslemi Naeni et al. (2013) introduced a novel fuzzy-based earned value model to assess and analyze the earned value parameters, along with the cost and time estimates at completion under uncertainty. Pajares and Lopez-Paredes (2011) proposed two new indicators called Cost Control Index and Schedule Control Index for integrating EVM with Project Risk Management to monitor and manage a project. They compared EVM schedule and cost variations with the project's allowed deviation under expected conditions of the risk analysis. Henderson (2004) investigated the reliability and applicability of the ES.

A fuzzy control chart approach based on $\boldsymbol{\alpha}$-cut was proposed by Noori et al. (2008) to monitor earned value performance variables containing linguistic terms. Acebes et al. (2013) presented an innovative and simple graphical framework to evaluate and monitor a project. They attempted to combine the dimensions of the cost and schedule of a project with risk management for improving EVM. For this purpose, they considered new control indexes and cumulative buffers. Lipke et al. (2009) provided project managers with an effective and reliable method to predict the final cost and duration. Their methodology and its evaluation take advantage of a well-established project management method, a recent strategy for analyzing schedule performance, and the mathematics of statistics to accomplish its goal; that is, EVM, ES and statistical forecasting and testing techniques, respectively. Mortaji et al. (2021) introduced directed earned value management (DEVM) in which ordered fuzzy numbers are used to express the so-called uncertainties as well as to capture more information about the trend of the project progress. Mousavi et al. (2015) proposed a new approach to model project cash flow under uncertain environments using Atanassov fuzzy sets or intuitionistic fuzzy sets (IFSs). The IFSs are presented to calculate project scheduling and cash flow generation.

Barraza et al. (2004) introduced a new strategy that uses the concept of stochastic S curves (SS curves) for determining predicted project estimates as an alternative to deterministic S curves and conventional forecasting techniques. In order to generate the stochastic S curves, they made use of a simulation technique based on the accepted variability in cost and duration of the individual activities within the process. Later, a novel probabilistic project control concept was introduced by Barraza and Bueno (2007) to ensure a satisfactory prediction of project's final performance. The methodology aimed to prevent exceeding planned budget and schedule risk levels. They proposed three distinct methods (i.e., quality, benchmarking, and incremental variance) for obtaining the project performance control limit curves to facilitate the project control process. None of these two papers considered statistical monitoring of project performance throughout its implementation.

Hadian and Rahimifard (2019) applied multivariate Hotelling's T^2 control chart to take into account possible correlations between EVM indicators and describe the entire capability of the project performance more accurately. Furthermore, in order to quantify how well a project can meet its requirements, some practical multivariate process capability indices (PCIs) are introduced.

Votto et al. (2020) used earned duration management (EDM) is used as a statistical project control method to monitor the performance of engineering, procurement, and construction (EPC) projects. The major contribution of their study lies both in the use of control charts with control limits obtained by simulations to monitor the new duration performance index (DPI) in a real EPC project, and in the assessment of its performance compared with that of the traditional EVM and ESM indexes. Soltan and Ashrafi (2020) presented a method for predicting project duration and cost of the project and selecting the best action plan. Control charts are used along with the earned value management method to increase accuracy. Song et al. (2021) extended project control approaches for resource-constrained projects to measure and evaluate whether the project progress is acceptable. The results show that the proposed scenarios and different project control approaches are efficient and reliable, but their use depends on project network structure and resource scarceness. Reviewing the recent studies shows the relationship of EVM and ES methods by applying MQCC and UQCC taking into account normality assumption has not been addressed. Also, in this study various case studies are investigated and results are compared.

In this paper, the relationship between two basic features of EVM and ES methods, i.e. time and cost is also taken into account in order to more accurately analyze the results obtained from these methods. It proposes using MQCC besides UQCCs in the analysis, management, exploration, and monitoring of a project performance to enhance the capability and efficiency of EVM and ES. Also, in the proposed case studies, normality assumption and its effect on the results is analyzed.

III. Methodology

This paper proposes using MQCC besides UQCCs for analyzing, investigation, managing and monitoring of a project to improve the capability, accuracy and efficiency of EVM and ES. Figure 4 presents the structure of the proposed algorithm.

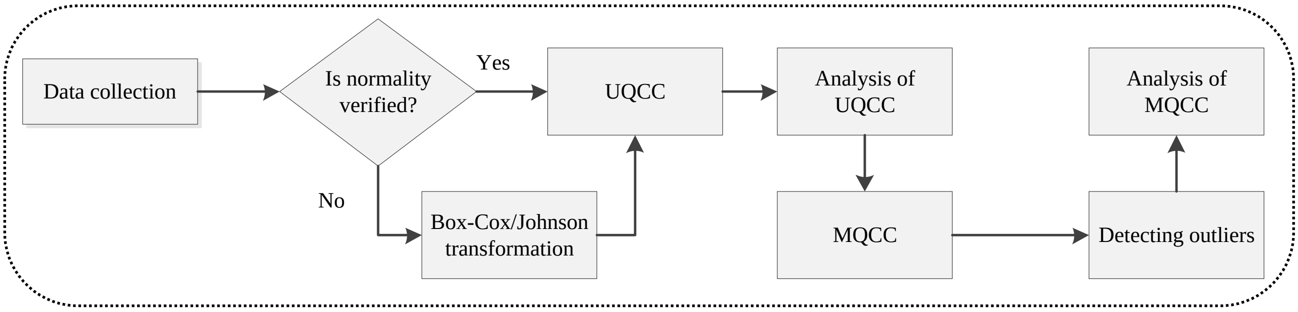


Fig 4. Flowchart of the proposed algorithm

In the proposed algorithm, required data are collected. The data sets in this study are CPI and SPI (or SPI(t)) values for a project. Statistical methods (including Box-Cox and Johnson transformation) are then applied to test the normality of the data sets. Note that the proposed methodology is not limited to the underlying distributions of SPI (or SPI(t)) and CPI measurements; therefore, regardless of the distribution, the method can successfully be applied to all projects. Univariate and multivariate quality control charts are used to evaluate and analyze the project and determine possible outliers. Lastly, a comprehensive analysis is carried out on the results obtained from both these tools. Moreover, the results of univariate and multivariate quality control charts are compared to show the applicability and usefulness of the proposed algorithm. In this study, to demonstrate the efficiency and superiority of the proposed methodology, three data sets which are related to three construction projects are selected from two distinct works, i.e. Nassar et al. (2005) and Czernigowska (2008) as our case studies.

To draw MQCC, CPI is depicted versus SPI (or SPI(t)) and the data related to these variables are displayed in $(\boldsymbol{x_i}, \boldsymbol{y_i})$ pairs, where $\boldsymbol{i}$ denotes the number of the sample, x is the value of CPI and y represents the value of SPI (or SPI(t)) for that particular sample. An ellipse with the center of (1, 1) as the "center point" is drawn to distinguish outliers from other data. We have:

$$Var(CPI + SPI) = Var(CPI) + Var(SPI) + 2\sigma(CPI, SPI) \tag{10}$$

where σ denotes the covariance between CPI and SPI variables. Covariance as a measure of the strength of correlation between two or more sets of random variables is defined as follows:

$$Cov(X, Y) = E[X - E(X)][Y - E(Y)] \tag{11}$$

Let $\lambda = Var(CPI + SPI)$. The formula of the ellipse is as follows:

$$\frac{(CPI-1)^2}{(\alpha\lambda)^2}+\frac{(SPI-1)^2}{(\beta\lambda)^2}=1 \tag{12}$$

where $\alpha\lambda$ and $\beta\lambda$ represent the radii of the ellipse on the CPI and SPI axes, respectively. Note that if $\alpha = \beta$, the shape of the frontier will become circular. α and β are two coefficients according to which this formula can be adjusted based on the criticality of the project; that is, if the project is of low priority and thus, even great deviations are not noteworthy, bigger α and β can be used. On the other hand, if the project under consideration is a high priority project, such that even trivial deviations from the plan can be troublesome, smaller values of the coefficients must be selected in order to tighten the acceptable area to detect outliers. An interesting aspect of this formula lies in the fact that these two coefficients do not have to be equal in all circumstances, and thus can take distinct values; i.e., in a project cost issues play a more critical role than those related to schedule, and consequently, more emphasis has to be put on CPI values, by assigning smaller values to α, the ellipse is more flattened along CPI axis to focus more on center point. The same is true for schedule and SPI (see the second case study). Note that for ES, SPI(t) replaces SPI.

IV. EXPERIMENT

In this section of the paper, to show the applicability of the proposed methodology, it is applied to three distinct case studies. As mentioned before, usually over the last third of the project, SPI becomes unreliable and loses its predictive ability. Therefore, to provide a comprehensive experiment, the first case study investigates ES, and therefore includes CPI and SPI(t), while the second and third case studies try to analyze EVM and thus contain CPI and SPI data sets.

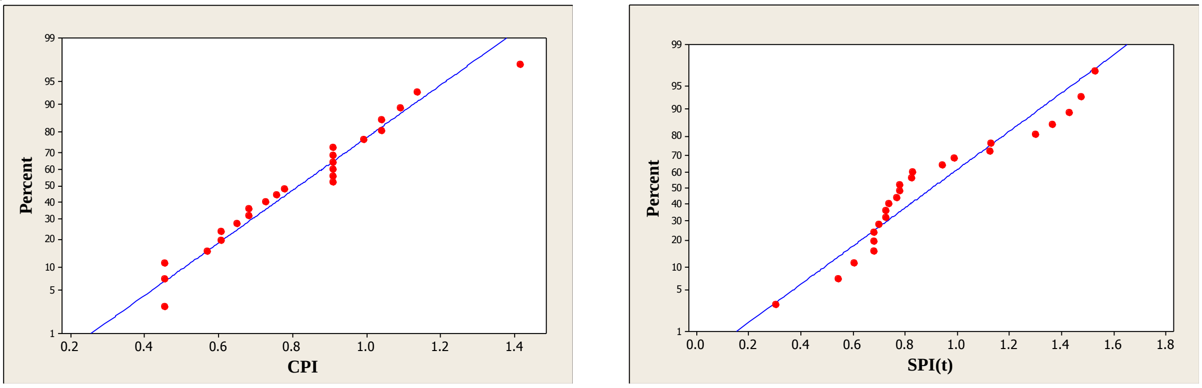
A. Case study 1

The first case study presents the SPI(t) and CPI measurements (samples) related to 24 months of a construction project provided by Nassar et al. (2005) which is still ongoing but approaching completion. The data are shown in Table III.

Table III. Data Related To CPI And SPI(T)

Sample	*CPI*	*SPI(t)*	*Sample*	*CPI*	*SPI(t)*
1	0.455	0.303	13	0.910	1.431
2	0.910	0.825	14	0.455	0.546
3	0.728	0.728	15	1.040	1.476
4	0.910	0.737	16	0.758	1.131
5	0.683	0.683	17	1.138	0.700
6	0.683	0.683	18	1.416	1.528
7	0.780	0.683	19	0.993	1.365
8	1.040	0.989	20	0.910	0.828
9	0.607	1.300	21	0.910	0.767
10	0.607	0.780	22	0.910	0.945
11	0.455	0.780	23	1.092	0.607
12	0.650	1.125	24	0.569	0.727

The value of Pearson correlation between CPI and SPI(t) variables is equal to 0.500 which is an acceptable value to prove that these two parameters are dependent. Following normal distribution is neither assumed nor necessary in the calculation of control limits, but it makes the ImR charts a very robust tool (Aliverdi et al., 2013). Yet, it is suggested against utilizing these control charts for non-normally distributed data (Montgomery, 2007; Shenoy, 2008). In this step, the test of normality is implemented on the data related to both indicators (i.e., CPI and SPI(t)). Figure 5 illustrates the normal probability plots of CPI and SPI(t) data.



a) CPI b) SPI(t)

Fig 5. Normal probability plots

Moreover, the normality test is performed for both CPI and SPI(t) data sets by SPSS software and the results are presented in Tables IV and V, respectively. As is shown in these tables, Shapiro-Wilk and Kolmogorov-Smirnov tests are selected to investigate the normality of the data sets, separately. The results demonstrate that CPI data set has acceptable p-values (i.e., 0.385 and 0.173 based on Shapiro-Wilk and Kolmogorov-Smirnov tests, respectively), and thus, there is no reason to reject the null hypothesis (i.e., normality of the data) for CPI variable considering the predefined values for α (i.e., 0.01, 0.02, 0.05 and 0.1). But, on the other hand, p-values obtained for SPI(t) are 0.041 and 0.005 according to Shapiro-Wilk and Kolmogorov-Smirnov tests, respectively. According to Table V, null hypothesis is rejected considering the predefined values for α (except for $\alpha = 0.01$ and $\alpha = 0.02$ in the Shapiro-Wilk test), and thus, the transformation has to be implemented.

Although there exist a number of approaches to improve robustness of ImR control charts in the presence of non-normally distributed samples, their application to non-normally distributed data is not recommended (Aliverdi et al., 2013). Therefore, non-normally distributed SPI(t) measurements have to be transformed into normally distributed ones. For this purpose, Johnson's transformation is used in this paper. Table VI presents the transformed data. Also, Figure 6 illustrates Minitab output for transformation. As is seen in this figure, the p-value after carrying out the transformation is equal to 0.244. Based on this p-value, the null hypothesis of the data set normality test is not rejected considering the given values for α.

Table IV. Result of implementing normality test over CPI samples

Shapiro-Wilk				
Sample size	24			
P-value	0.385			
α	0.1	0.05	0.02	0.01
Critical value	0.917	0.901	0.879	0.863
Reject?	No	No	No	No
Kolmogorov-Smirnov				
Sample size	24			
P-value	0.173			
α	0.1	0.05	0.02	0.01
Critical value	0.27136	0.30143	0.33685	0.36117
Reject?	No	No	No	No

TABLE V. Result of implementing normality test over SPI(t) samples

Shapiro-Wilk				
Sample size	24			
P-value	0.041			
α	0.1	0.05	0.02	0.01
Critical value	0.917	0.901	0.879	0.863
Reject?	Yes	Yes	No	No
Kolmogorov-Smirnov				
Sample size	24			
P-value	0.005			
α	0.1	0.05	0.02	0.01
Critical value	0.27136	0.30143	0.33685	0.36117
Reject?	Yes	Yes	Yes	Yes

TABLE VI. Johnson transformation output for SPI(t)

Sample	*Transformed data*	*Sample*	*Transformed data*
1	-1.844	13	0.960
2	0.216	14	-1.473
3	-0.355	15	0.985
4	-0.268	16	0.740
5	-0.840	17	-0.666
6	-0.840	18	1.012
7	-0.840	19	0.921
8	0.572	20	0.227
9	0.878	21	-0.044
10	0.028	22	0.502
11	0.028	23	-1.288
12	0.734	24	-0.365

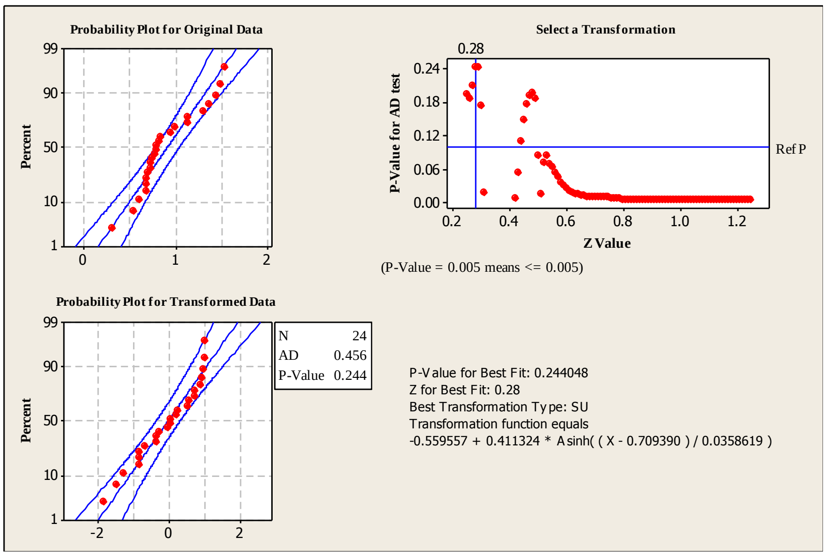


Fig 6. Johnson transformation for SPI(t)

Figures 7 and 8 illustrate the three-standard-deviation ImR charts related to the data set provided in Table III. As mentioned before, the center line should be equal to 1, since it shows the desired situation. Also, Figure 9 depicts ImR charts of the data set presented in Table VI.

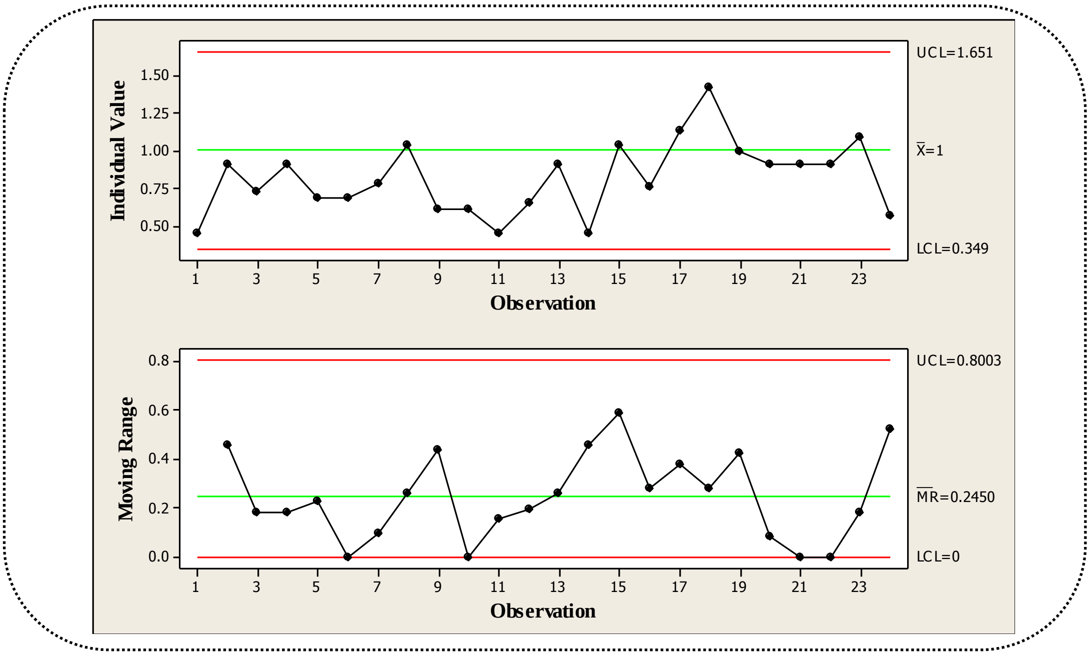


Fig 7. ImR chart of CPI

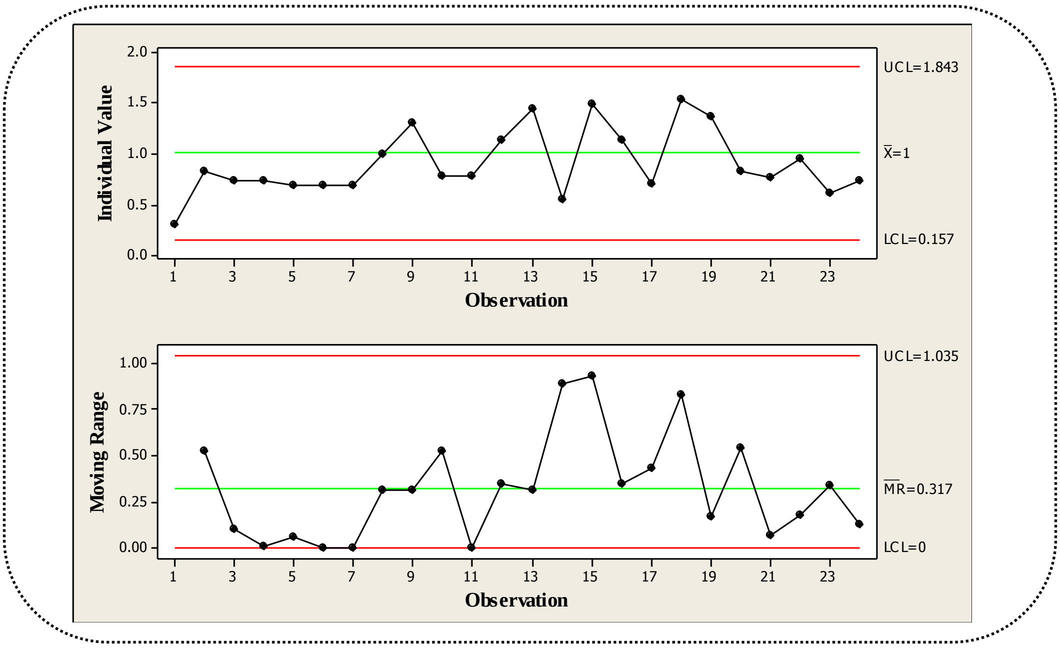


Fig 8. ImR chart of SPI(t) (original data)

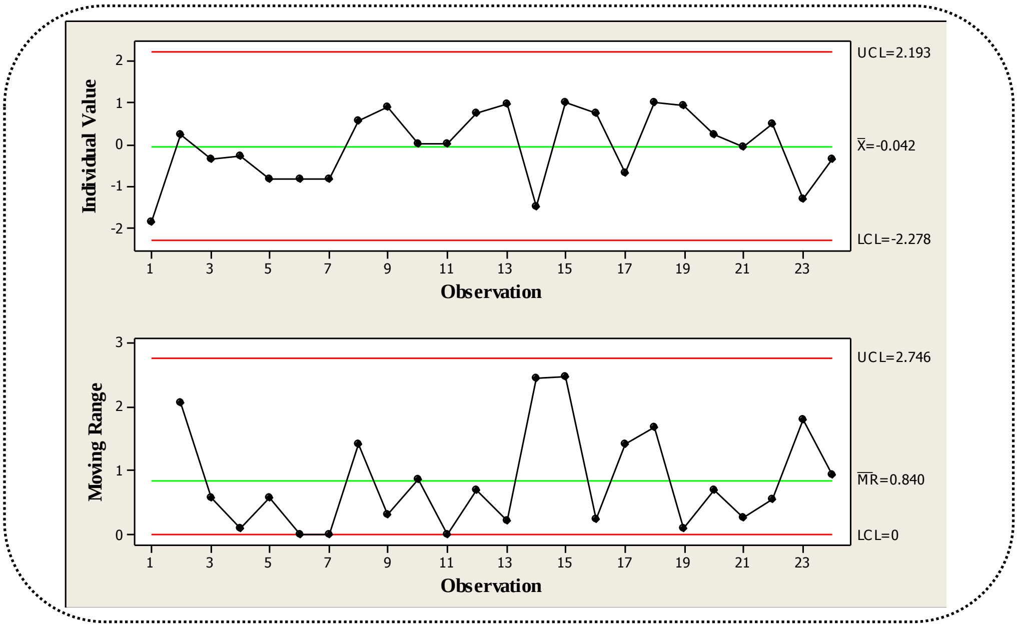


Fig 9. ImR chart of SPI(t) (transformed data)

Although some points have fallen right on the lower control limit, no point is out of the control limits of any of the variables, i.e. CPI and SPI(t), and thus, no sample has to be removed and the charts remain unchanged. Moreover, as is clear from the Xbar chart of CPI, not a point associated with samples has fallen out of the limits and besides, no particular trend is recognized; hence the project is declared to be under control. But with a more precise look, it is realized that samples 1, 11, 14, and 24 in Xbar chart of CPI are close to the control limits and consequently are considered warning points for decision makers. Referring to Xbar chart related to SPI(t) variable data (both original and transformed), it is found that there is no sign of being out of control; that is, neither is there a single point related to a measurement beyond the control limits, nor there seems to be a non-random trend between the points. In addition, point 1 is close to the lower control limit, and hence, might need to be investigated. No other considerable problem is realized from this chart.

Now, consider the MQCC of the data and point (1, 1) (Figure 10). The project is of moderate priority and also monitoring and analyzing time deviations are of equal importance for the management. Hence, the value of both α and β are set to 3; that is, $\alpha = \beta = 3$.

As is clear from this figure, samples 1, 14, and 18 (which were within the control limits of UQCCs) are out of the frontier and away from other measurements as well as from the center point, and thus are labeled outliers. However, these points can easily be identified visually as outliers. When we refer to the CPI and SPI(t) values presented in Table VI, samples 1 (CPI=0.455, SPI(t)=0.303), 14 (CPI=0.455, SPI(t)=0.546), and 18 (CPI=1.416 and SPI(t)=1.528) have noteworthy CPI and SPI(t) values and are clearly out of control. But with only focusing on UQCCs, one may ignore these points, due to the fact that they have fallen within the control limits. Samples 11 and 24 which were close to the control limits of (CPI) UQCCs are close to the frontier of MQCC as well. Considering MQCC, the points which are close to the frontier, such as 9, 13 and 15 might attract the attention of decision makers to analyze them. However, in UQCCs, these points are distributed around the center line and might be ignored by the decision makers. Referring to the table of data sets, we have CPI=0.607 and SPI(t)=1.300 for sample 9, CPI=0.910 and SPI(t)=1.431 for sample 13, and CPI=1.040 and SPI(t)=1.476 for sample 15. These values prove their significance and, perhaps, suitability for benchmarking. In fact, MQCC acts as a useful tool to reinforce individual quality control charts and accordingly ES for efficiently monitoring and managing the performance and progress of the project. Consequently, the efficient tool which is capable of highlighting these points and in this way helps UQCCs to improve the efficiency of ES is MQCC. Note that, as mentioned before, the diameter of the frontier may change based on the criticality of the project.

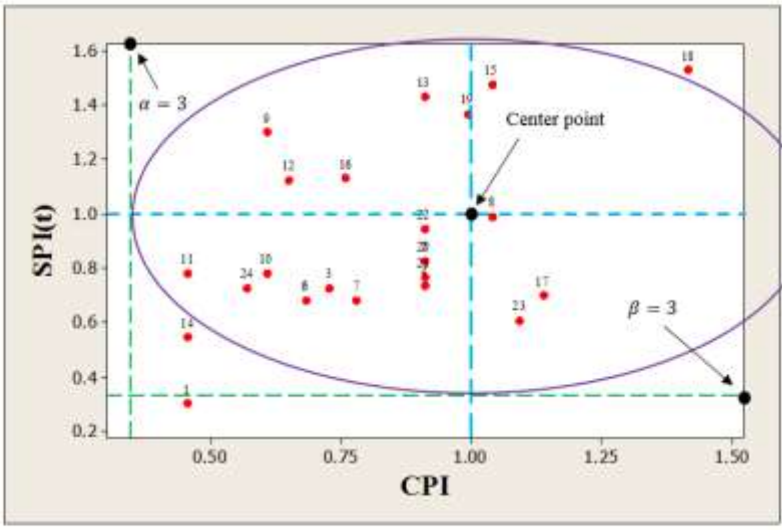


Fig 10. MQCC of CPI vs SPI(t)

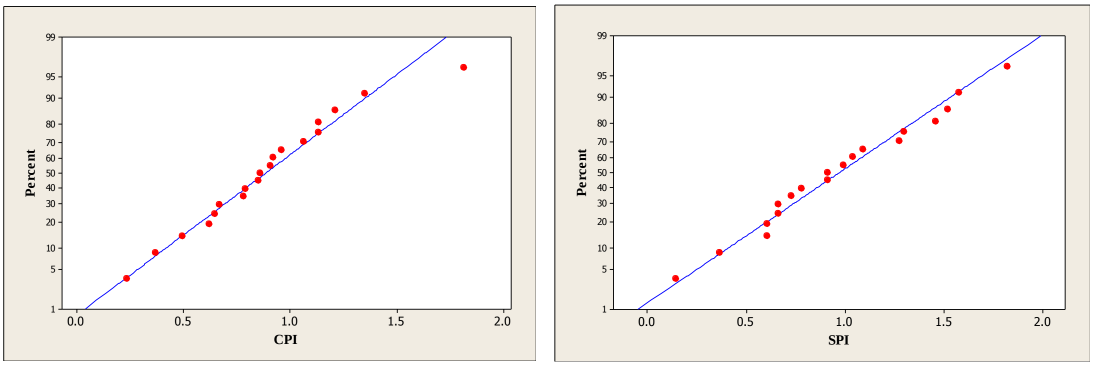
B. Case study 2

The second case study, which is also provided by Nassar et al. (2005), presents the SPI and CPI measurements related to 19 months of an ongoing construction project. Table VII illustrates the data.

Table VII. Collected data related to CPI and SPI

Sample	*CPI*	*SPI*	*Sample*	*CPI*	*SPI*
1	0.780	1.820	11	0.646	0.662
2	0.919	0.910	12	0.789	1.040
3	1.132	1.274	13	1.815	1.577
4	0.670	0.607	14	0.958	0.910
5	1.064	1.300	15	1.352	0.993
6	1.135	1.456	16	1.213	0.728
7	0.851	1.092	17	0.494	0.607
8	0.908	1.517	18	0.861	0.662
9	0.621	0.780	19	0.235	0.142
10	0.369	0.364			

In this case study, the value of Pearson correlation between CPI and SPI variables is equal to o.647 which demonstrates these two parameters' dependence. Subsequently, the normality test is carried out on CPI and SPI data sets. Figure 11 depicts the normal probability plots of CPI and SPI data.



a) CPI b) SPI

Fig 11. Normal probability plots

The normality test results obtained by SPSS for both CPI and SPI data sets are presented in Tables VIII and IX, respectively. It can be seen that both CPI and SPI data sets have acceptable p-values (i.e., 0.797 and 0.956 based on Shapiro-Wilk for CPI and SPI, respectively. Also, the lower bound of true significance is equal to 0.200 based on Kolmogorov-Smirnov for both of them), and thus, there is no reason to reject the null hypothesis (i.e., normality of the data) for either of CPI and SPI variables considering the given values for α.

TABLE VIII. Result of implementing normality test over CPI samples

Shapiro-Wilk				
Sample size	19			
P-value	0.797			
α	0.1	0.05	0.02	0.01
Critical value	0.917	0.901	0.879	0.863
Reject?	No	No	No	No
Kolmogorov-Smirnov				
Sample size	19			
P-value	> 0.200			
α	0.1	0.05	0.02	0.01
Critical value	0.27136	0.30143	0.33685	0.36117
Reject?	No	No	No	No

TABLE IX. Result of implementing normality test over SPI samples

Shapiro-Wilk				
Sample size	19			
P-value	0.956			
α	0.1	0.05	0.02	0.01
Critical value	0.917	0.901	0.879	0.863
Reject?	No	No	No	No
Kolmogorov-Smirnov				
Sample size	19			
P-value	> 0.200			
α	0.1	0.05	0.02	0.01
Critical value	0.27136	0.30143	0.33685	0.36117
Reject?	No	No	No	No

ImR charts related to the data set provided in Table VII are depicted in Figures 12 and 13.

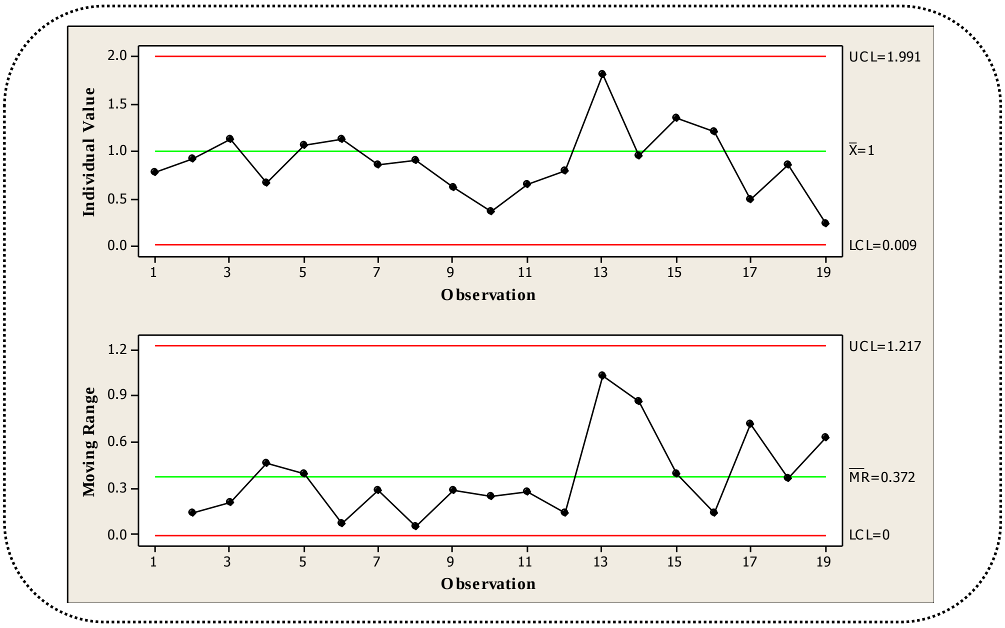


Fig 12. ImR chart of CPI

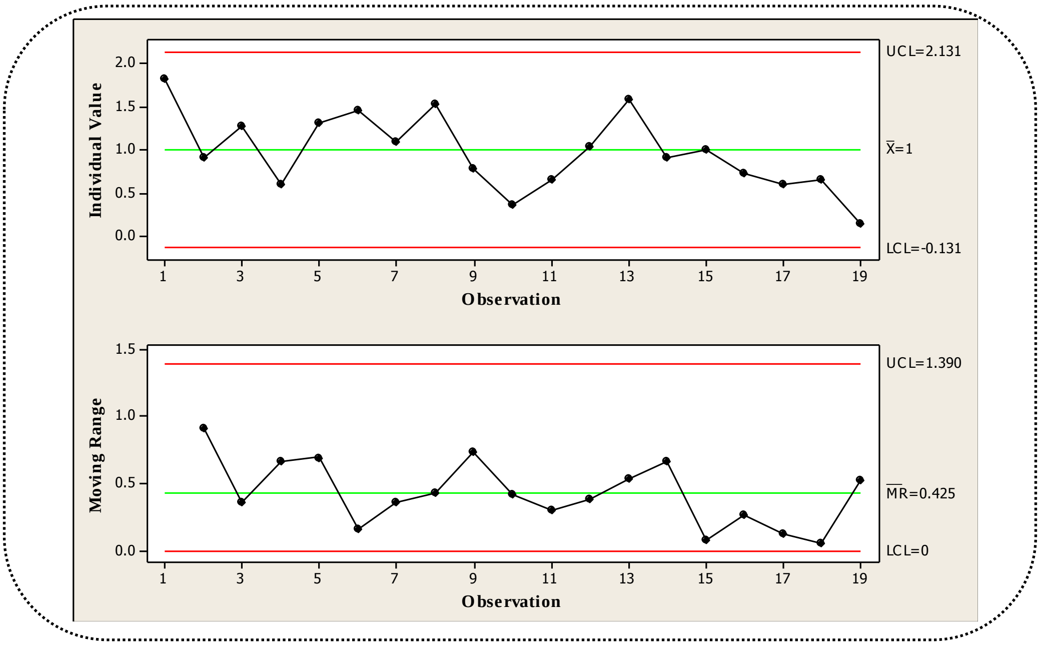


Fig 13. ImR chart of SPI

As it is clear from ImR charts, no sample has fallen out of the control limits of any of the variables, and consequently, no measurement has to be eliminated from the data set and the charts remain unchanged. Also, Xbar chart of CPI shows that no point has fallen out of the limits, nor is a particular trend recognized; Therefore, the project is under control. Again, if we look more carefully, we see that samples 13 and 19 are close to the UCL and LCL, respectively and consequently are warning points. On the other hand, there seems to be no sign of being out of control in the Xbar chart of the SPI. The only noteworthy issue in this chart is that two points (i.e., 1 and 19) are slightly close to the control limits, and therefore might need to be analyzed.

Here, MQCC of the data sets is depicted. Suppose monitoring and analyzing time deviations are of higher importance for the management compared to cost overruns. Hence, the value of β is set to 1.5, while $\alpha = 2$. The resulting figure will be as Figure 14.

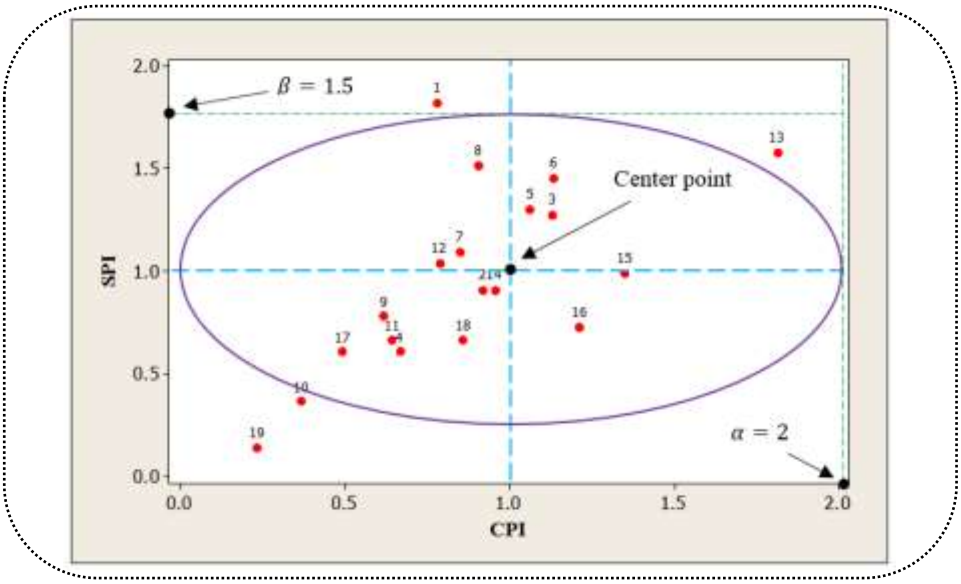


Fig 14. MQCC of CPI vs SPI

Based on Figure 14, samples 1, 10, 13, and 19 are out of the frontier, and therefore are outliers. These points can easily be identified visually as outliers. Referring to the table of data sets, the values of CPI and SPI for samples 1 (CPI=0.780, SPI=1.820), 10 (CPI=0.369, SPI=0.364), 13 (CPI=1.815 and SPI=1.577), and 19 (CPI=0.235, SPI=0.142) indicate that they are clearly out of control. But with only focusing on UQCCs, as these points have fallen within the control limits, they might be ignored. Particularly, see sample 1 which is so close to the center line of Xbar chart related to CPI. Considering individual charts alone, this sample will definitely be ignored.

Referring to MQCC, points 8 and 17 which are adjacent to the frontier, might need to be investigated. Note that in UQCCs, these points are distributed around the center line and might be neglected by the decision makers. In this case, MQCC, also, acts as an efficient tool to identify noteworthy points and in this way helps UQCCs to enhance the efficiency of EVM. Note that the main purpose of the UQCCs in this case was to monitor and analyze the behavior of the performance indicators.

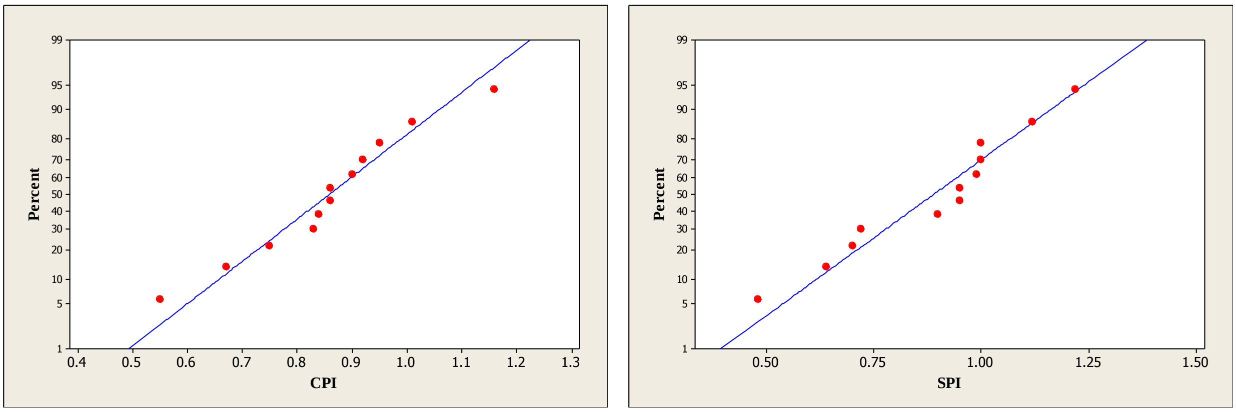
C. Case study 3

A data set related to a 12-month completed construction project provided by Czernigowska (2008) has been considered as our third case study. The measurements regarding CPI and SPI variables are presented in Table X. These data indicate a situation where both cost and schedule have fluctuated and change tendencies have been variable (alternative savings and overruns), which shows wrong decisions have been made to ameliorate variances, or the baseline was wrong.

Table X. Collected data related to CPI and SPI

Sample	*CPI*	*SPI*	*Sample*	*CPI*	*SPI*
1	0.90	0.64	7	1.01	1.12
2	0.67	0.48	8	0.95	1.00
3	0.86	0.72	9	0.92	0.95
4	0.55	0.70	10	0.86	0.95
5	0.75	0.90	11	0.84	0.99
6	1.16	1.22	12	0.83	1.00

The value of Pearson correlation between CPI and SPI values is equal to 0.727. This value demonstrates the dependency between these two variables. The normal probability plots of CPI and SPI data sets are depicted in Figure 15. Also, Tables XI and XII provide the results of the normality test obtained from SPSS software. The results show that both CPI and SPI data sets have an acceptable p-value, and thus follow normal distribution considering the predefined α values.



a) CPI b) SPI

Fig 15. Normal probability plots

Table XI. Result of implementing normality test over CPI samples

Shapiro-Wilk				
Sample size	12			
P-value	0.937			
α	0.1	0.05	0.02	0.01
Critical value	0.883	0.859	0.828	0.805
Reject?	No	No	No	No
Kolmogorov-Smirnov				
Sample size	12			
P-value	0.200			
α	0.1	0.05	0.02	0.01
Critical value	0.33815	0.37543	0.41918	0.44905
Reject?	No	No	No	No

Table XII. Result of implementing normality test over SPI samples

Shapiro-Wilk				
Sample size	12			
P-value	0.615			
α	0.1	0.05	0.02	0.01
Critical value	0.883	0.859	0.828	0.805
Reject?	No	No	No	No
Kolmogorov-Smirnov				
Sample size	12			
P-value	0.200			
α	0.1	0.05	0.02	0.01
Critical value	0.33815	0.37543	0.41918	0.44905
Reject?	No	No	No	No

ImR charts related to the CPI and SPI data sets are depicted in Figures 16 and 17, respectively. Furthermore, Figure 18 shows the MQCC of these data sets.

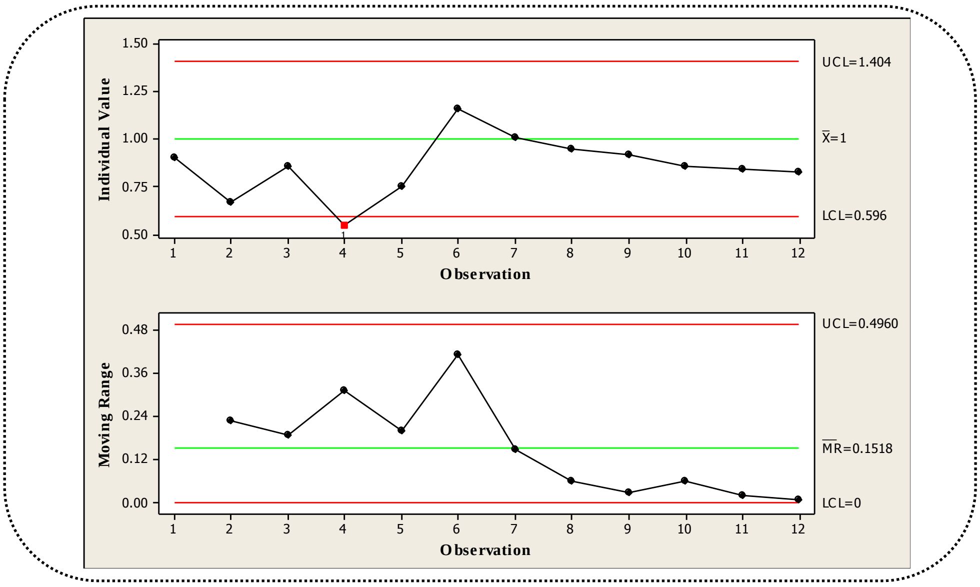


Fig 16. ImR chart of CPI

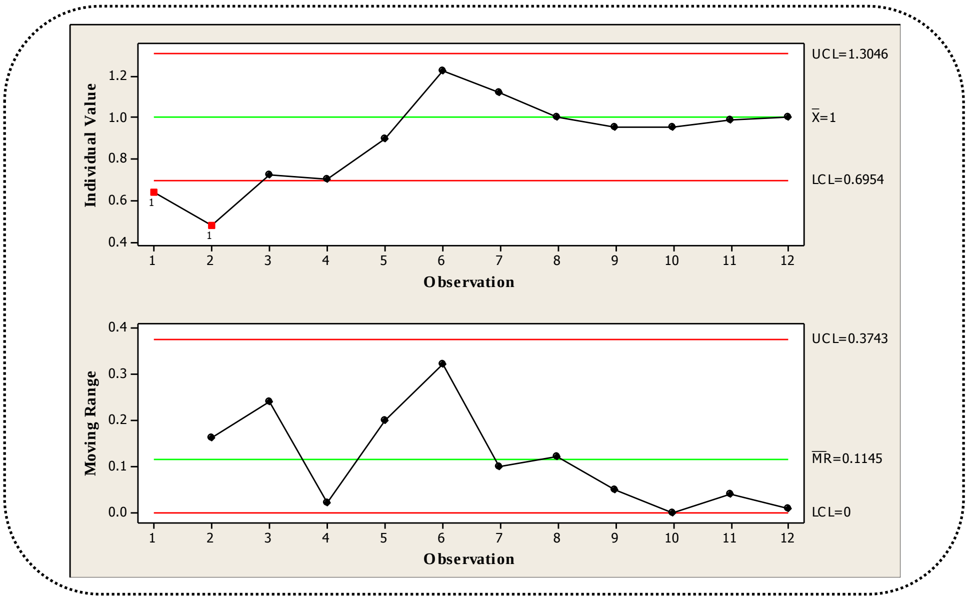


Fig 17. ImR chart of SPI

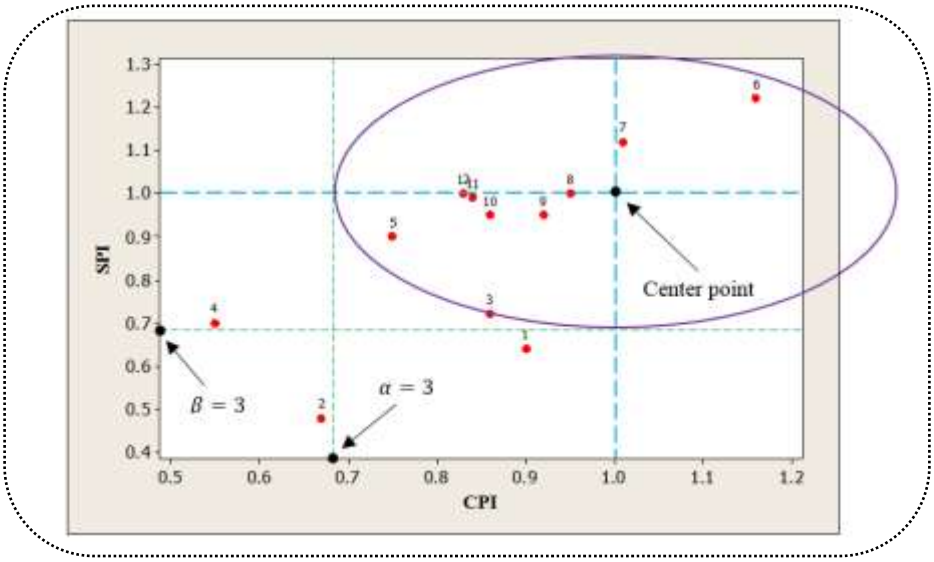


Fig 18. MQCC of CPI vs SPI

According to the moving range charts of both CPI and SPI, there is no sign of being out of control. Based on Xbar chart of CPI, sample 4 has fallen out of the control limits, and thus the project cost is out of control. Also, it is clear from Xbar chart of SPI that measurements 1 and 2 are out of the control limits. There exists no other point out of control limits. Also, samples 3 and 4 are so close to the LCL in SPI control chart. On the other hand, referring to the MQCC and considering center point (1, 1), it is realized that points 1, 2, and 4 have fallen out of the frontier, and therefore, all three of them are considered as outliers. Also, measurement No. 3 has fallen right on the frontier and could be considered an outlier. Referring to Table X, we have CPI=0.86 and SPI=0.72 for sample 3. According to these values, this sample seems to be worth analyzing. Note that CPI and SPI have been considered with the same importance ($\alpha = \beta = 3$).

In this case, UQCCs and MQCC yielded almost analogous results. When we refer to both of the techniques, it is found that (despite being close to the control limits in UQCCs and to frontier in MQCC) points 5 and 6 are within the limits, considered to be under control and therefore, might be ignored. According to Table X, CPI and SPI values for these samples are CPI=0.75 and SPI=0.90 for sample 5 and, CPI=1.16 and SPI=1.22 for sample 6. These values may motivate decision makers to analyze them. Other measurements have been distributed around the center line in UQCCs and center point in MQCC.

V. CONCLUSION

This study aims at making use of statistical quality control charts to control two leading indicators of project performance, i.e. time and cost. In historical studies, using univariate quality control charts (UQCCs) is proposed as an efficient instrument to help raise the capability of EVM. This paper proposes using a multivariate quality control chart (MQCC) besides UQCCs for improving both EVM and ES. The reason for this claim is that the parameters of cost and time in a project are not independent. The most important advantage of UQCCs is that it is simple to identify the behavior of EVM indices through these tools. On the other hand, UQCCs monitor the variables (i.e., SPI or SPI(t) and CPI) separately, whereas MQCC takes them as a single dependent pair and analyses these two variables in relation to each other in order to monitor multivariate variability. Three case studies related to three construction projects were considered and both UQCCs and MQCC were depicted and analyzed on them. Lastly, the results obtained from both techniques were interpreted and then compared with each other. Before considering the dependency between the variables (SPI or SPI(t) and CPI) and drawing indicators individually in UQCCs, the results showed that the first and second projects were under control, and the third one contained only three points out of control limits; however, when the relationship between projects' performance indices were included and both indicators were plotted simultaneously in MQCCs, the results demonstrated that several points fell out of the barrier line, and thus were outliers. Having outliers in a MQCC indicates that the project is out of control. Referring to the data set tables, the results obtained from the MQCCs were confirmed. The proposed methodology can be extended by considering other EVM indices, including cause and effect analysis and incorporating parameter uncertainty into the model.

REFERENCES

Abba, W., and Niel, F., 2010, Integrating technical performance measurement with earned value management: The Measurable News, v. 4, p. 6-8.

Acebes, F., Pajares, J., Galán, J. M., and López-Paredes, A., 2013, Beyond earned value management: A graphical framework for integrated cost, schedule and risk monitoring: Procedia-Social and Behavioral Sciences, v. 74, p. 231-239.

Aliverdi, R., Moslemi Naeni, L., and Salehipour, A., 2013, Monitoring project duration and cost in a construction project by applying statistical quality control charts: International Journal of Project Management, v. 31, no. 3, p. 411-423.

Al-Jibouri, S. H., 2003, Monitoring systems and their effectiveness for project cost control in construction: International Journal of Project Management, v. 21, no. 2, p. 145-154.

Barraza, G. A., and Bueno, R. A., 2007, Probabilistic control of project performance using control limit curves: Journal of Construction Engineering and Management, v. 133, no. 12, p. 957-965.

Barraza, G. A., Back, W. E., and Mata, F., 2004, Probabilistic forecasting of project performance using stochastic S curves: Journal of Construction Engineering and Management, v. 130, no. 1, p. 25-32.

Bersimis, S., Psarakis, S., and Panaretos, J., 2007, Multivariate statistical process control charts: an overview: Quality and Reliability Engineering International, v. 23, no. 5, p. 517-543.

Cerioli, A., 2010, Multivariate outlier detection with high-breakdown estimators: Journal of the American Statistical Association, v. 105, no. 489, p. 147-156.

Cioffi, D. F., 2006, Designing project management: A scientific notation and an improved formalism for earned value calculations: International Journal of Project Management, v. 24, no. 2, p. 136-144.

Czernigowska, A., 2008, Earned value method as a tool for project control: Budownictwo i Architektura, v. 3, p. 15-32.

Fan, S. K. S., Huang, H. K., and Chang, Y. J., 2013, Robust Multivariate Control Chart for Outlier Detection Using Hierarchical Cluster Tree in SW2: Quality and Reliability Engineering International, v. 29, no. 7, p. 971-985.

Flyvbjerg, B., 2013, From Nobel prize to project management: getting risks right: Project Management Journal, v. 37, no. 3, p. 5-15.

Gharib, A., Amiri, A. and Jalilibal, Z. 2021. Designing a multivariate exponentially weighted moving average control chart with measurement errors. Journal of Quality Engineering and Production Optimization, v. 6, no. 1, p. 215-232.

Ghute, V., and Shirke, D., 2008, A multivariate synthetic control chart for monitoring process mean vector: Communications in Statistics—Theory and Methods, v. 37, no. 13, p. 2136-2148.

Hadian, H. and Rahimifard, A. (2019). Multivariate statistical control chart and process capability indices for simultaneous monitoring of project duration and cost. Computers & Industrial Engineering, 130, 788-797.

Henderson, K., 2004. Further developments in earned schedule. The measurable news, Spring 2004 15–22.

Henderson, K., 2007. Earned Schedule: A Breakthrough, Extension to Earned Value Management, in Proceedings of PMI Global Congress Asia Pacific.

Hotelling, H., 1947, Multivariate quality control: Techniques of statistical analysis.

Jacob, D., 2003, Forecasting project schedule completion with earned value metrics: The Measurable News, v. 1, no. 1, p. 7-9.

Kalgonda, A., and Kulkarni, S., 2004, Multivariate quality control chart for autocorrelated processes: Journal of Applied Statistics, v. 31, no. 3, p. 317-327.

Kim, B.-C., and Reinschmidt, K. F., 2011, Combination of project cost forecasts in earned value management: Journal of Construction Engineering and Management, v. 137, no. 11, p. 958-966.

Kourti, T., and MacGregor, J. F., 1995, Process analysis, monitoring and diagnosis, using multivariate projection methods: Chemometrics and intelligent laboratory systems, v. 28, no. 1, p. 3-21.

Kramer, H. G., and Schmid, L., 1997, EWMA charts for multivariate time series: Sequential Analysis, v. 16, no. 2, p. 131-154.

Leu, S.-S., and Lin, Y.-C., 2008, Project performance evaluation based on statistical process control techniques: Journal of Construction Engineering and Management, v. 134, no. 10, p. 813-819.

Lipke, W., 2003, Schedule is different: The Measurable News, v. 31, no. 4, p. 31-34.

Lipke, W., 2004, The probability of success: The Journal of Quality Assurance Institute, p. 14-21.

Lipke, W., 2011, Further Study of the Normality of CPI and SPI (t): PM World Today XIII (X).

Lipke, W., Zwikael, O., Henderson, K., and Anbari, F., 2009, Prediction of project outcome: The application of statistical methods to earned value management and earned schedule performance indexes: International journal of project management, v. 27, no. 4, p. 400-407.

Montgomery, D. C., 2007, Introduction to statistical quality control, John Wiley & Sons.
Mortaji, Taha & Noori, Siamak & Bagherpour, Morteza. (2021). Directed earned value management based on ordered fuzzy numbers. Journal of Intelligent & Fuzzy Systems, 297(2): Pages 451-466.
Moslemi Naeni, L., Shadrokh, S., and Salehipour, A., 2013, A fuzzy approach for the earned value management: International Journal of Project Management.
Mousavi, S., Mohagheghi, V. and Vahdani, B., 2015. A New Uncertain Modeling of Production Project Time and Cost Based on Atanassov Fuzzy Sets. Journal of Quality Engineering and Production Optimization, v. 1, no. 2, p. 57-70.
Nassar, K. M., Gunnarsson, H. G., and Hegab, M. Y., 2005, Using Weibull analysis for evaluation of cost and schedule performance: Journal of construction engineering and management, v. 131, no. 12, p. 1257-1262.
Noori, S., Bagherpour, M., and Zareei, A., 2008, Applying fuzzy control chart in earned value analysis: a new application: World Applied Sciences Journal, v. 3, no. 4, p. 684-690.
Pajares, J., and Lopez-Paredes, A., 2011, An extension of the EVM analysis for project monitoring: The Cost Control Index and the Schedule Control Index: International Journal of Project Management, v. 29, no. 5, p. 615-621.
PMI, 2004. Project Management Body of Knowledge (PMBOK®), 3rd ed. Project Management Institute.
PMI, 2005. Practice Standard for Earned Value Management. Project Management Institute.
Shenoy, R. R., 2008, Misuse and performance of individuals charts in statistical process control for single parameter distributions of unknown stability: Operations Research Master's Theses, p. 1.
Soltan, S., and Ashrafi, M. 2020. Predicting project duration and cost, and selecting the best action plan using statistical methods for earned value management. Journal of Project Management, 5(3), 157-166.
Song, J., Martens, A. and Vanhoucke, M. 2021. Using Earned Value Management and Schedule Risk Analysis with resource constraints for project control. European Journal of Operational Research. 40(8):1-14.
Theodossiou, P. T., 1993, Predicting shifts in the mean of a multivariate time series process: an application in predicting business failures: Journal of the American Statistical Association, v. 88, no. 422, p. 441-449.
Vandevoorde, S., and Vanhoucke, M., 2006, A comparison of different project duration forecasting methods using earned value metrics: International Journal of Project Management, v. 24, no. 4, p. 289-302.
Vanhoucke, M. (2016). Integrated Project Management Sourcebook. Gent, Belgium: Springer
Vanhoucke, M., and Vandevoorde, S., 2007, A simulation and evaluation of earned value metrics to forecast the project duration: Journal of the Operational Research Society, v. 58, no. 10, p. 1361-1374.
Votto, R., Lee Ho, L. and Berssaneti, F. 2020. Applying and assessing performance of earned duration management control charts for EPC project duration monitoring. Journal of Construction Engineering and Management, 146(3), 04020001.
Zhan, Z., Wang, C., Hui Yap, J.B., Samsudin, S. and Abdul-Rahman, H. 2019, Earned Value Analysis, Implementation Barriers, And Maturity Level In Oil & Gas Production, South African Journal of Industrial Engineering, v. 30, no. 4, p. 44-59.