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Self-starting control chart and post signal diagnostics for monitoring project earned value management indices

Fatemeh Sogandi[1], Seyed Meysam Mousavi[1*], Amirhossein Amiri[1]

[1]*Department of Industrial Engineering, Faculty of Engineering, Shahed University, Tehran, Iran*

f.sogandi@shahed.ac.ir, sm.mousavi@shahed.ac.ir, amiri@shahed.ac.ir

Abstract

Earned value management (EVM) is a well-known approach in a project control system which uses some indices to track schedule and cost performance of a project. In this paper, a new statistical framework based on self-starting monitoring and change point estimation is proposed to monitor correlated EVM indices which are usually auto-correlated over time and non-normally distributed. Also, a new change point estimator is developed to find the real time of change in the indices mean. Furthermore, a new diagnosing method is presented to recognize the deviated mean index. The performance of the proposed methods is evaluated through simulation studies and an illustrative example.

Keywords: Correlated EVM indices, self-starting monitoring, auto-correlated non-normal indices, change point, diagnosing method, projects

1- Introduction

The earned value management (EVM) methodology leads the engineers to monitor time and cost during projects progress. In reality, the EVM indices are regarded as important tools to appraise project performance in terms of cost and schedule deviations along project lifecycle. Usually, schedule performance index (SPI) and cost performance index (CPI) are measured as project performance indices to conduct project on planned time and cost. The EVM indices can be calculated using dividing earned value (EV) on planned value (PV) and actual cost (AC), respectively. The project performance is suitable when both EVM indices are equal or larger than 1. That is projects will be finished on the planned time and budget or with less needed time and cost. On the other hand, when SPI and CPI are smaller than 1, required time or cost is more than the planned values, and the project progress is not desirable. In these conditions, corrective actions should be performed to achieve project goals effectively.

There are many works on the application of EVM indices. One of the earliest works goes back to Lipke (1999). Afterwards, Burke (2003) claimed that applying the EVM indices can considerably affect the improvement of project performance. Henderson (2004) and Lipke (2003) showed that earned schedule has become a dimension to integrate technical performance with the EVM indices. Also, Fleming and Coppelman (2005) demonstrated that the EVM indices are as the main tools for evaluating performance of the software projects. In addition, Cioffi (2006) developed an improved formalism by considering scientific notations for the CPI and SPI indices.

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*Corresponding author
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Besides, Moslemi Naeni et al. (2011) proposed a fuzzy-based EV model in which the EV index was developed. Then, Moslemi Naeni and Salehipour (2011) presented an approach to deal with fuzzy EV index by applying alpha cuts. Pajares and Paredes (2011) developed the analysis of the EVM to monitor project considering cost and time criteria. Moreover, Zheng and Bi (2013) optimized schedule performance indices through describing schedule performance and the weight value. Chen (2014) proposed an approach to improve the forecasting EV and AC value accuracy. Recently, Acebes et al. (2016) developed an approach for monitoring projects under uncertainty using EVM. Also, Wei et al. (2016) incorporated EVM into engineering project management practices.

Although EVM indices can appraise project performance, they cannot show accepted levels of time and cost deviations. Therefore, applying control mechanism of earned value metrics to monitor continual projects progress state during the time is necessary. In this regard, statistical process control (SPC) tools are used as the important tools to appraise project performance persistently so that deviations are detected in trends of the project more quickly. On the other side, control charts are one of the most important SPC techniques in process monitoring. So far, there are many researches in which control charts are effectually used in process monitoring. For example, Ahmad et al. (2014) proposed Shewhart $\overline{X}$ chart under the repetitive sampling scheme to monitor process mean. Similarly, in monitoring the status of a project, applying control charts for the EVM indices provides useful information. Notably, each variance between earned value and planned value is considered as a signal. In these situations, control charts trigger the out-of-control signal when mean of the EVM indices deviates from expected values to perform prevention or correction actions. Hence, it provides fast feedback on any corrective actions due to effect of boundaries of variances on the project success. In other words, although engineers know state of project from duration and cost point of view by comparison the indices with planned values, they do not understand magnitude of deviations from planned value. In this regard, project managers are more interested in knowing whether the deviations from expected values are or not in agreement with the deviations expected from activities variability.

Several researches have been done about SPC techniques in analysis of the SPI and CPI indices. For instance, Lipke and Vaughn (2000) utilized individuals and moving range (I/MR) control charts and calculated the corresponding control limits. Bauch and Chung (2001) applied the control charts for the EVM indices and assessed single observations related to historical data from twenty similar projects. Afterwards, Anbari (2003) proposed a control chart called target performance chart to appraise the SPI and CPI indices. Wang et al. (2006) also used the control charts with these indices for thirty software projects with non-normality assumption of the indices. Besides,Leu et al. (2006) suggested a new method to control project performance indices. Lombard (2007) controlled the project scheduling and cost baseline. Afterwards, Leu and Lin (2008) enhanced the EVM indices performance by applying individual control charts, in which control limits are obtained from 120 projects gathered in a consulting institution. In addition, Noori et al. (2008) utilized fuzzy control chart to analyze EVM indices. Moreover, MoslemiNaeni et al. (2011) developed fuzzy control charts for controlling the EVM indices. Lipke et al. (2009) improved the capability of engineers to make a better decision using proposing a valid estimating technique of the completion cost and duration. Recently, Aliverdi et al. (2013) used I/MR control charts to evaluate EV indices. Colin and Vanhoucke (2014) presented SPC procedure based on tolerance limits to improve distinguishing power between progresses that occur under the project baseline schedule. After that Colin and Vanhoucke (2015) developed a general framework for SPC approaches in project management. Recently, Bancescu (2016) utilized both EVM methodology and SPC to better control a project schedule progress.

With considering SPC applications for the analysis of EVM indices in the literature, the mentioned works are summarized in table 1 in terms of their main contributions. Moreover, the proposed monitoring scheme is compared with the other studies in this table. As shown in table 1, firstly, related works usually analyze the EVM indices independently, while in some situations this assumption is violated and the SPI and CPI indices are correlated with each other. In other words, increasing or decreasing one of these indices leads to increasing or decreasing the other index, respectively. Therefore, there is a correlation structure between these indices and ignoring this correlation leads to misleading results. Secondly, the most researchers assumed that the EVM indices are normally distributed while this assumption may be violated in real world.

Table 1. The main contributions of researches about integrating SPC tools and monitoring project performance

Contribution / The work	Indices monitoring	Non-normality assumption	Correlation between indices	Auto correlation for any index	Non-certainty	Self-starting monitoring	Diagnosing deviated indices	Change point estimation
Lipke and Vaughn (2000)	✔						✔	
Bauch and Chung (2001)	✔						✔	
Wang et al. (2006)	✔						✔	
Leu et al. (2006)	✔						✔	
Leu and Lin (2008)	✔						✔	
Noori et al. (2008)	✔						✔	
MoslemiNaeni et al.(2011)	✔						✔	
Aliverdi et al. (2013)	✔	✔					✔	
Colin and Vanhoucke (2014)	✔	✔		✔				
Marrero et al. (2014)	✔						✔	
Colin and Vanhoucke (2015)	✔							
Acebes et al. (2015)	✔				✔		✔	
Acebes et al. (2016)	✔				✔			
Băncescu (2016)	✔	✔						
Wei et al. (2016)	✔						✔	
Proposed new statistical approach	✔	✔	✔	✔		✔	✔	✔

Consequently, in this paper independency and normality assumptions are removed. Unlike previous works, an auto-correlation structure is considered for both indices. So far, some researches such as Acebes et al. (2013), Acebes et al (2014, 2015), and Colin and Vanhoucke (2014) used simulation to overcome the problem of lack of data. However, in this study a self-starting control chart is developed to monitor the EVM indices. After getting signal from the proposed control chart, a maximum likelihood estimation approach is used to estimate the real time of a step change in indices. Furthermore, a diagnosing method is applied to demonstrate deviated index from expected performance.

The structure of the paper is organized as follows: next section explains procedure in removing assumptions. Section 3, at first, proposes an approach for self-starting monitoring the EVM indices, and then, a maximum likelihood estimation approach is provided to estimate a step change in EVM indices. Also, a signal diagnostic method in monitoring EVM indices is presented. Section 4 shows a performance evaluation for proposed procedure, and section 5 provides an illustrate example in detail. Finally, conclusions are given in section 6.

2- Developed framework

The EVM indices are used to measure project progress state. Analysis of these indices is a critical issue for the success of the project. Integrating the control charts with the EVM indices allows engineers to monitor continually the performance indices because the EVM indices provide a snapshot of performance during the time. Hence, using control charts in the EVM leads to reduction in project cost and time and decrease the problem of project team judgments.

Usually, based on underlying assumptions in applying control charts, observations should be normally and identically distributed. Moreover, they should be statistically independent of each other i.e., an observation should not effect on the other observations. Hence, firstly, it is necessary that assumptions of applying SPC are established with considering projects real aspects. In this regard, Lipke (2002) declared that the analysis of control charts may be affected when the normality assumption is not satisfied. For this aim, Lipke (2011) utilized logarithm transformation of the EVM indices in eight projects to obtain normal distributed indices in which the EVM indices are computed for labor. As Wang and Romagnoli (2005) stated "process data are conventionally characterized by normal distribution and techniques based on this assumption could suffer performance and efficiency losses when the assumption is violated". Hence, the data with non-normal distribution need to be transformed to the normal distribution using some transformation methods. For example, Aslam et al. (2015) presented a new control chart by transforming quality characteristics. In this paper, the Johnson transformation technique is used to transform EVM indices to normal distribution. It should be noted that cost performance is strongly correlated with the time performance. Hence, monitoring of the EVM indices simultaneously provides very useful result for project progress state analysis. Therefore, in this paper correlation between the EVM indices is also investigated. On the other hand, it is clear that the SPI and CPI indices have auto-correlated nature during project lifecycle. In fact, these indices are affected by previous indices in the project progress. On the other hand, Martin and Morris (1996) claimed that a basic requirement of SPC techniques is that the data are independent. However, process control typically generates auto-correlated data, and this tends to increasing false alarm rate. In this regard, some approaches are utilized to consider auto-correlated structure. One of the main approaches for describing structure of the auto-correlated EVM indices is using time series models. It should be noted that control chart is applied in the residuals to reduce the autocorrelation structure from the EVM indices. Often, it is assumed that the auto-correlated indices come from a multivariate first-order autoregressive (MAR (1)) as the following equation:

$$\mathbf{x_t} = \mathbf{\Phi}\,\mathbf{x_{t-1}} + \mathbf{a_t}, \tag{1}$$

in which $\mathbf{x_t} = (SPI_t, CPI_t)$ and $\mathbf{\Phi}$ is a constant matrix equal to $\begin{bmatrix} \phi_{SPI} & \phi_{SPI\ CPI} \\ \phi_{SPI\ CPI} & \phi_{CPI} \end{bmatrix}$ and $\mathbf{a_t}$ is defined as random shock with mean vector $\underline{\mathbf{0}}$ and covariance-variance matrix of $\mathbf{\Sigma_0} = \begin{bmatrix} \sigma^2_{a_{SPI}} & \rho\sigma_{a_{SPI}}\sigma_{a_{CPI}} \\ \rho\sigma_{a_{SPI}}\sigma_{a_{CPI}} & \sigma^2_{a_{CPI}} \end{bmatrix}$ where ρ is correlation between indices ($-1 \le \rho \le 1$). On another hand, the (MAR(1)) is defined as equation (2).

$$\mathbf{x_t} - \boldsymbol{\mu} = \mathbf{\Phi}\,(\mathbf{x_{t-1}} - \boldsymbol{\mu}) + \mathbf{a_t},$$

(2)

in which $\boldsymbol{\mu}$ is mean vector of the observation. We assume that the mean vector and covariance-variance matrix and $\boldsymbol{\mu}$ in Equation (2) are known based on a historical dataset. It should be noted that $\mathbf{e_t} = (e_{SPI,t}, e_{CPI,t})$ vectors are observation residuals achieved by using difference between $\mathbf{x_t}$ and its forecasted values in t^{th} period. To summarize proposed methodology, first a scheme of the schedule and cost performance indices monitoring is given in figure 1. Then, the steps are discussed in the next section in details.

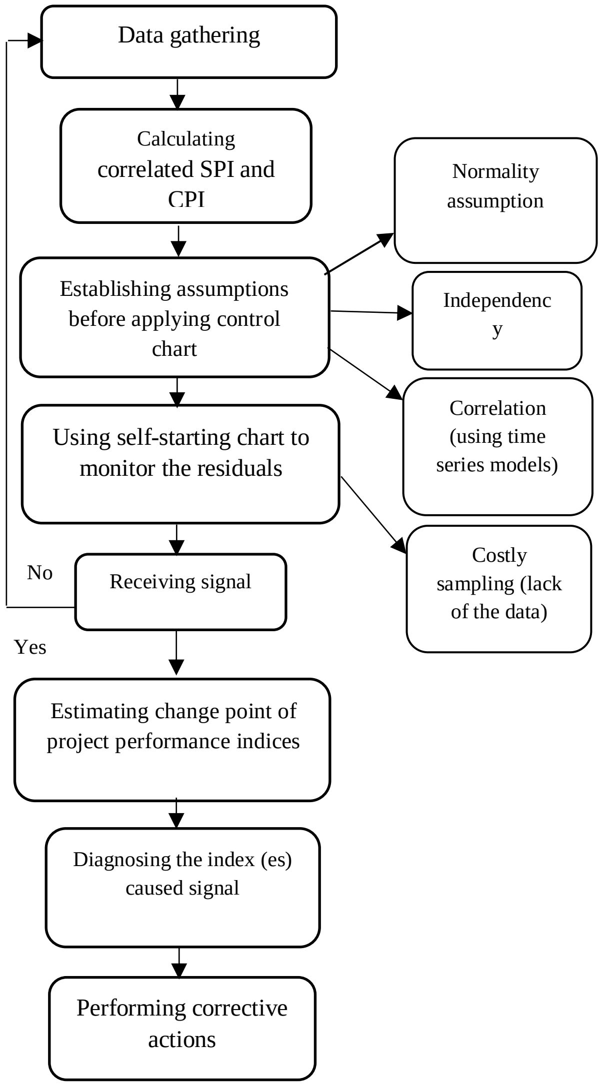

Fig. 1 Flowchart of the proposed statistical approach for monitoring of EVM indices

3- Proposed procedure of the monitoring framework

Based on the aforementioned explanations, the SPC-based EVM gives effective information to engineers about the trend of the performance indices during the project progress. In this section, a statistical procedure is discussed to appraise project performance indices in details. Note that, in real applications, usually the project performance is auto-correlated and non-normally distributed. In addition, there is correlation structure between indices. Also, the number of data is not enough to estimate the parameters. Hence, in this paper, a multivariate self-starting residual based control chart is utilized for monitoring purpose. Moreover, an estimator is proposed to find the real time of a step change in the mean of project performance indices. Thereafter, a diagnostic method is applied to find deviated index from expected performance. The proposed procedures of the framework for monitoring the EVM indices monitoring are described in steps following subsections.

3-1- Self-starting control chart for EVM indices monitoring

Usually traditional control charts are used assuming that process parameters are determined or may be estimated using large historical dataset. In addition, large samples lead to the estimates close to the true value. However, there are not enough historical data to estimate the process parameters because projects are not repetitive. Also, large sample cannot be collected owing to lack of data during the time or costly sampling. Therefore, the self-starting control charts are more suitable than the classic control charts in this situation. In fact, they use consecutive samples to update the EVM indices estimates during project progress (for more details see Quesenberry (1991)). Not that in this situation, there is little data, so statistic can be updated from previous samples is method. So, we initiate using a self-starting control chart to monitor the EVM indices among different phases of the project. In this respect, a self-starting statistic proposed by Quesenberry (1991) called as **Q** statistic is applied according to equation (3).

$$\mathbf{Q_r}(\mathbf{x_r}) = \Phi^{-1}\left\{\mathbf{G_{r\text{-}2}}\left[\left(\frac{r-1}{r}\right)^{\frac{1}{2}}\left(\frac{\mathbf{x_r}-\bar{\mathbf{x}}_{\mathbf{r\text{-}1}}}{\mathbf{s_{r\text{-}1}}}\right)\right]\right\},\ r=3,4,... \tag{3}$$

In which r is the sample number, $\mathbf{x_r}$ and $\mathbf{s_r}$ are the EVM indices mean vector and their standard deviation, respectively. Also, $\mathbf{G_{r\text{-}2}}$ is the Student's t distribution function with r-2 degrees of freedom and Φ^{-1} denotes the inverse of the standard normal distribution function. Also, the residuals obtained from the time series model (MAR (1)) are used in the **Q** statistic instead of the vector $\mathbf{x_r}$. The self-starting control chart monitors the EVM indices without using an historical dataset. It utilizes the deviation of each project performance index vector from the average of all previous indices and allows starting effectual monitoring of the EVM indices as soon as possible. In addition, the Q statistics follow standardized normal distribution. Afterwards, this statistic is plotted on a multivariate control chart named as T^2 control chart according to equation (4) (See Twigg and Thomson (1995) for more information).

$$T_r^2 = (\mathbf{Q_r}-\mathbf{Q_0})\Sigma_0^{\mathbf{-1}}(\mathbf{Q_r}-\mathbf{Q_0}),\ r=3,4,... \tag{4}$$

where $\mathbf{Q_0}$ and $\mathbf{\Sigma}_0$ denote mean vector and covariance-variance matrix of the **Q** statistic. So, they are equal to vector $\underline{0}$ and $\begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix}$, respectively. The correlation coefficient of ρ in **Q** statistics is estimated by 10000 simulation runs. After that, the upper control limit (UCL) of the T_r^2 control chart is set in such a way that a probability of Type I error is obtained by simulation. For this purpose, first an initial value is set for UCL and the probability of Type I error is computed as the portion of out-of-control signals to the total number of iterations through simulation runs. Then, through a trial-and-error process, the UCL is set such that a predetermined probability of Type I error is obtained. The T_r^2 statistic exceeds the UCL when the mean vector of the EVM indices changes. When a negative shift in the mean vector of EVM indices occurs, project team should be considered corrective actions. In contrast, if the mean vectors of the EVM indices are faced to positive shift, project team should be considered an opportunity to modify planning of the current project schedule and cost.

3-2- Change point estimation in EVM indices monitoring

Control charts have been proven to be effective in detecting abnormal conditions in project performance indices. They are effectual tools to reduce variation of project performance by monitoring EVM indices during the time. In other words, the control charts demonstrate project cost and schedule performance indices over time against project control limits. The control limits usually define the area of three standard deviations on both sides of the centerline. After that, the statistics plotted on a control chart until a signal is observed. Often, time the control chart alarms is not exactly the real time of a shift in the EVM indices. Figure 2 demonstrates a schematic example from a control chart. As seen in this figure, there are some delays from signal point to real change point in project performance indices.

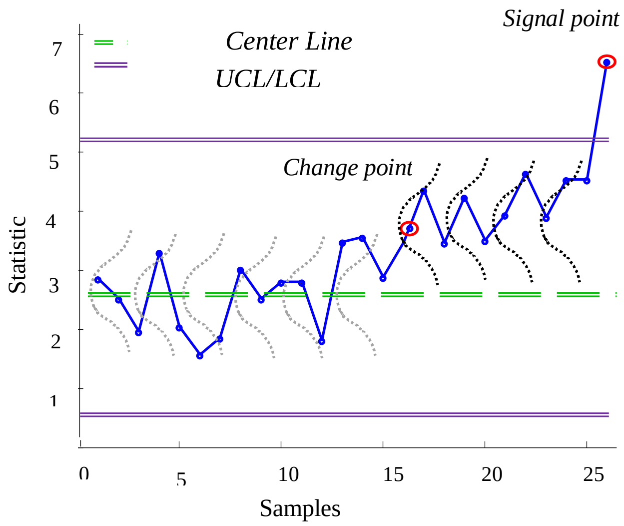

Fig 2. A schematic example from a delay between signal point and change point

Hence, identification of exact time that EVM indices have changed would simplify explorations, removing of the assignable cause, and improving project progress. Consequently, having an estimation of the change point of the EVM indices mean would be very useful. Since using this estimation leads to elimination the sources of control chart signals as soon as possible. The change point estimation in monitoring project performance indices mean vector is worth especially in mega projects due to saving considerable cost and time.

According to previous section, to apply control chart, project performance indices should be independent and normally distributed. For this purpose, the residuals distributions of performance indices are transformed to Normal distribution. So, let $\mathbf{e}_i^{'} = (e_{i1}^{'}, e_{i2}^{'})^T$ as the bivariate Normal distribution residual vector in the i^{th} period after transformation. Assume further that when the project is under ordinary condition, the $\mathbf{e}_\mathbf{i}^{'}$'s are independent and identically distributed and follow a bivariate Normal distribution with mean vector of $\mathbf{e}_\mathbf{0}^{'}$ and covariance-variance matrix of $\sum_0^{'}$ where it can be estimated in 10000 simulation runs. Since, we consider a step shift in the EVM indices, the parameters of residual vector remain at the new level until the source of the assignable cause is identified and omitted. Hence, the parameters of residual vector are equal to the corresponding in-control state for $i = 1, 2, ..., \tau$ and they become equal to unknown parameters of $\mathbf{e}_1$ for periods $i = \tau + 1, \tau + 2, ..., T$. Moreover, T is the last EVM indices vector sampled. There are two unknown values τ and $\mathbf{e}_1$ which represent the last period in the in-control process and the out-of-control residual mean vector of EVM indices, respectively. To estimate this unknown mean vector along with the change point, we use the MLE approach. MLE of $\tau(\hat{\tau})$ is estimate mean vector such that maximizes the likelihood function of observations (See Nedumaran et al.(2000) in details). The proposed change point estimator using the MLE approach is computed as follows:

$$\hat{\tau} = \arg\max\{M_t\},\ t = 0, 1, ..., T-1. \tag{5}$$

The value of M_t in Equation (5) is calculated based on the following equation:

$$M_t = (T - t)(\overline{\mathbf{e}_{\mathbf{t,T}}^{'}} - \overline{\mathbf{e}^{'}})^T \textstyle\sum_{\mathbf{e}^{'}}^{-1}(\overline{\mathbf{e}_{\mathbf{t,T}}^{'}} - \overline{\mathbf{e}^{'}}), \tag{6}$$

where

$$\overline{\mathbf{e}'_{\mathbf{t,T}}} = \frac{\sum_{i=t+1}^{T} \mathbf{e}'_{\mathrm{i}}}{T-t}. \tag{7}$$

3-3- Signal diagnostic in monitoring EVM indices

The SPC-based EVM integrates variations into budget and schedule within the project scope to provide variation of current performance indices for project manager. Common cause of variation is defined as the permissible variation present in the project progress because of its own nature. In contrast, special cause of variation is caused by unrespectable events on the project. The control chart is used to show whether a project is affected by either common cause of variation or special cause of variation. On the other hand, it should be noted that one of the problems with any multivariate control charts is determining the quality characteristic responsible for out-of-control signal.

So far, the EVM indices have been monitored by using the proposed methodology. Also, the real change point is estimated by the maximum likelihood method to save the time and cost for corrective actions. It is worth mention that diagnosing deviated performance index increases effectiveness corrective actions. In other words, if mean of schedule performance index is changed, engineers should be concentrated on corrective action recommendations related to modification of schedule plan, and vice versa. Moreover, the corrective actions on time and cost should be balanced when the EVM indices mean have been shifted simultaneously because the performance indices have a reciprocal effect on project progress. Overly, accurate corrective actions lead to save project resources.

Hence, we apply an approach to diagnose responsible index from Hotelling's T^2 control chart. This method decomposes the T^2 statistic into elements that reflect the contribution of each individual index. Assume the current statistic and $T^2_{(SPI)}$ is the statistic when the index SPI is omitted from the calculation. Also, $T^2_{(CPI)}$ is T^2 statistic when the index CPI is omitted. Runger et al. (1996) showed that $d_{(SPI)}$ and $d_{(CPI)}$statistics are relative contribution of the SPI and CPI indices to the overall T^2 statistic, respectively and declared that the $d_{(SPI)}$ and $d_{(CPI)}$ statistics are computed as follows, respectively:

$$d_{SPI} = T^2 - T^2_{SPI}, \tag{8}$$

$$d_{SPI} = T^2 - T^2_{SPI}, \tag{9}$$

Then, the UCL of the $d_{(SPI)}$ and $d_{(CPI)}$statistics is set in such a way that a probability of type I error is obtained by simulation. Similarly, first an initial value is set for UCL and the probability of type I error is computed as the portion of out-of-control signals to the total number of iterations through simulation runs. Then, through a trial-and-error process, the UCL is set such that a desirable probability type I error is obtained. Finally, if each of the $d_{(SPI)}$ and $d_{(CPI)}$ statistics exceed corresponding control limits, it shows that index is responsible for out-of-control project performance.

4- Performance evaluation

In this section, a Monte Carlo simulation is conducted to evaluate performance of the proposed methodology using well known criteria with 10000 replications. For this aim, it is assumed that the random shocks corresponding to the schedule and cost performance indices are generated from a uniform distribution with mean vector $\underline{\mathbf{0}}$, and their covariance-variance matrix is equal to $\begin{bmatrix} 1 & 0.375 \\ 0.375 & 1 \end{bmatrix}$. Also, the SPI and CPI indices are generated according to time series model (MAR(1)) in equation (1) in which $\begin{bmatrix} \phi_{SPI} & \phi_{SPI\ CPI} \\ \phi_{SPI\ CPI} & \phi_{CPI} \end{bmatrix} = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix}$ and μ is considered equal to [1 1]. As aforesaid, the residuals of the time series model are monitored instead of recessive project performance indices to make the statistic independent over time. So, residuals of the time series model are calculated by using difference between the actual EVM indices, $\mathbf{x_t}$ and the value $\hat{\mathbf{x}}_{\mathbf{t}}$ that would be obtained from a least squares fit of the underlying analysis of variance model to the observations. Now, residuals of time series model (MAR (1)) also, follow a uniform distribution. Here, the Johnson transformation technique is utilized to transform distribution of the residuals to normal. In this regard, the best transformation function for residuals of the time series model of the SPI and CPI are obtained by 10000 simulations as follow, respectively.

$$e'_{SPI,t} = 0.014 + 1.231 \times log\left(\left(e_{SPI,t} + 0.018\right) / \left(0.019 - e_{SPI,t}\right)\right),$$

$$e'_{CPI,t} = -0.032 + 1.268 \times log\left(\left(e_{CPI,t} + 0.019\right) / \left(0.018 - e_{CPI,t}\right)\right).$$

Recall from the previous section, the $\mathbf{Q_r}$ control chart begins monitoring the process without the need for preliminary data for the EVM indices and updates the parameter estimates with each new sample and simultaneously monitors the project performance indices. Hence, we use corresponding residuals to in $\mathbf{Q_r}$ (r=3,4, …) statistic according to equation (2) to monitor project performance indices. The initial mean vector of $\mathbf{Q}$ statistic is equal to $[0\ 0]$ and the correlation coefficient of ρ between residuals is estimated equal to 0.368 by 10000 simulation runs, so the $\mathbf{\Sigma}_0$ is equal to $\begin{bmatrix} 1 & 0.368 \\ 0.368 & 1 \end{bmatrix}$. On the other hand, HotellingT^2 control chart accounts for the correlation structure of EVM indices. Hence, this chart can show an evidently perspective of the project performance indices. Hence, we apply the $\mathbf{Q_r}$ statistic in the HotellingT^2 statistic to monitor the residuals corresponding to project performance indices.

In this respect, a well-known criterion named as Average Run Length (ARL) is utilized to evaluate the performance of the control chart. The ARL is the average of the number of periods which should pass before a statistic falls out of control limits. When the project is out-of-control or subject to risk, ARL_1 is the average numbers of periods passes until a control chart alarms. Note that the lower ARL_1 leads to better performance control charts in detecting shifts. In this respect, the UCL is set equal to 7.58 using simulation runs. Then, we impose the shifts magnitude δ in the EVM indices mean in 100th period, and then obtain ARL_1 under different step shifts in EVM indices separately or simultaneously to evaluate proposed method.

Afterwards, a change point estimator is proposed because control charts usually tardily alarm when mean values of the EVM indices shift. Hence, a change point estimator is suggested using equations (5-7) in which $\Sigma_{\mathbf{e}}^{-1}$ and $\overline{\mathbf{e}}$ in equation (6) are obtained with averaging 10000 simulation runs as follows:

$$\overline{\mathbf{e}'} = [0.002 \quad 0.003],\ \mathbf{\Sigma}_{\mathbf{e}'}^{-1} = \begin{bmatrix} 1.0350 & 0.3676 \\ 0.3676 & 1.0720 \end{bmatrix}.$$

The performance of the proposed method in shift detecting is evaluated in terms of ARL_1 in the mean values of the EVM indices. Moreover, the mean value and standard deviation of the change point estimator referred to accuracy and precision, respectively, determine the performance of the proposed estimator under different step mean shifts in the EVM indices. The mean value and standard deviation of the estimator are shown in tables 2 to 4 and denoted by $\overline{\hat{\tau}}$ and Std($\hat{\tau}$), respectively. Also, precisions of change point estimator are given in terms of the probability that $\hat{\tau}$ lies in the specified tolerance from τ. This criterion is defined with $p(|\hat{\tau} - \tau| \le i)$ and denoted by Pr_i where i is considered equal to 0, 1, 2, 3, 4 and 5. Results coming from Mont Carlo simulation are shown in tables 2 to 4 for negative shift in indices mean vector of the EVM indices. In addition, performance evaluation of the proposed approach is appraised under positive shifts in tables 5 to 7.

Table 2. The ARL_1 and performance of change point estimator under negative shifts in the SPI index

	Shift	-0.001	-0.005	-0.01	-0.02	-0.05	-0.1	-0.5
Accuracy	ARL_1	165.19	161.69	153.33	140.56	137.85	124.82	104.12
	$\bar{\hat{\tau}}$	97.87	97.9	98.57	98.85	99.11	99.97	99.99
	Std($\hat{\tau}$)	1.12	1.1	1.15	1.1	1.04	0.91	0.95
Estimator Precision	Pr_0	0.05	0.07	0.13	0.15	0.19	0.24	0.28
	Pr_1	0.11	0.16	0.18	0.19	0.21	0.26	0.33
	Pr_2	0.19	0.22	0.29	0.28	0.3	0.35	0.39
	Pr_3	0.24	0.36	0.39	0.38	0.41	0.49	0.51
	Pr_4	0.27	0.4	0.46	0.45	0.47	0.51	0.57
	Pr_5	0.31	0.42	0.49	0.52	0.53	0.55	0.62

Table 3. The ARL_1 and performance of change point estimator under negative shifts in the CPI index

	Shift	-0.001	-0.005	-0.01	-0.02	-0.05	-0.1	-0.5
Accuracy	ARL_1	166.18	164.38	152.2	150.56	140.76	133.92	125.09
	$\bar{\hat{\tau}}$	97.11	97.55	98.06	98.21	99.35	99.98	99.99
	Std($\hat{\tau}$)	1.93	1.12	1.04	0.89	1.01	0.9	0.92
Estimator Precision	Pr_0	0.08	0.15	0.16	0.2	0.23	0.24	0.35
	Pr_1	0.23	0.22	0.23	0.25	0.27	0.26	0.42
	Pr_2	0.26	0.25	0.3	0.34	0.35	0.35	0.51
	Pr_3	0.35	0.4	0.42	0.45	0.47	0.46	0.58
	Pr_4	0.41	0.42	0.49	0.51	0.55	0.55	0.63

Table 4. The ARL_1 and performance of change point estimator under negative shifts in the EVM indices

	Shift	-0.001	-0.005	-0.01	-0.02	-0.05	-0.1	-0.5
Accuracy	ARL_1	161.15	159.55	147.93	141.8	134.55	131.13	125.8
	$\bar{\hat{\tau}}$	97.55	97.99	98.51	98.75	99.21	99.97	99.98
	Std($\hat{\tau}$)	1.5	1.03	0.95	1.11	0.97	0.81	0.92
Estimator Precision	Pr_0	0.12	0.14	0.18	0.25	0.26	0.29	0.33
	Pr_1	0.19	0.25	0.26	0.26	0.3	0.31	0.37
	Pr_2	0.25	0.29	0.32	0.34	0.36	0.38	0.42
	Pr_3	0.36	0.35	0.45	0.45	0.46	0.48	0.51
	Pr_4	0.41	0.42	0.47	0.52	0.58	0.58	0.64

Table 5. The ARL_1 and performance of change point estimator under positive shifts in the SPI index

	Shift	0.001	0.005	0.01	0.02	0.05	0.1	0.5
	ARL_1	163.15	160.79	155.33	149.96	147.25	132.72	120.56
Accuracy	$\bar{\hat{\tau}}$	97.67	97.88	98.28	98.64	99.41	99.95	99.98
	Std($\hat{\tau}$)	1.3	1.09	1.1	0.96	1.01	0.89	0.96
Estimator Precision	Pr_0	0.06	0.08	0.13	0.15	0.19	0.25	0.35
	Pr_1	0.12	0.15	0.17	0.18	0.2	0.27	0.31
	Pr_2	0.18	0.24	0.26	0.27	0.33	0.34	0.39
	Pr_3	0.23	0.37	0.38	0.38	0.42	0.45	0.49
	Pr_4	0.28	0.41	0.45	0.46	0.46	0.49	0.55
	Pr_5	0.32	0.39	0.48	0.51	0.53	0.54	0.62

Table 6. The ARL_1 and performance of change point estimator under positive shifts in the CPI index

	Shift	0.001	0.005	0.01	0.02	0.05	0.1	0.5
	ARL_1	164.18	163.38	153..2	148.56	144.55	132.94	130.5
Accuracy	$\bar{\hat{\tau}}$	97.11	97.55	98.06	98.21	99.35	99.97	99.98
	Std($\hat{\tau}$)	1.53	1.12	1.04	0.89	1.01	0.9	0.98
Estimator Precision	Pr_0	0.06	0.08	0.13	0.15	0.19	0.25	0.28
	Pr_1	0.12	0.15	0.17	0.18	0.2	0.27	0.35
	Pr_2	0.18	0.24	0.26	0.27	0.33	0.34	0.41
	Pr_3	0.23	0.37	0.38	0.38	0.42	0.45	0.52
	Pr_4	0.28	0.41	0.45	0.46	0.46	0.49	0.65
	Pr_5	0.32	0.39	0.48	0.51	0.53	0.54	0.71

Table 7. The ARL_1 and performance of change point estimator under positive shifts in the EVM indices

	Shift	0.001	0.005	0.01	0.02	0.05	0.1	0.5
	ARL_1	160.17	158.25	146.91	140.8	135.75	130.21	125.32
Accuracy	$\bar{\hat{\tau}}$	98.75	98.98	98.35	98.1	99.89	99.98	99.99
	Std($\hat{\tau}$)	0.96	0.98	1.1	1.01	0.99	0.8	0.82
Estimator Precision	Pr_0	0.06	0.08	0.13	0.15	0.19	0.25	0.34
	Pr_1	0.12	0.15	0.17	0.18	0.2	0.27	0.37
	Pr_2	0.18	0.24	0.26	0.27	0.33	0.34	0.44
	Pr_3	0.23	0.37	0.38	0.38	0.42	0.45	0.51
	Pr_4	0.28	0.41	0.45	0.46	0.46	0.49	0.59
	Pr_5	0.32	0.39	0.48	0.51	0.53	0.54	0.64

The results show that the proposed procedure performs well in monitoring project cost and scheduling performance indices under different shifts. In addition, the simulation results show that the performance of the change point estimator is satisfactory under different shifts in terms of the precision and accuracy criteria. In addition, as the magnitude of the step shift in the mean of EVM indices increases, the detection power of shift and performance of the change point estimator enhance. By comparison between different shifts in the EVM indices (separately and simultaneously), it is concluded that the proposed approach has more ability in detecting the simultaneously shifts against the separate shifts in the mean of EVM indices. It is claimed that the proposed approach could handle auto-correlated cost and schedule performance indices coming from time series model (MAR(1)). Afterwards, the change point estimator can estimate the real change point using the proposed approach to improve planning of the engineers.

Identification of the EVM indices responsible for unstable condition in project is a critical issue in project management as well, because signal diagnostic leads to saving time and cost in conducting corrective actions. So, we performed diagnosing procedure of releasing signal from T^2 control charts in order to identify the responsible index for out-of-control. For this purpose, the d_{CPI} and d_{SPI} statistics are calculated according to discussed method in subsection 3.3. Also, the UCL for the d_{CPI} and d_{SPI} statistics is set equal to 6.67 and 5.75, respectively. Then, if each of the statistic exceeds the corresponding UCL, it is introduced as the index responsible for the out-of-control condition.

Signal diagnosing percent is provided the responsible index under different shifts. Hence, in Tables 8 and 9 diagnosing percent of the EVM indices under different mean shifts is provided under negative and positive shift, respectively. As seen in the results, when a shift is occurred in CPI, diagnosing percent of the CPI are more than other states (SPI and simultaneously shift). Also, the proposed approach gives more diagnosing percent for the SPI when the SPI mean shifts. Similarly, it provides more diagnosing percent for the both of indices when the CPI and SPI mean shifts simultaneously. In addition, when the magnitude of both positive and negative shifts increases, the performance of diagnosing procedure improves and the percent of correct diagnostic increases. This shows the satisfactory performance of the proposed diagnosing procedure.

Table 8. The performance of diagnosis method in monitoring project under negative shifts in the mean of EVM indices.

Shift		-0.001	-0.005	-0.01	-0.02	-0.05	-0.1	-0.5
Shift in SPI	SPI	0.41	0.43	0.40	0.38	0.45	0.40	0.42
	CPI	0.28	0.35	0.25	0.29	0.26	0.28	0.30
	CPI & SPI	0.16	0.12	0.21	0.20	0.15	0.17	0.19
Shift in CPI	SPI	0.29	0.31	0.26	0.34	0.25	0.28	0.30
	CPI	0.43	0.45	0.41	0.39	0.43	0.39	0.41
	CPI & SPI	0.18	0.16	0.2	0.21	0.19	0.21	0.23
Simultaneous Shift	SPI	0.24	0.25	0.31	0.29	0.29	0.24	0.26
	CPI	0.33	0.30	0.28	0.31	0.22	0.30	0.32
	CPI & SPI	0.36	0.34	0.34	0.37	0.39	0.41	0.43

Table 9 The performance of diagnosis method in monitoring project under positive shifts in the mean of EVM indices.

Shift		0.001	0.005	0.01	0.02	0.05	0.1	0.5
Shift in SPI	SPI	0.43	0.41	0.40	0.42	0.44	0.41	0.43
	CPI	0.27	0.33	0.24	0.28	0.27	0.27	0.29
	CPI & SPI	0.16	0.14	0.18	0.19	0.18	0.19	0.21
Shift in CPI	SPI	0.31	0.30	0.26	0.33	0.27	0.30	0.32
	CPI	0.43	0.44	0.42	0.39	0.42	0.41	0.43
	CPI & SPI	0.16	0.16	0.20	0.18	0.17	0.18	0.20
Simultaneous Shift	SPI	0.24	0.24	0.26	0.29	0.26	0.25	0.27
	CPI	0.32	0.29	0.27	0.32	0.21	0.28	0.30
	CPI & SPI	0.37	0.33	0.35	0.38	0.41	0.42	0.44

5- An illustrative example in projects

An illustrative example is given to illustrate the application of the proposed methodology. The **Q** statistics are generated according to the previous section. Afterwards, a shift is imposed with δ =-0.02 magnitude in 20th period in the CPI mean. This negative shift shows that project exceeds its devoted cost. So, in these situation engineers should try on enhancement of the project progress after signals are discarded. Figure 3 shows a self-starting Hotelling's T^2 control chart constructed based on the **Q** statistics. The Hotelling's T^2 control chart alarms tardily unfavorable condition of project in 35th period. Hence, the proposed change point estimator in equations (5-7) is applied to estimate the real change point in project performance indices. The change point is computed in 26th period that it is close to exact change point in project performance. Also, the proposed diagnostic method in subsection 3.3 can utilized to identify the responsible index that caused the signal under probability of type I error equal to 0.01.

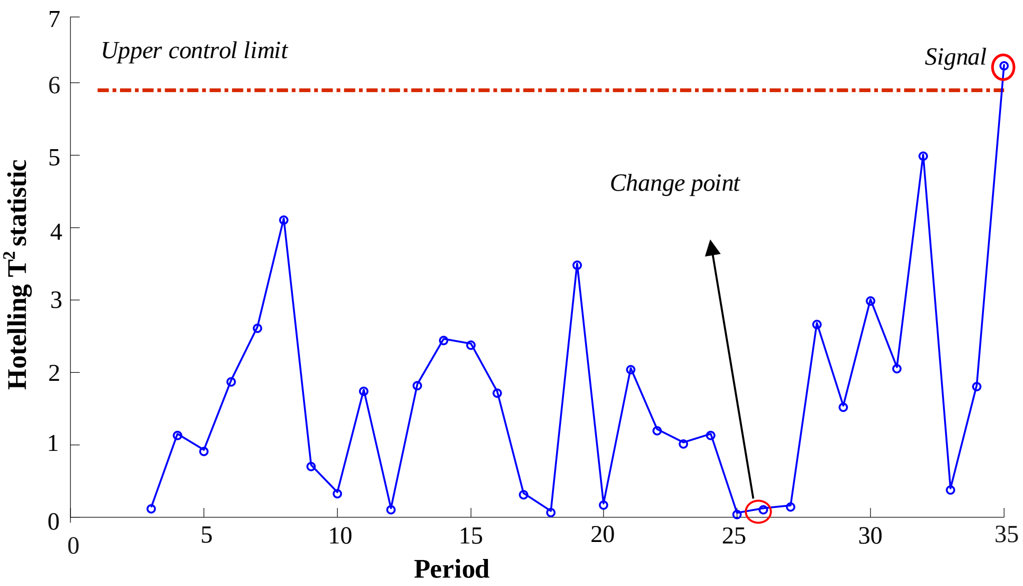

Fig 3. Simultaneously monitoring of EVM indices under shift in CPI index

6-Conclusion

The earned value management indices cannot give results about variation of the project progress during the time. This study introduced a novel statistical approach based on a self-starting monitoring using multivariate control chart to analyze EVM performance indices. So, a self-starting monitoring was proposed in monitoring earned value indices owing to costly sampling and lack of historical dataset. In addition, EVM indices can be auto-correlated and follow a non-Normal distribution in which these indices are considered correlated. On the other hand, an estimator was proposed for the first time in the literature of projects to find the real time of a step change in indices mean. In this regard, performance of the proposed change point estimator appraised by Mont Carlo simulation. Moreover, a diagnosing method was applied, unlike the previous studies, to show deviated index from expected performance. The performance of the proposed procedure was investigated through an illustrative example in projects. Finally, it was concluded that the proposed framework for the EVM indices monitoring enhanced considerably the project controlling scheme and saving in time and cost.

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